Self-Harming Trade Policy? Protectionism and Production Networks*

Alessandro Barattieri†
ESG UQAM

Matteo Cacciatore‡
HEC Montréal, Bank of Canada, and NBER

September 2, 2021
(First Draft: March 2019)

Abstract

Using monthly data on temporary trade barriers (TTBs), we estimate the dynamic employment effects of protectionism through vertical production linkages. First, exploiting high-frequency data and TTB procedural details, we identify trade policy shocks 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. The effects in downstream industries are negative, sizable, and significant. The employment decline follows an increase in intermediate-input and final goods prices, and a decline in stock market returns.

JEL Codes: F13; F14; F62.

Keywords: Protectionism; Input-Output Linkages; Local Projections;

*For very helpful comments, we thank our discussants Carlo Altomonte and Dennis Novy, as well as George Alessandria, Pol Antràs, Andrew Bernard, Marinho Bertanha, Emily Blanchard, Hafedh Bouakez, Paola Conconi, Jonathan Eaton, Gabriel Felbermayr, Nuno Limão, Sophie Osotimehin, Walter Steingress, and audiences at the Bank of Canada, the 2019 CEPR IMF Programme Meeting, the 2019 Sardinia Empirical Trade Conference, the 2020 CEBRA Annual Conference, the 2021 Asian Meeting of the Econometric Society, the University of Rochester Trade and Macroeconomics Workshop. We are grateful to Neil Maru for excellent research assistance. All remaining errors are ours.

†ESG UQAM. Mail: Case Postale 8888, sucursale Centre-ville Montreal (Quebec) H3C 3P8. E-mail: barattieri.alessandro@uqam.ca. URL: https://www.sites.google.com/site/barattierialessandro/..

‡HEC Montréal, Institute of Applied Economics, 3000, chemin de la Côte-Sainte-Catherine, Montréal (Québec). E-mail: matteo.cacciatore@hec.ca. URL: http://www.hec.ca/en/profs/matteo.cacciatore.html.

1 Introduction

In 2018, the U.S. administration imposed new tariffs on roughly 12% of imports, and the ensuing trade war sparked debates on the effects of protectionism to unprecedented levels. One of the distinguishing features of recent U.S. trade policy is the involvement of global supply chains (Krugman, 2018, and Baldwin, 2018). Such a focus 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 for the last two decades.

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-chain considerations, systematic econometric evidence on protectionism's effects through vertical production linkages remains scant. We address this issue by studying the employment effects of TTBs in protected and downstream industries.

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 use of monthly data allows us to exploit features of TTB procedures that impose short-run restrictions relevant to identifying trade policy shocks. Fifth, the use of TTBs allows us to conduct the analysis at NAICS 4-digit industries—encompassing 70 narrowly defined manufacturing sectors—the most detailed level at which comprehensive data for employment, producer prices, and input-output relationships are available at a consistent level of aggregation.

We construct monthly time series for the U.S. 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 outcomes (e.g., duties), since the latter are likely to be anticipated by economic agents—for instance, the opening

[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`.

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, a key economic outcome in the policy discussions that motivate protectionism.

We first 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 (e.g., Romer and Romer, 2004, and Auerbach and Gorodnichenko, 2013). The idea is to purge a given series (TTB protection in our case) of movements representing a response to past, current, and expected dynamics of a given variable of interest (e.g., employment). The remaining variation allows us to identify the effects of protectionism within and across industries.

We identify trade-policy shocks using within-industry time-series variation in TTBs. For robustness, we also consider a specification that uses the data's panel dimensions. 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 since TTBs respond to business cycle dynamics (e.g., Bown and Crowley, 2013). Moreover, we address the potential forward-looking nature of protection's demand, a hypothesis typically disregarded by the trade literature since TTBs address pre-existing trade injuries. Using firm-level data, we construct for each industry a benchmark measure of expected returns from the finance literature, the market-to-book ratio (e.g., Pontiff and Schall, 1998, and subsequent literature). We show these sectoral measures have forecasting power for industry-employment growth and contain information about TTB petitioners' expected profitability. We also include industry and time fixed effects with panel data, thus controlling 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 TTB 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).

We estimate panel local projections using the identified trade-policy shocks to determine the dynamic effects of protectionism in protected and downstream industries. Local projections construct impulse responses as a direct multistep forecasting regression without imposing (potentially inappropriate) dynamic restrictions. Since Jorda (2005), local projections have become a well-established tool 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, 2020). We then investigate the aggregate effects of upstream protectionism by considering the most significant TTB episodes in our sample and the impact of average upstream-industry shocks. We account for general equilibrium effects by measuring employment spillovers across manufacturing sectors and estimating local projections using aggregate data.

Finally, we inspect the main economic mechanisms through which upstream protectionism affects downstream employment outcomes. We use industry-level price and stock-market data. We construct input price measures to test whether upstream protectionism leads to higher input costs and final producer prices. We use (daily) stock market data to confirm whether upstream protectionism leads to lower downstream profitability.

Our analysis yields three main results. First, protectionism has small and short-lived beneficial effects on industry employment. The effects are, in general, statistically insignificant.[2]

Second, protectionism has negative, persistent, and statistically-significant effects on employment in downstream industries. A uniform one-percentage-point increase in the share of imports subject to new TTBs—approximately corresponding to a one-percentage-point uniform import tariff—generates an average industry employment decline equal to 0.15 percentage point after one year. When analyzing manufacturing and aggregate employment response, we find that TTB tariffs result in a statistically significant decline in both variables. While TTBs have small aggregate effects on average—for instance, the average aggregate employment loss after one year is 0.034%—the impact is larger in the most important historical episodes—the employment loss is 0.29% in our sample's most significant case. The results suggest that more extensive use of TTBs—or a broader application of similar tariffs—would lead to considerable long-lasting negative employment effects through vertical production linkages.

Third, a loss of competitiveness can rationalize the negative downstream-employment effects. Both intermediate-input and final producer prices increase following upstream protectionism, and the increase in prices precedes the employment decline. Using daily data, we also find that new TTBs lead to a statistically significant and lagged reduction in downstream-industry stock returns, confirming the decline in downstream industry profitability. The delayed response is consistent

[2] This finding is consistent with different explanations, including possible heterogeneous responses across producers (e.g., different exposure to products covered by TTBs), offsetting forces determining industry's output demand (e.g., expenditure switching versus negative income effects), foreign retaliation, and import substitution towards countries not affected by TTBs.

with finance literature that documents lead-lag effects among equities along the supply chain (e.g., Cohen and Frazzini, 2008, and Menzly and Ozbas, 2010).

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

Related Literature Recent contributions study the 2018-2019 trade war. Amiti, Redding, and Weinstein (2019) find that the U.S. experienced substantial increases in intermediates and final goods prices, reductions in the availability of imported varieties, and complete tariff pass-through on imported goods. Fajgelbaum, Goldberg, Kennedy, and Khandelwal (2020) estimate import demand and export supply elasticities using changes in U.S. and retaliatory tariffs. Using a general equilibrium framework that matches these elasticities, they find substantial aggregate and regional impacts of U.S. tariffs. Flaaen and Pierce (2019) document a decline in U.S. manufacturing employment and an increase in producer prices. Rising input costs and retaliatory tariffs contributed to these outcomes.[3] Our analysis differs from these studies along three main dimensions. First, we estimate how protectionism in sectors producing key intermediate-input affects the dynamics of employment, prices, and stock-market returns along the supply chain. Second, we propose a novel approach to deal with protectionism's endogeneity, using monthly data to identify trade policy shocks. Third, we use twenty years of data, exploiting TTB variation over time and across industries and countries. Our analysis and approach provide new insights that complement the literature on the U.S. trade war.

Another strand of the literature focuses on the consequences of value chains for tariff settings. Blanchard, Bown, and Johnson (2016) show that global supply chains modify countries' incentives to impose import protection, while Erbahar and Zi (2017) find that protection granted to intermediate manufacturers leads to petition for protection by their downstream users. Baqaee and Farhi (2019) show that global value chains increase protectionism's welfare cost. We contribute to this literature by providing empirical evidence on the dynamic effects of protectionism through vertical production linkages. In a paper complementary and subsequent to ours, Bown, Conconi, Erbahar, and Trimarchi (2020) use TTB data to study the long-run effects of trade protection along supply

[3] 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.

chains.

Recent literature studies the effects of TTBs abstracting from production networks. A strand of the literature focuses on the effects of antidumping on trade flows (Bown and Crowley, 2007, and Durling and Prusa, 2006) and aggregate trade volumes (Lu, Tao, and Zhang, 2013, and Vandenbussche and Zanardi, 2010). Barattieri, Cacciatore, and Ghironi (2021) study the effects of both TTBs and tariffs on macroeconomic outcomes.[4] Trimarchi (2018) addresses the role of U.S. antidumping duties to contain the so-called "China Syndrome," i.e., the effects of rising Chinese import competition on U.S. local labor markets. Except Barattieri, Cacciatore, and Ghironi (2021), all these studies focus on annual data, and none of them addresses the effects of protectionism through input-output linkages.

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. Also, there are significant 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.[5] Second, while trade liberalization reduces tariffs against a large set of countries, protectionism targets selected exporters. Third, trade liberalization typically occurs with other structural reforms, rendering identifying the effects of a given policy change more challenging.

Finally, our paper is also related to the burgeoning literature that studies the emergence of global value chains—see Antràs and Chor (2021) for an exhaustive review—and their implications for aggregate dynamics (e.g., di Giovanni and Levchenko, 2010).

[4] 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. 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 to economic fundamentals.

[5] 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)

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 sell goods in a country at less than fair value ("dumped"). Countervailing duties proceedings determine whether foreign governments unfairly subsidize their exporters. Global safeguards actions determine whether imports of a particular good are a substantial cause of injury or threat 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 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 industry's establishment 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 TTB policy actions, three aspects matter for our analysis. Consider the case of antidumping for illustrative purposes (countervailing duties 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. We exploit such decision lags when identifying trade-policy shocks. Second, the opening of an investigation is immediately announced to the public, and agents can access the supporting evidence about dumping margins. The disclosed evidence implies that tariffs are predictable at the time of the investigation since antidumping duties are commensurate to the dumping margins. To avoid possible anticipatory effects, we focus on investigations rather than on their outcome.[6] Finally, imposed tariffs can be

[6] 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

retroactive (up to the beginning of the investigation).

Descriptive Statistics

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.[7] 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 TTB 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 Appendix G, we show that considering global safeguards does not qualitatively affect the results.

The use of TTBs is concentrated in a few industries. In Table 1, we consider the eight industries that feature the highest number of TTB episodes in the sample period, accounting for approximately 70% of all investigations. The first column records both the number of TTB 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 industry "Iron, Steel, and Ferro-Alloy" accounts for approximately 50% of all investigations.

The second column in Table 1 shows that most investigations end up with duties' imposition. For instance, in "Iron, Steel, and Ferro-Alloy," 82% of the investigations result in tariffs. 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). The average tariff duration (reported in brackets in the third column) ranges between eight and ten years across industries.

Column 4 reports the average sectoral import share affected by TTB episodes. Column 5 reports

the mere opening of an antidumping investigation has effects on imports.

[7] 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.

Table 1: Top TTB Users, Descriptive Statistics

Top TTB Users (NAICS-4 Code)	Episodes (Products)	% Success	Median Tariff (Duration in Months)	New TTBs, Average Import Share	New TTBs, Max Import Share	2007 Sectoral Imports/Output
Iron, Steel and Ferro Alloy (3311)	60 (457)	82%	35.1% (111)	1.87%	8.89%	33.55%
Basic Chemical (3251)	44 (63)	75%	101.0% (107)	0.21%	2.26%	14.56%
Other Fabricated Metals (3329)	15 (28)	80%	57.5% (125)	1.53%	8.14%	37.04%
Steel Products From Purchased Steel (3312)	11 (33)	64%	27.9% (116)	11.09%	31.50%	8.61%
Resin, Rubber, Fibers (3252)	10 (14)	90%	24.8% (98)	1.04%	3.18%	14.56%
Spring and Wire Products (3326)	9 (11)	100%	116.3% (125)	7.23%	21.33%	36.49%
Agr., Constr., and Mining Machinery (3331)	8 (21)	88%	193.5% (115)	1.34%	4.97%	59.37%
Nonferrous Metal Production (3314)	7 (17)	86‘%	60.5% (102)	0.73%	2.09%	64.99%

the maximum value of this import share. The broadest import coverage occurs in "Steel Product Manufacturing from Purchased Steel" (11.09%), with a peak equal to 31.5%. For the industry that uses TTBs the most ("Iron, Steel, and Ferro-Alloy"), new TTBs involve approximately 2% of industry imports on average, although the largest episode covers 9% of imports. Finally, column 6 shows that the top TTB users display high imports-to-output ratios.

TTB Users and Production Linkages

We now address 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) cell in the table reports 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.[8] The latter 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

[8] 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.

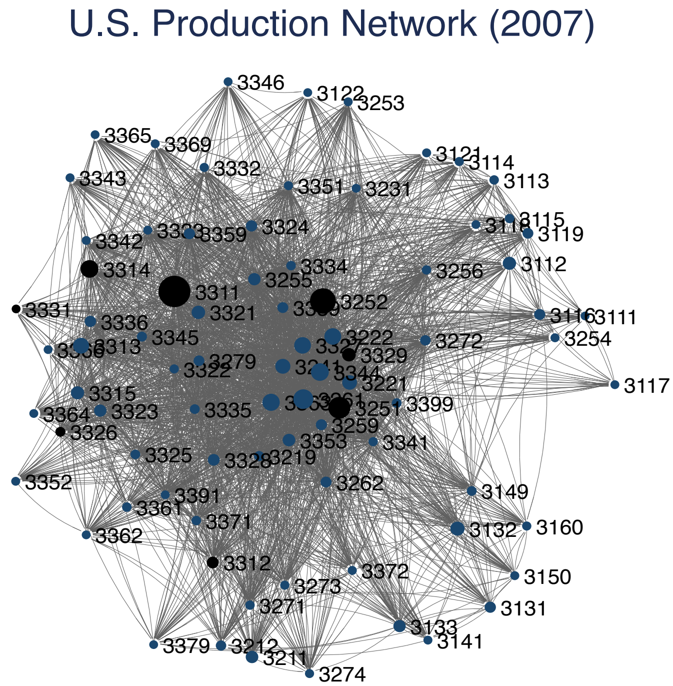

Figure 1: Production network using 2007 NAICS 4-digit input-output tables.

Parts," then "Motor Vehicle Parts" uses "Steel&Iron" as an input indirectly).

Figure 1 plots the U.S. production network in 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. A larger circle in the network implies a larger input usage by downstream industries. The figure shows the centrality of the industries that actively use TTBs.

Table 2 provides additional quantitative information. The first column measures each industry's output share relative to the total U.S. manufacturing output in 2007. Columns 2 and 3 report the average direct requirement and the maximum requirement in downstream industries, respectively. Columns 4 and 5 consider total requirements. The table shows the largest TTB users are also important intermediate-input suppliers. For instance, the industry that uses TTB the most ("Iron, Steel, and Ferro-Alloy") accounts, on average, for approximately 5% of all intermediate inputs used by other manufacturing industries (column 4); the maximum input share is 45%. The total intermediate-input share of the top TTB users averages 21.5% (column 4), whereas the same industries account for approximately 13% of manufacturing output (column 1).[9]

[9] The entries in columns 2 and 4 are summable since we express them as a weighted average of downstream requirements. The weights correspond to the output share of downstream users.

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%	2.27%	35.70%	4.79%	44.80%
Basic Chemical (3251)	4.23%	2.15%	44.72%	8.25%	84.56%
Other Fabricated Metals (3329)	0.59%	0.66%	3.63%	1.14%	4.77%
Steel Products From Purchased Steel (3312)	0.18%	0.42%	17.68%	0.40%	19.15%
Resin, Rubber, Fibers (3252)	1.92%	1.69%	36.77%	3.16%	41.78%
Spring and Wire Products (3326)	0.43%	0.09%	6.85%	0.16%	7.38%
Agr., Constr., and Mining Machinery (3331)	1.59%	0.003%	0.255%	0.25%	1.00%
Nonferrous Metal Production (3314)	1.10%	1.00%	18.29%	3.41%	35.59%
Total	**12.7%**	**7.96%**		**21.50%**	

Baseline Measure of TTB Protection

We now describe the baseline measure of TTB 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 each month. We use previous-year import data to construct the weights. We focus on the import coverage of new TTBs to account for the fact that both the number of product lines under investigation and the value of imports affected by TTBs change over time. This approach ensures that a case involving a single HS code that entails a large value of trade is not 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:

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

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 investigations on 27 imported products against 11 trading partners.[10] The imports covered by the investigations represented 3.7% of the steel sector's imports in 1999. This is our measure for November 2000.

While the use of previous-year weights addresses endogeneity concerns, it potentially introduces measurement error in τ_{it}. In Section 6 and Appendix G, we show the results are robust to considering alternative approaches to measure protectionism.

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 most important TTB episodes (see Table 1).[11] Over time, the industry "Iron, Steel, and Ferro-Alloy" features the most significant variation in the share of imports subject to new investigations. Across sectors, τ_{it} displays weak autocorrelation—the autocorrelation function is never significantly different from zero across industries. Similarly, τ_{it} features a weak correlation across industries—the average bilateral contemporaneous cross-correlation is equal to 0.045. Finally, the TTB import shares display some modest countercyclicality, with a few spikes occurring at times of negative employment growth.

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 identify import protection movements that are plausibly exogenous to employment dynamics. In the second stage, we use the identified TTB shocks to estimate industry employment's monthly response following protectionism. We now describe the identification strategy and the measure of exposure to protectionism through vertical production linkages—"upstream protectionism" henceforth.

Identification Strategy

Our approach builds on a consolidated strategy in the monetary and fiscal policy literature (e.g., Romer and Romer, 2004, and Auerbach and Gorodnichenko, 2013). The idea is to purge a given series (TTB protection, τ_{it}, in our case) of movements that represent an endogenous response to

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

[11] See Appendix A for the industries not reported in Table 1.

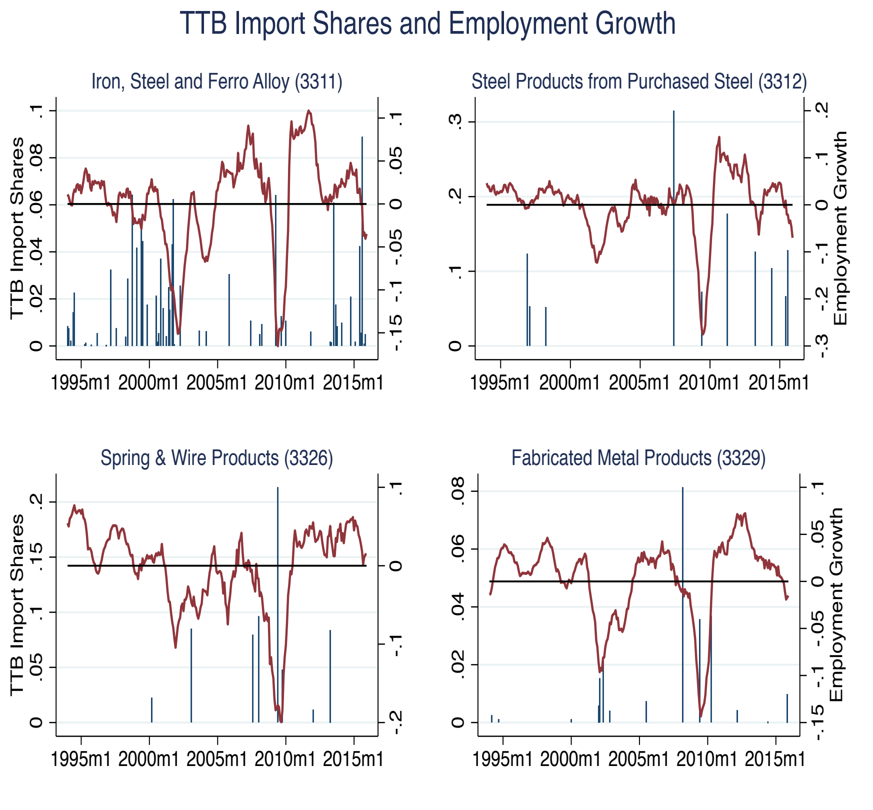

Figure 2: Share of imports affected by new TTB investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

past, current, and expected dynamics of a given variable of interest (employment in our case).[12] Once this is accomplished, it is possible to use the remaining variation to estimate causal effects.

We identify TTB variation plausibly exogenous to employment dynamics using within-industry time-series variation in TTBs. We also consider a specification that exploits the data's panel dimensions, including fixed effects, for robustness. In both cases, we regress the import share subject to new TTBs (τ_{it}) on specific industry-level controls and exploit features of TTB procedures to impose short-run restrictions.

First, we control for lagged employment growth since the trade literature shows that TTBs respond to past economic conditions (e.g., Bown and Crowley, 2013). Second, we exploit regulation-induced lags in the opening of new investigations to address simultaneity concerns—TTB inves-

[12] Romer and Romer (2004) estimate the effects of monetary policy by removing movements in the policy rate taken in response to past, current, and expected outcomes in the interest variable (e.g., output). Auerbach and Gorodnichenko (2013) use a smilar strategy to identify the effects of fiscal shocks. In contrast to these studies, we use stock market data (rather than aggregate Greenbook projections) to control for industry-level expectations—NAICS 4-digit employment forecasts are not available.

tigations cannot react to economic shocks within a month, as discussed in Section 2. Third, we address the potential forward-looking nature of protection's demand. The trade literature typically dismisses such a possibility since TTBs address pre-existing trade injuries.[13] Nevertheless, using firm-level data, we construct industry-specific, time-varying measures of expected profitability. We focus on the market-to-book ratio, a benchmark measure in the accounting and finance literature to proxy growth opportunities and expected returns. Results are robust to considering a different expected profitability measure, the price-to-earnings ratio. We show these sectoral measures contain information about TTB petitioners' expected profitability.

We also control for downstream employment growth and a downstream-measure of the market-to-book ratio to address reverse-causality concerns when studying protectionism's propagation through vertical production linkages. We deal with aggregate shocks and expectations using time fixed effects and macroeconomic forecast data.

The identified trade-policy shocks are conditionally exogenous to employment dynamics in protected industries and downstream sectors. As highlighted by the trade and antitrust literature, the remaining variation in TTBs reflects several factors, including 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).

The identified shocks may also contain variation that reflects economic factors uncorrelated with employment. While this possibility does not prevent the consistent estimation of employment outcomes (e.g., Cochrane, 2004), it may affect the estimated effects of TTB shocks on other economic variables—in our context, the response of input and final producer prices discussed in Section 5. Since price data are available at a consistent level of aggregation (NAICS 4-digit) from 2004, we control for price dynamics only when studying price responses. To provide additional robustness, in Appendix G, we also consider a broader set of industry-level controls in the first stage regression, including hourly earnings, imports, the price-to-earnings ratio, sales, and commodity prices. This strategy purges the identified shocks from additional economic forces driving TTB variation over time.

We consider the industries that use TTBs the most since too few episodes in an industry (if any) pose econometric challenges that prevent consistent identification. We focus on the eight industries

[13] Petitions must contain statistical data to support the allegation that the domestic industry has been materially injured, and the data must cover the three most recent complete calendar years.

in Table 1. We now present in detail the two identification approaches.

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 between $[0,1]$.[14] Also, 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 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:

$$\begin{aligned}\mu_{it} \equiv \delta_i &+ \sum_{\kappa=1}^{p_L} \phi_{L_i}^{\kappa} \Delta L_{it-\kappa} + \sum_{\kappa=1}^{p_{L^{DI}}} \phi_{L_i^{DI}}^{\kappa} \Delta L_{it-\kappa}^{DI} \\ &+ \sum_{\kappa=1}^{p_{MB}} \phi_{MB_i}^{\kappa} MB_{it-\kappa} + \sum_{\kappa=1}^{p_{MB^{DI}}} \phi_{MB_i^{DI}}^{\kappa} MB_{it-\kappa}^{DI} + \sum_{\kappa=1}^{p_x} \mathbf{\Phi}_x^{\kappa} \mathbf{x}_{t-\kappa},\end{aligned} \tag{3}$$

where δ_i is a constant term, and $\mathbf{x}_t$ is a vector of aggregate controls. Industry-level variables include lags of the following controls: the growth rate of employment (ΔL_{it}), the growth rate of employment in downstream industries (ΔL_{it}^{DI}), the median market-to-book ratio (MB_{it}), and its downstream counterpart (MB_{it}^{DI}). Aggregate controls include the real exchange rate's growth rate and the median expected industrial production's growth (four quarters ahead) from the Survey of Professional Forecasters. The inclusion of time fixed effects in the second stage regression further controls for aggregate shocks and expectations. We include twelve lags for the growth rate of

[14] Empirical studies explaining fractional responses have proliferated in recent years. A few examples include pension plan participation rates, industry market shares, television ratings, the fraction of land area allocated to agriculture, and test pass rates.

employment, as well as three lags for ΔL_{it}^{DI}, MB_{it}, MB_{it}^{DI}, and the aggregate variables. We do not include lags of the dependent variable given the absence of autocorrelation in τ_{it}.

We discuss the data in Appendix A. Here we focus on the construction of the market-to-book ratio, MB_{it}. Using firm-level data from Compustat/CRSP covering more than 7,000 companies, we take 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. The industry-level market-to-book ratio, MB_{it}, corresponds to the median market-to-book ratio across firms within each manufacturing NAICS 4-digit code.

The market-to-book ratio contains information about future industry employment growth. Appendix A plots MB_{it} for the industries in Table 1.[15] Visual inspection shows that a decrease (increase) in industry employment (ΔL_{it}) typically follows a decrease (increase) in MB_{it}. Table 3 reports the results of a test of Granger causality. We use data for all NAICS 4-digit manufacturing industries, regressing employment growth on lags of ΔL_{it} and MB_{it} (Column I). We also include industry-fixed effects (column II) and time-fixed effects (column III). An F-test of the joint significance of the market-to-book ratio coefficients always rejects the null hypothesis of zero significance at the 1-percent level, showing MB_{it} has forecasting power for employment growth.[16]

The market-to-book ratio also contains information about TTB petitioners' expected profitability. To illustrate this result, we construct a petitioner-specific market-to-book ratio for the industry that uses TTBs the most ("Iron, Steel, and Ferro-Alloy," industry 3311). For each of the sixty TTB episodes in that industry, we identify the petitioners present in Compustat and CRSP through a match by company name. In industry 3311, about 20% of firms are also TTB petitioners in our sample period. We use those firms to compute a petitioner-specific median market-to-book ratio. This variable has a very high correlation (approximately equal to 0.95) with the market-to-book ratio for the whole industry, $MB_{3311,t}$—see Appendix A for additional details.

The own-industry market-to-book ratio captures the overall industry's expected profitability, including the effects of downstream dynamics. Nevertheless, we use input-output tables to construct

[15] We do not include the market-to-book ratio in the first stage regression for industry 3326 since there are missing observations. The results are robust to excluding this industry from the analysis.

[16] Excluding the market-to-book ratio increases the mean squared error by approximately 10% across the three specifications.

Table 3: Granger Causality

Dep Variable: Empl. Growth	(1)	(2)	(3)
MB_{t-1}	0.00002	0.00000	-0.00005
	(0.00018)	(0.00008)	(0.00007)
MB_{t-2}	0.00007	0.00006	-0.00001
	(0.00018)	(0.00009)	(0.00007)
MB_{t-3}	0.00021**	0.00020**	0.00010
	(0.00019)	(0.00009)	(0.00007)
MB_{t-4}	0.00030***	0.00029***	0.00017**
	(0.00019)	(0.00009)	(0.00007)
MB_{t-5}	0.00032***	0.00030***	0.00015**
	(0.00018)	(0.00009)	(0.00007)
MB_{t-6}	0.00042***	0.00040***	0.00021***
	(0.00018)	(0.00008)	(0.00007)
Joint F-test	17.99	13.97	4.65
P-value	0.000	0.000	0.000
Lagged Empl. Growth (12 lags)	Yes	Yes	Yes
NAICS4 FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.790	0.797	0.850
N	17710	17710	17710

a downstream measure of the market-to-book ratio (from the perspective of upstream industries that use TTBs). A primary advantage of including the downstream market-to-book ratio is that it allows us to control better for expected profitability in industries where the own-industry market-to-book ratio is a less precise predictor of future employment outcomes. The downstream market-to-book ratio is

$$MB_{it}^{DI} \equiv \sum_{j \neq i} \lambda_{ij} MB_{jt},$$

where MB_{jt} is industry-j's market-to-book ratio in month t. The fixed weight λ_{ij} measures the share of industry-j's use of industry-i's output using the 2007 input-output table.[17] The definition of MB_{it}^{DI} implies the market-to-book ratio in industry j is more important for industry-i's expected outcomes when the sector-j is a larger buyer of sector-i's output.

[17] The use of fixed weights has the advantage of addressing endogeneity concerns (at the cost of potentially introducing measurement error).

We construct employment growth in downstream industries, ΔL_{it}^{DI}, similarly:

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

Panel Approach

We consider an alternative approach that exploits both cross-sectional and time-series variation in TTB protection. Using the panel of upstream sectors, we can include industry and time fixed effects in the first stage regression, adding to those included in the second-stage estimation. Fixed effects allow us to control for unobserved heterogeneity and further remove the effects of aggregate shocks and expectations from TTB dynamics. However, fixed effects potentially remove variation in τ_{it} unrelated to economic conditions, which we would not like to discard. Also, this approach imposes symmetric coefficients across industries.

We consider the following regression:

$$\begin{aligned} \tau_{it} = \alpha_i &+ \sum_{\kappa=1}^{p_L} \phi_L^{\kappa} \Delta L_{it-\kappa} + \sum_{\kappa=1}^{p_{L^{DI}}} \phi_{L^{DI}}^{\kappa} \Delta L_{it-\kappa}^{DI} \\ &+ \sum_{\kappa=1}^{p_{MB}} \phi_{MB}^{\kappa} MB_{it-\kappa} + \sum_{\kappa=1}^{p_{MB^{DI}}} \phi_{MB^{DI}}^{\kappa} MB_{it-\kappa}^{DI} + \eta_t + \varepsilon_{it}, \end{aligned} \tag{4}$$

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. 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.[18]

Results

The estimated residuals from equation (2) and (4) are the identified TTB shocks. Regardless of the econometric model, 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 on each industry-specific residual $\hat{\varepsilon}_{it}$ to detect the presence of serial autocorrelation. We also consider

[18] We use the within-group estimator. This estimator potentially induces a correlation between the regressors and the error term when demeaning the data (Nickell, 1981). However, the long temporal dimension of the panel ("large T") substantially mitigates endogeneity concerns since the bias decreases asymptotically with T. This is confirmed by the fact that we obtain very similar results when estimating (4) by OLS or in first difference.

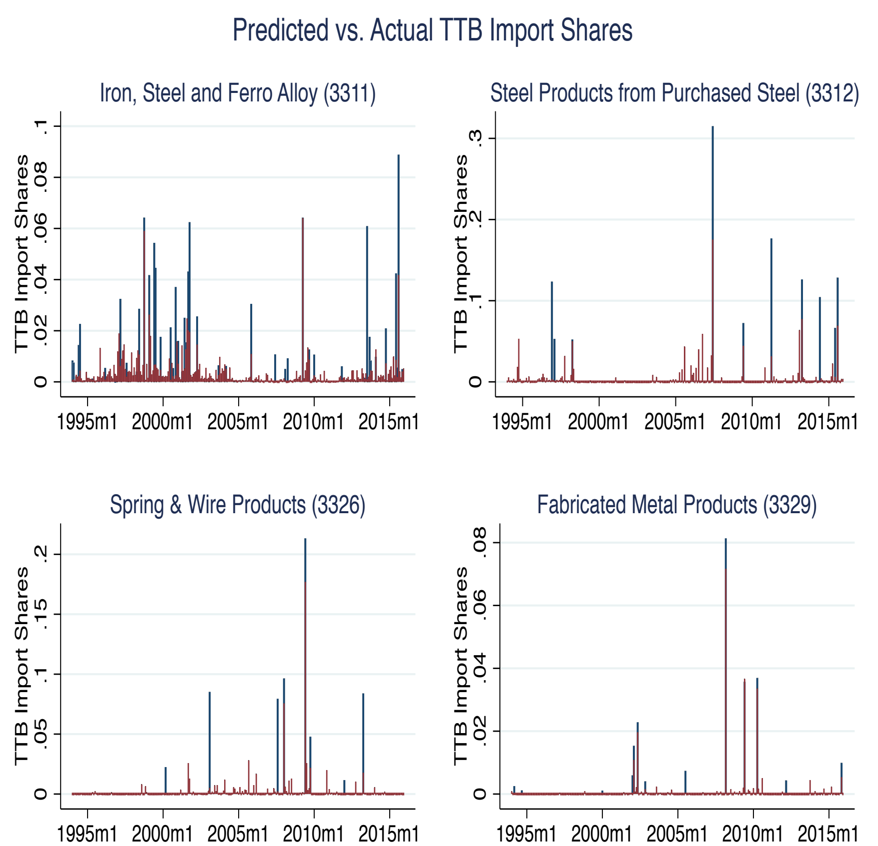

Figure 3: Share of imports affected by new TTB investigations in selected NAICS-4 industries (light, red histograms) and predicted values from the fractional-response model (dark, blue histograms).

a multivariate Ljung-Box test to detect potential correlation across industries. As shown in Table 4, we cannot reject the null hypotheses of zero serial autocorrelation and zero contemporaneous cross-correlation at the 5% significance level.

Figure 3 plots the predicted sectoral TTB import shares estimated by the fractional-response model against the data (see also Appendix B for the remaining industries). 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 for several spikes in TTBs across industries, particularly in the second part of the 2000s. When considering spikes in τ_{it} that are larger than one standard deviation, the predicted τ_{it} explains, on average, 46% of the actual variation. At the same time, there remains unexplained TTB variation in various episodes. The pseudo-R^2 varies between 40% and 12% across industries (see Table 4).

The trade-policy shocks identified with the panel approach—equation (4) above—are positively

Table 4: First-Stage Estimation, Shock Properties

		NAICS-4 Industry Code							
Identification Approach	Statistics	3311	3251	3329	3312	3326	3252	3314	3331
Time Series	Pseudo R-squared	0.12	0.11	0.37	0.29	0.33	0.32	0.40	0.35
(Fractional Logit)	Industry Ljung-Box Test (p-value)	0.85	0.78	0.99	0.83	0.96	0.96	0.96	0.47
	Joint Ljung-Box Test (p-value)	0.67							
Panel	R-squared	0.18							
	Industry Ljung-Box Test (p-value)	0.17	0.97	0.23	0.99		0.94	0.98	0.23
	Joint Ljung-Box Test (p-value)	0.44							

correlated with the estimated residuals from the fractional-response model. For the industry "Iron, Steel, and Ferro Alloy"—the most important TTB user in our sample—the correlation is 0.76, while on average it is 0.44.

Measuring Upstream Protectionism

We now turn to the construction of the industry-specific measure of upstream protectionism. We follow the trade literature that studies the long-run effects of input-tariff reductions (e.g. Amiti and Konings, 2007). We combine the identified TTB 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 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.[19] 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 TTBs in protected industries and through vertical production linkages. We estimate impulse response functions using Jorda (2005)'s local projection method. The approach

[19] When aggregating the sectoral shocks, $\hat{\varepsilon}_{it}^{IO}$ ignores that $\hat{\varepsilon}_{jt}$ are sectoral trade-share residuals. As discussed in Section 6, the results are robust to expressing each $\hat{\varepsilon}_{jt}$ as a share of aggregate imports.

consists of running a sequence of predictive regressions of a variable of interest on a structural shock for different prediction horizons. The impulse responses correspond to the sequence of regression coefficients of the structural shock.

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

The Effects of TTBs in Protected Industries

Let $\Delta L_{it+h} \equiv \log L_{it+h} - \log L_{it-1}$ denote the cumulative employment difference between time t and $t+h$. Let $\hat{\varepsilon}_{it}$ denote the trade-policy shocks identified in the first stage for sector i. We estimate the following set of h-steps ahead predictive panel regressions, for $h = 0, .., H$:

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

where ν_{ih} denotes an industry fixed effect, ψ_{t+h} is a time fixed effect, 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 time trends is important, as industries 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.

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 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.[20]

[20] We conduct wild-bootstrap tests of the linear hypothesis $\gamma_h = 0$ for each $h = 0, .., H$. We consider 1000 replications and cluster by NAICS 4-digit industries.

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:

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

As in equation (6), we include both industry and time fixed effects. The coefficients of interest are γ_h^{IO} for $h = 0, .., H$. We include all the manufacturing industries in the sample when estimating equation (7).[21]

Results

Figure 4 plots the impulse responses using the trade-policy shocks identified with the time-series approach in (2). The continuous line reports the point estimate of each γ_h, while the grey area plots the 90% bootstrapped confidence interval.

The top panel plots the average response of employment in protected industries. We consider a 1% increase in the share of imports subject to new TTBs.[22] The employment response is never statistically significant, a result consistent with Flaaen and Pierce (2019) who document a similar finding when analyzing the U.S.-China trade war. Alternative possible explanations exist for the lack of significant employment effects in protected industries. First, there could be heterogeneous responses across producers within the protected industry, including a different exposure to products covered by TTBs. Second, as discussed in Barattieri, Cacciatore, and Ghironi (2021), trade protection triggers both expenditure switching and income effects, two offsetting forces. Expenditure switching increases demand in protected industries, while the negative income effect due to higher prices has an opposite effect. Third, there could be trading partners' retaliation following U.S. TTBs and import substitution towards countries that do not face U.S. protectionism.

The picture is different when looking at the downstream effects of protectionism. The bottom panel in Figure 4 plots the employment response following protectionism in upstream industries. We consider a uniform 1% increase in the share of imports subject to new TTBs across upstream sectors. On average, protectionism triggers statistically significant negative effects on downstream-

[21] Since TTBs are used only in a few manufacturing industries, we do not control for $\hat{\varepsilon}_{it}$ when estimating downstream effects. Results are robust to including ε_{it}.

[22] This value is a mid-point between the average shock identified across TTB episodes (1.2%) and the shocks' standard deviation (0.81%).

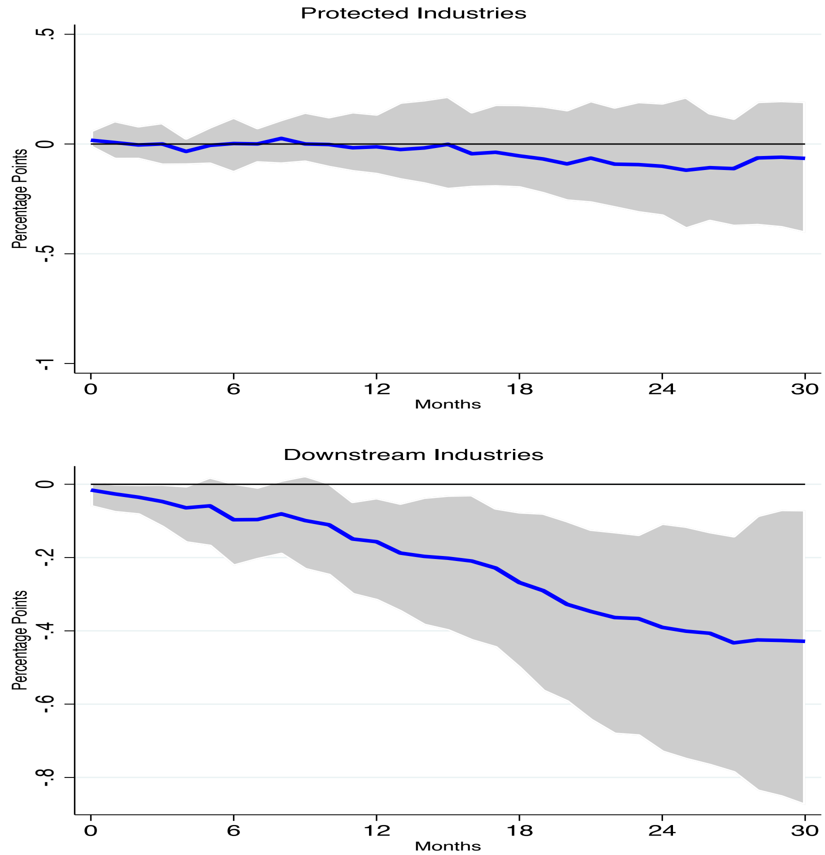

Figure 4: Impulse responses following a protectionism shock. *Top panel*: Average employment response in protected industries. *Bottom panel*: Average downstream-industry employment response. First stage: Fractional-response model.

industry employment. Employment declines approximately by 0.15 percentage point after one year. The persistent decline is consistent with the fact that TTB duties are long-lasting (see Table 1).

Figure 5 plots the impulse responses using the trade-policy shocks identified with the panel regression (4). The main message is unaffected. Protectionism does not trigger a statistically significant employment increase in protected industries—although in this case, the point response is positive—and it lowers employment in downstream industries. The magnitude of the negative downstream effects is somewhat smaller, reflecting the inclusion of fixed effects in the first-stage panel regression—quantitatively, the results become more similar when time fixed effects are excluded in the first-stage.

To gain some perspective about the economic significance of TTB shocks and the associated industry-level responses, we map TTB shocks in a corresponding sectoral uniform-tariff variation. First, for each of the eight upstream industries, we compute an average tariff rate that, if applied

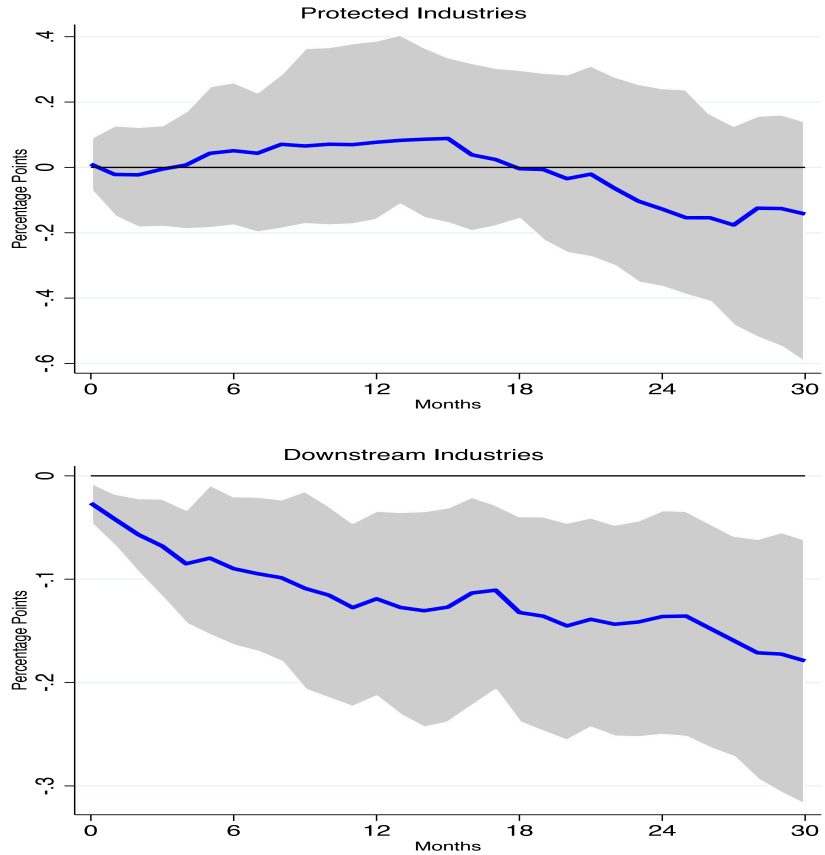

Figure 5: Impulse responses following a protectionism shock. *Top panel*: Average employment response in protected industries. *Bottom panel*: Average downstream-industry employment response. First stage: Panel regression.

to all sectoral imports, would result in a tariff revenue equivalent to that generated by the stock of products subject to TTB tariffs. To obtain this measure, we compute the stock of HS 6-digit products subject to TTB tariffs each month. We then average the applied tariffs across products using their corresponding import shares. As shown in Appendix D, in the industry that uses TTBs most intensively ("Iron, Steel, and Ferro-Alloy"), the uniform-tariff equivalent reaches up to 22%. The series displays substantial persistence in all industries, reflecting that TTB tariffs remain in place for several years. The change in the uniform tariff following new TTBs can reach up to 50%. We then estimate the average uniform-tariff elasticity to the share of imports subject to new TTBs, η_{τ_U}. We obtain $\eta_{\tau_U} = 1.02$, which implies that a uniform 1% increase in the share of imports subject to new TTBs corresponds to a 1.02% uniform import tariff.

Which economic mechanisms can rationalize the negative response of downstream employment? What is the aggregate relevance of the industry-level results? We address these issues in the next section.

5 Economic Mechanisms and Quantitative Implications

We first explore the mechanisms behind the negative response of downstream employment. We show a loss of competitiveness can rationalize the employment decline. Both intermediate-input and final producer prices increase following upstream protectionism, and the increase in prices precedes the employment decline. Using daily data, we also find that new TTBs lead to a statistically significant and lagged reduction in downstream-industries stock returns, confirming the decline in downstream industry profitability.

Second, we address the relevance of the results from an aggregate perspective. We find that TTB tariffs result in a statistically significant decline in manufacturing and aggregate employment. These negative effects reflect a sizable and long-lasting tariff increase in key industries that supply intermediate inputs. More extensive use of intermediate-input tariffs would have hefty adverse effects through vertical production linkages.

In Appendix C, we report additional results. We show that U.S. TTBs lead to a reduction in bilateral U.S. imports. Also, using custom data on unit values (which exclude tariffs), we do not find evidence that foreign producers absorb TTB tariffs. This result is consistent with recent evidence that documents full tariff pass-through (Cavallo, Gopinath, Neiman, and Tang, 2021).

Price Dynamics

There exist possible alternative 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 replace it, ending up paying a higher price. Alternatively, producers may switch to potentially less-efficient suppliers, facing relatively higher prices. 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 sectors. We use Producer Price Index (PPI) data for NAICS 4-digit industries from the Bureau of Labor Statistics. 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):

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

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

$$\Delta P_{it+h}^I = \nu_{ih} + \pi_h^I \hat{\varepsilon}_{it}^{IO} + \sum_{s=1}^{p} \phi_{sh} \Delta P_{it-s}^I + \psi_{t+h} + \epsilon_{it+h}, \tag{8}$$

where $\hat{\varepsilon}_{it}^{IO}$ is estimated using the fractional-response model in (2). The coefficient π_h^I measures the response of input prices at time $t+h$ following a trade-policy shock at time t.

As discussed in Section 3, in the first-stage regression, we do not control for prices since data are available at a consistent level of aggregation (NAICS 4-digit) only from 2004. However, as highlighted by the WTO Antidumping Agreement's technical criteria, industries that face rapidly falling prices are more likely to pursue TTBs. For this reason, we include three lags of ΔP_{it}^I to control for TTB variation potentially correlated to past upstream prices.

We estimate the response of final-producer prices in a similar fashion:

$$\Delta P_{it+h} = \nu_{ih} + \pi_h \hat{\varepsilon}_{it}^{IO} + \sum_{s=1}^{p} \phi_{sh} \Delta P_{it-s} + \psi_{t+h} + \epsilon_{it+h}. \tag{9}$$

We include three lags of ΔP_{it} to control for TTB variation potentially correlated to past downstream prices. The coefficient π_h measures the response of final prices at time $t+h$ following a trade-policy shock at time t.

In Figure 6, Panels A and B show the response of intermediate-input prices and final-producer prices, respectively. As before, we consider a uniform 1 percentage-point increase in the share of imports subject to TTBs. Both input and final prices increase, peaking approximately 18 months after the shock. The increase is statistically significant. Intermediate-input prices increase by approximately 0.4 percentage point at the peak, while final-producer prices increase by approximately

0.2 percentage points.[23]

From a timing perspective, the peak of the price increase precedes the downstream employment trough. Also, input prices already start to increase in the months that follow the TTB shock, whereas the employment response is statistically insignificant (or marginally significant) for several months.[24] This result suggests that a loss of competitiveness in downstream industries causes the employment decline.

Using the uniform-tariff elasticity discussed in the previous section, we perform a back-of-the-envelope calculation to interpret the industry-level input price response. Recall that a uniform 1% increase in the share of imports subject to new TTBs corresponds to a 1.02% uniform import tariff in the eight upstream industries. On average, these industries directly account for 29% of manufacturing intermediate inputs.[25] Their average openness—measured by their imports over output—is approximately 35%. Thus, assuming complete tariff pass-through (Cavallo, Gopinath, Neiman, and Tang, 2021), the uniform upstream tariff raises the average downstream input price by approximately 0.1% other things equal.[26] This figure lies within the 90-percent confidence interval of the average input price response at all horizons. It is also very close to the point estimate for the first six months—a reasonable time frame for comparison since the back-of-the-envelope calculation abstracts from general-equilibrium effects.

Stock Market Returns

We use stock market data to provide additional evidence about declining profitability in downstream industries. For each NAICS 4-digit sector, we compute median daily returns using firm-level data from CRSP (see Appendix A for the details). Let P_{id} be the the median stock price in industry i on day d, and let $R_{id} = (P_{id} - P_{id-1})/P_{id-1}$ be the corresponding stock return. We estimate the following panel local projections using daily data:

$$\Delta R_{id+h} = \nu_{ih} + \rho_h^{IO} \hat{\varepsilon}_{id}^{IO} + \rho_h \Delta R_{d+h}^m + \epsilon_{id+h}, \tag{10}$$

[23] Appendix C shows that producer prices also increase in protected industries.

[24] Employment also displays longer-lasting effects relative to input prices. However, local-projection estimates become less precise as the time horizon increases (indeed, the 90-percent confidence bands widen substantially after 18 months).

[25] We obtain this figure by converting the direct-requirement total input share in Table 2 into a corresponding total intermediate-input share.

[26] To obtain this figure, we compute $100 \times 0.29 \times 0.35 \times 0.0102$.

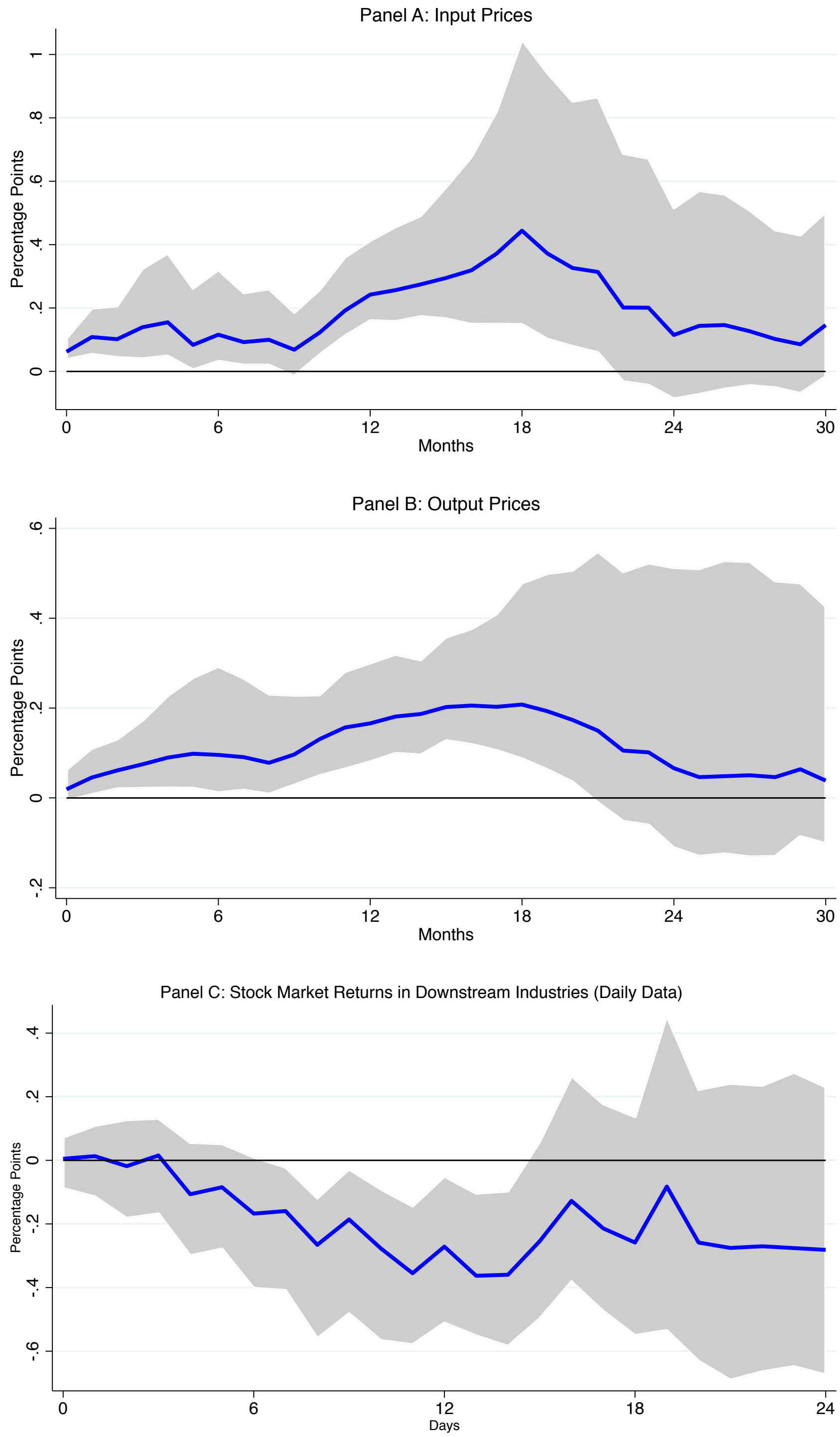

Figure 6: Impulse responses following protectionism in upstream industries. *Panel A*: Intermediate-input price response in downstream industries. *Panel B*: Producer-price response in downstream industries. *Panel C*: Median cumulative downstream stock-market return (daily data). First stage: Fractional-response model.

where ΔR_{id+h} denotes the median industry return between day d and $d+h$, ν_{ih} is an industry fixed effect, and ΔR^m_{d+h} is the market-portfolio return between d and $d+h$. As shown in Appendix E, we obtain very similar results when considering abnormal returns. The daily upstream shock is $\hat{\varepsilon}^{IO}_{id} \equiv \sum_{j \neq i} \theta_{ij} \hat{\varepsilon}_{jd}$, where $\hat{\varepsilon}_{jd}$ is the upstream shock identified with monthly data imputed to the exact day in which it occurred—the one-to-one mapping between the monthly shock, $\hat{\varepsilon}_{jt}$, and its daily counterpart, $\hat{\varepsilon}_{jd}$, occurs because new investigations never happen more than once a month within each NAICS 4-digit industry in our sample. The weight θ_{ij} is defined as in (5).

Panel C in Figure 6 shows that upstream protectionism leads to a statistically significant decline in the median downstream-industry returns. Following a uniform 1% increase in the share of imports subject to new TTBs, the cumulative return declines by approximately 0.25% after seven days. At the trough, the cumulative return declines by 0.35%. To gain perspective about the economic significance, notice in our sample the standard deviation of the seven-days cumulative return averages to 8.68% (the range across industries is 5.1% to 23.9%).[27]

The lagged response of downstream-industry stock returns is consistent with finance literature that documents lead-lag effects among equities along the supply chain. The slow diffusion of information in the stock market reflects investors' attention constraints, implying that stock prices do not immediately incorporate news about economically-related firms. For instance, in a very influential paper, Cohen and Frazzini (2008) find that customer companies' lagged equity returns correlate positively with suppliers' contemporaneous equity returns. Menzly and Ozbas (2010) also provide evidence supporting the hypothesis that value-relevant information diffuses gradually in financial markets due to investors' specialization and market segmentation. They show that stocks that are in economically related supplier and customer industries cross-predict each other's returns.

Aggregate Effects

We address the aggregate relevance of our findings using two alternative approaches. The first approach builds on standard practice in the trade literature. The second approach uses aggregate data. When following the trade literature (e.g., Acemoglu, Autor, Dorn, Hanson, and Price, 2016), we interact the estimated average employment response—$\hat{\gamma}^{IO}_h$ in the local projections (7)—with the industry-specific exposure to protectionism ($\hat{\varepsilon}^{IO}_{it}$). For industry i, the predicted employment change between time t and $t+h$ is $\hat{g}_{Lit+h} = e^{\hat{\gamma}^{IO}_h \hat{\varepsilon}^{IO}_{it}} - 1$. Summing the employment response across

[27] Appendix C shows that publicly traded companies' profits in downstream industries decline following upstream protectionism.

industries yields a manufacturing-wide response.

Although standard in the literature, this approach abstracts from general equilibrium effects. Time-fixed effects in (7) remove variation in industry employment due to aggregate dynamics that follow TTB shocks, including the potential response of macroeconomic policy. Also, there could be unmeasured employment spillovers across industries. Since TTBs affect only a subset of manufacturing imports, aggregate feedback effects are not likely to have a first-order effect on industry employment. However, sectoral spillovers in downstream industries are more likely to materialize. We turn to this issue next.

Consider an industry i that does not face immediate exposure to TTBs. Industry spillovers arise in two situations: (i) employment in industry i changes because some of its suppliers face upstream protectionism; (ii) employment in industry i changes because some of its buyers face upstream protectionism. The use of total-requirements implies that ε_{it}^{IO} accounts for (i) but not for (ii).[28] In addition, with spillovers from treated to untreated industries, the local-projection estimate γ_h^{IO} measures the average relative (rather than absolute) downstream-employment response (e.g., Chodorow-Reich, 2020).[29]

To address these issues, we follow the literature on regional fiscal multipliers (e.g., Dupor and Guerrero, 2017) and include a measure of downstream-employment spillovers in the second-stage local projections (7). We measure industry-i's exposure to protectionism faced by its downstream buyers—the channel (ii) discussed above—by constructing $\hat{\varepsilon}_{it}^{DI} = \sum_{j \neq i} \lambda_{ij} \hat{\varepsilon}_{jt}^{DI}$, where $\hat{\varepsilon}_{jt}^{DI}$ is the TTB shock faced by the downstream buyer j at time t. The fixed weight λ_{ij} measures the share of industry-j's use of industry-i's output. We then estimate the following set of panel local projections for $h = 1, .., H$:

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

For industry i, the predicted employment change between time t and $t{+}h$ is $\hat{g}_{L_i t+h} \equiv e^{\hat{\gamma}_h^{IO} \hat{\varepsilon}_{it}^{IO} + \gamma_h^{DI} \hat{\varepsilon}_{it}^{DI}} - 1$, where γ_h^{DI} captures the downstream employment spillover at horizon h. We note the inclusion of downstream spillovers does not substantially change the estimated coefficient γ_h^{IO} relative to the baseline specification in (7).

[28] Suppose there are four industries: A (e.g., the steel sector), B, C, and D. Assume that A supplies goods to B, while B and C supply goods to D. Suppose are new TTBs in industry A, i.e., $\hat{\varepsilon}_{A,t} > 0$. The definition of $\hat{\varepsilon}_{i,t}^{IO}$ implies $\hat{\varepsilon}_{B,t}^{IO} > 0$, $\hat{\varepsilon}_{C,t}^{IO} = 0$, and $\hat{\varepsilon}_{D,t}^{IO} > 0$. The use of total requirements allows us to capture employment spillovers to industry D (since $\hat{\varepsilon}_{D,t}^{IO} > 0$). However, any employment response in industry C would not be accounted for (since $\hat{\varepsilon}_{C,t}^{IO} = 0$)—for instance, employment in C may change if D changed its demand for C's output.

[29] In this case, γ_h^{IO} measures the effect that an increase in upstream protectionism in one industry relative to another has on their relative employment levels.

For quantification purposes, we consider two exercises. First, we focus on the largest TTB shock in the industry that uses TTB the most ("Iron, Steel, and Ferro-Alloy," industry 3311). The episode occurred in August 2015, when the share of imports subject to new TTBs increased by 8.9%.[30] Second, we consider the average shock identified in TTB episodes for each upstream industry. In this case, the average import share of goods subject to new TTBs ranges between 11.09% (industry 3312, "Steel Products from Purchased Steel") and 0.21% (industry 3251, "Basic Chemicals").

In the most important episode in industry 3311, the cumulative manufacturing employment loss after one year is 0.34% (0.24% abstracting from downstream-industry spillovers). When considering average shocks, the one-year cumulative employment loss is 0.15% (0.11% abstracting from spillovers).[31] All the estimates are statistically significant at the 90-percent confidence level.

A complementary approach to quantify aggregate effects is to use aggregate data. In this case, we estimate the following monthly aggregate local projections for $h = 1, .., H$:

$$\Delta L_{t+h} = \gamma_h^A \hat{\varepsilon}_t^A + \sum_{\kappa=1}^{p} \mathbf{\Phi}_{xh}^{\kappa} \mathbf{x}_{t-\kappa} + \epsilon_{t+h}, \tag{11}$$

where $\hat{\varepsilon}_t^A$ aggregates the identified sectoral TTB shocks, ΔL_{t+h} is the aggregate employment log-difference between time t and $t+h$, and $\mathbf{x}_t$ is a vector of controls. The latter includes three lags of the employment growth rate, the real exchange rate, the oil price, and the Fed funds rate. The coefficient γ_h^A represents the cumulative employment response at horizon h. Estimates using (11) complement but differ from those obtained with industry-level data. The latter identifies industry-specific TTB shocks' average effects, while the aggregate regression considers all shocks simultaneously. Thus, γ_h^A informs about the overall employment effects of overall upstream TTBs.

For the largest TTB episode in industry 3311 (August 2015), the cumulative aggregate employment loss after one year is 0.29%. When considering the average shock across TTB episodes, the figure is 0.034%. Although the estimates are statistically significant at the 90-percent level, the confidence interval includes a broad range of values—for instance, for the largest episode in industry 3311, the employment response ranges between 0.05% and 0.53%. In Appendix F, we plot the impulse responses for the aggregate local projections.

To summarize, TTB tariffs result in a statistically significant decline in both variables. While

[30] In the same month, industry 3312 ("Steel Products from Purchased Steel") also opened TTB investigations covering 12.8% of imports (the third-largest episode in that industry).

[31] In this case, the percentages refer to the average manufacturing employment in our sample period.

TTBs have small effects on average, the impact is larger in the most important historical episodes. The results suggest that more extensive use of TTBs—or, equivalently, a broader application of similar tariffs—would lead to considerable negative employment effects through vertical production linkages.

6 Robustness

We assess the robustness of our findings 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, $\hat{\varepsilon}_{it}^{IO}$, and an alternative measure of protectionism. In Appendix G, we report additional results. We consider more industry-level controls in the first-stage regression (hourly earnings, imports, quarterly sales, and commodity prices). We also consider a trade policy measure that exploits TTB tariff variation.

Trade-Policy Shocks Identification

Probit Model

A potential concern is measurement error due to lagged imports when constructing the share of imports subject to protection (τ_{it}). To address this issue, we consider an alternative specification 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):

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

Panel A in Figure 7 plots the local projection estimates using the probit model in the first stage of the estimation. We consider a unitary increase in upstream protection. 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 is statistically significant at all horizons.

An Alternative Measure of Industry Expectations

In Section 3, we use the market-to-book ratio to capture industry expected returns. Here we consider a second benchmark measure of expected profitability, the price-to-earnings ratio. At the firm level, the measure considers the ratio of the current share price to the trailing twelve-month earnings per share (see Appendix A for the details). A decrease in the price-to-earnings ratio may indicate negative growth prospects.

For each NAICS 4-digit industry, we construct the price-to-earnings ratio, PE_{it}, as the median price-to-earnings ratio across firms each month. The average correlation between this measure and the market-to-book ratio is 0.40. We also construct a downstream measure of the price-to-earnings ratio (for the industries that use TTBs): $PE_{it}^{DI} \equiv \sum_{j \neq i} \lambda_{ij} PE_{jt}$, where λ_{ij} measures industry j's use of industry i's output. We then re-estimate the first-stage regression replacing MB_{it} and MB_{it}^{DI} with PE_{it} and PE_{it}^{DI} in (3). Panel B in Figure 7 shows we obtain similar results when using these alternative controls.

Alternative Measures of Protectionism

Exposure to 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 approach is to express the sectoral-trade shocks as:

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

where s_j is the previous-year import share of sector j relative to total imports of the eight upstream industries considered in the first stage. Also in this case, we consider a uniform 1-percentage-point increase in upstream protectionism. Panel C in Figure 7 shows that the results remain similar to the benchmark specification.[32]

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 investigations that ultimately do not lead to trade protection drive

[32] Appendix G considers sectoral weights that account for upstream industries' trade openness—measured by imports over sectoral output.

our results. Panel D in Figure 7 shows that the results are robust to this alternative choice.

7 Conclusions

We used monthly data on U.S. temporary trade barriers to estimate protectionism's effects on economic activity in protected industries and through input-output linkages. We found that protectionism has small, short-lived, and mostly insignificant effects in protected industries. In contrast, protectionism has long-lasting and significant negative effects in downstream industries.

A loss of competitiveness and profitability can rationalize the employment decline. Both intermediate-input and final producer prices increase following upstream protectionism, and the increase in prices precedes the employment decline. New TTBs also lead to a statistically significant and lagged reduction in daily downstream-industries stock returns.

Finally, we found that TTB tariffs result in a statistically significant decline in manufacturing and aggregate employment. While TTBs have small effects on average, the impact is larger in the most important historical episodes. The results suggest that more extensive use of TTBs—or, equivalently, a broader application of similar tariffs—would lead to considerable and long-lasting negative employment effects through vertical production linkages.

Our results suggest avenues for future research. First, considering firm-level data would allow uncovering potential heterogeneity in the effects of protectionism through production networks. Second, addressing the role of foreign retaliation would provide additional insights into the overall cost of upstream protectionism.

References

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016): "Import Competition and the Great US Employment Sag of the 2000s," *Journal of Labor Economics*, 34, 141–198.

Amiti, M., and J. Konings (2007): "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia," *American Economic Review*, 97, 1611–1638.

Amiti, M., S. J. Redding, and D. E. Weinstein (2019): "The Impact of the 2018 Tariffs on Prices and Welfare," *Journal of Economic Perspectives*, 33, 187–210.

Antràs, P., and D. Chor (2021): "Global Value Chains," *mimeo*.

Auerbach, A. J., and Y. Gorodnichenko (2013): "Output Spillovers from Fiscal Policy," *American Economic Review*, 103, 141–146.

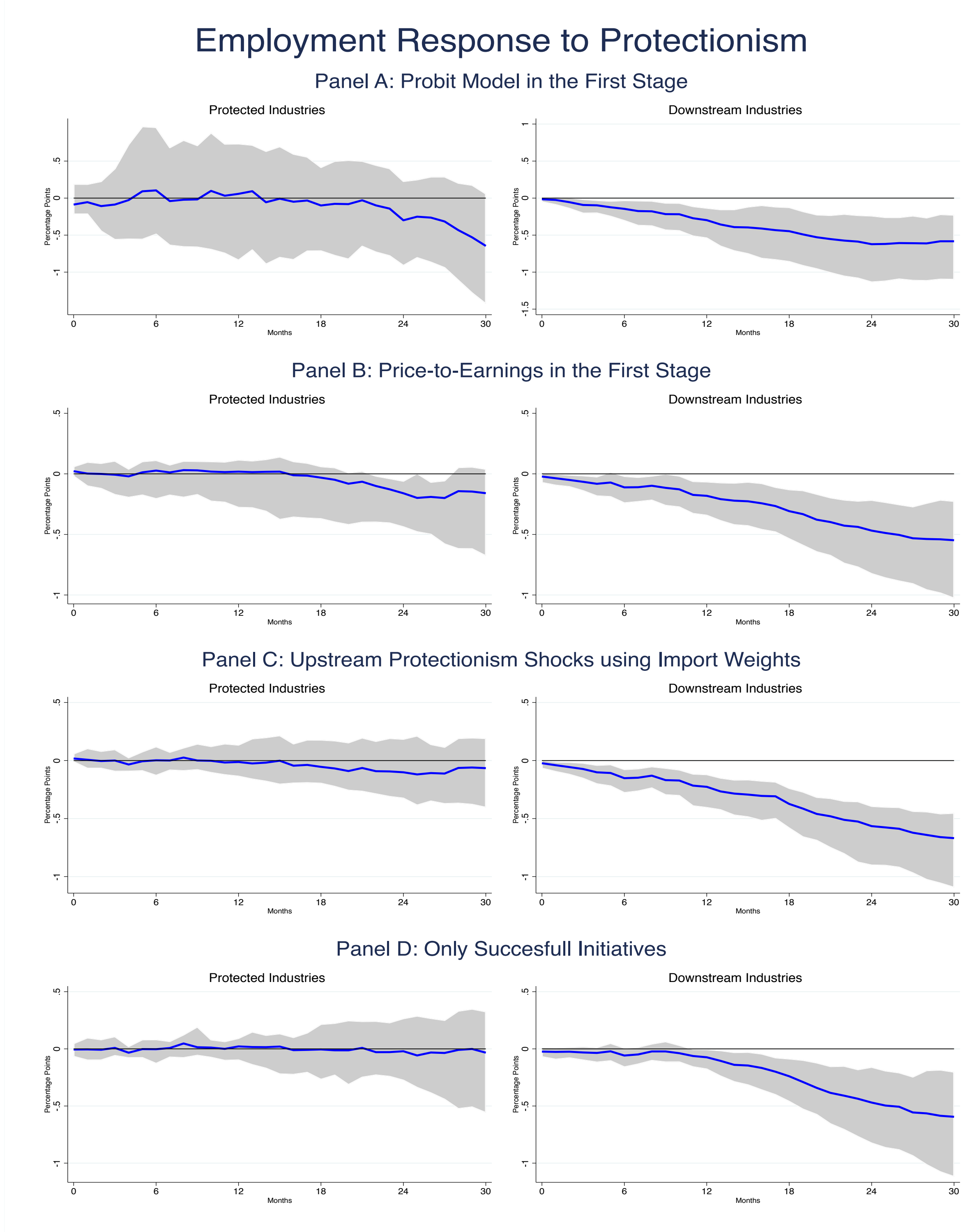

Figure 7: Impulse responses following a protectionism shock. *Panel A*: Probit model in the first-stage regression. *Panel B*: First-stage regression includes the price-to-earnings ratio. *Panel C*: τ_{it} constructed using average import shares. *Panel D*: Only succesful investigations.

Baldwin, R. (2018): "Trump Can't Fix a 21st Century Problem with 20th Century Thinking," VoxEU.org, 27 September.

Baqaee, D. R., and E. Farhi (2019): "Networks, Barriers, and Trade," Discussion paper.

Barattieri, A., M. Cacciatore, and F. Ghironi (2021): "Protectionism and the business cycle," *Journal of International Economics*, 129(C).

Blanchard, E. J., C. P. Bown, and R. C. Johnson (2016): "Global Supply Chains and Trade Policy," NBER Working Papers 21883, National Bureau of Economic Research, Inc.

Blonigen, B. A., and T. J. Prusa (2015): "Dumping and Antidumping Duties," NBER Working Papers 21573, National Bureau of Economic Research, Inc.

Bown, C., P. Conconi, A. Erbahar, and L. Trimarchi (2020): "Trade Protection Along Supply Chains," Discussion paper, mimeo.

Bown, C. P. (2011): "Taking Stock of Antidumping, Safeguards and Countervailing Duties, 1990-2009," *The World Economy*, 34, 1955–1998.

——— (2016): "Temporary Trade Barriers Database, The World Bank," available at http://econ.worldbank.org/ttbd/.

Bown, C. P., and M. A. Crowley (2007): "Trade Deflection and Trade Depression," *Journal of International Economics*, 72, 176–201.

——— (2013): "Import Protection, Business Cycles, and Exchange Rates: Evidence from the Great Recession," *Journal of International Economics*, 90, 50–64.

Cavallo, A., G. Gopinath, B. Neiman, and J. Tang (2021): "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy," *American Economic Review: Insights*, 3, 19–34.

Chodorow-Reich, G. (2020): "Regional Data in Macroeconomics: Some Advice for Practitioners," *Journal of Economic Dynamics and Control*, 115.

Cochrane, J. H. (2004): "Comments on "A New Measure of Monetary Shocks: Derivation and Implications" By Christina Romer and David Romer," Discussion paper, NBER Economic Fluctuations and Growth, July 2004 meeting.

Cohen, L., and A. Frazzini (2008): "Economic Links and Predictable Returns," *Journal of Finance*, 63, 1977–2011.

Decamps, J.-P., S. Gryglewicz, E. Morellec, and S. Villeneuve (2017): "Corporate Policies with Permanent and Transitory Shocks," *The Review of Financial Studies*, 30, 162–210.

di Giovanni, J., and A. A. Levchenko (2010): "Putting the Parts Together: Trade, Vertical Linkages, and Business Cycle Comovement," *American Economic Journal: Macroeconomics*, 2, 95–124.

Dupor, B., and R. Guerrero (2017): "Local and Aggregate Fiscal Policy Multipliers," *Journal of Monetary Economics*, 92, 16–30.

Durling, J. P., and T. J. Prusa (2006): "The Trade Effects Associated with an Antidumping Epidemic: The Hot-Rolled Steel Market, 1996-2001," *European Journal of Political Economy*, 22, 675–695.

Erbahar, A., and Y. Zi (2017): "Cascading Trade Protection: Evidence from the US," *Journal of International Economics*, 108, 274–299.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2020): "The Return to Protectionism," *The Quarterly Journal of Economics*, 135, 1–55.

Flaaen, A., and J. Pierce (2019): "Disentangling the Effects of the 2018-2019 Tariffs on aGlobally Connected U.S. Manufacturing Sector," Finance and Economics Discussion Series 2019-08.

Furceri, D., S. Hannan, J. D. Ostry, and A. K. Rose (2018): "Macroeconomic Consequences of Tariffs," Cepr discussion papers, C.E.P.R. Discussion Papers.

Goldberg, P. K., A. K. Khandelwal, N. Pavcnik, and P. Topalova (2010): "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India," *The Quarterly Journal of Economics*, 125, 1727–1767.

Huang, Y., C. Lin, S. Liu, and H. Tang (2018): "Trade Linkages and Firm Value: Evidence from the 2018 US-China Trade War'," Discussion paper.

Jorda, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Jorda, O., and A. M. Taylor (2016): "The Time for Austerity: Estimating the Average Treatment Effect of Fiscal Policy," *Economic Journal*, 126, 219–255.

Krugman, P. (2018): "How to Lose a Trade War," New York Times, 7 July.

Leduc, S., and D. Wilson (2013): "Roads to Prosperity or Bridges to Nowhere? Theory and Evidence on the Impact of Public Infrastructure Investment," *NBER Macroeconomics Annual*, 27, 89–142.

Lettau, M., and S. C. Ludvigson (2004): "Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption," *American Economic Review*, 94, 276–299.

LU, Y., Z. TAO, AND Y. ZHANG (2013): "How Do Exporters Respond to Antidumping Investigations?," *Journal of International Economics*, 91, 290–300.

MENZLY, L., AND O. OZBAS (2010): "Market Segmentation and Cross-predictability of Returns," *Journal of Finance*, 65, 1555–1580.

NICKELL, S. J. (1981): "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 49, 1417–1426.

OTTONELLO, P., AND T. WINBERRY (2020): "Financial Heterogeneity and the Investment Channel of Monetary Policy," *Econometrica*, 88, 2473–2502.

PAPKE, L. E., AND J. M. WOOLDRIDGE (1996): "Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates," *Journal of Applied Econometrics*, 11, 619–632.

PAPKE, L. E., AND J. M. WOOLDRIDGE (2008): "Panel data methods for fractional response variables with an application to test pass rates," *Journal of Econometrics*, 145, 121–133.

PIERCE, J. R., AND P. K. SCHOTT (2009): "Concording U.S. Harmonized System Categories Over Time," NBER Working Papers 14837, National Bureau of Economic Research, Inc.

PONTIFF, J., AND L. D. SCHALL (1998): "Book-to-Market Ratios as Predictors of Market Returns," *Journal of Financial Economics*, 49, 141–160.

ROMER, C. D., AND D. H. ROMER (2004): "A New Measure of Monetary Shocks: Derivation and Implications," *American Economic Review*, 94, 1055–1084.

STAIGER, R. W., AND F. A. WOLAK (1994): "Measuring Industry-Specific Protection: Antidumping in the United States," *Brookings Papers on Economic Activity*, 25, 51–118.

TOPALOVA, P., AND A. KHANDELWAL (2011): "Trade Liberalization and Firm Productivity: The Case of India," *The Review of Economics and Statistics*, 93, 995–1009.

TRIMARCHI, L. (2018): "Trade Policy and the "China Syndrome"," Discussion paper.

USITC (2015): "Antidumping and Countervailing Duty Handbook ," Publication 4540.

VANDENBUSSCHE, H., AND M. ZANARDI (2010): "The Chilling Trade Effects of Antidumping Proliferation," *European Economic Review*, 54, 760–777.

Online Technical Appendix to: "Self-Harming Trade Policy? Protectionism and Production Networks"

(Not For Publication)

A Data and Descriptive Statistics

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.[33] Monthly producer-price data correspond to the Producer Price Index PC from the U.S. Bureau of Labor Statistics. Monthly import data are from the Census Bureau.[34] Data on the daily market return and risk-free rate are from Kenneth French's website.[35] We construct stock returns using stock price data from CRSP (the variable *prc*). 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*.[36] 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 firm-level market-to-book ratio 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 price of a share (the variable *prc* in CRSP) on the last trading day of the month times the number 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).[37] We convert SIC 4-digit firms' codes to NAICS 4-digit

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

[34] 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 codes by using their average import share (relative to the SITC code total imports) in a given period.

[35] The data are available at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html`.

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

[37] 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*).

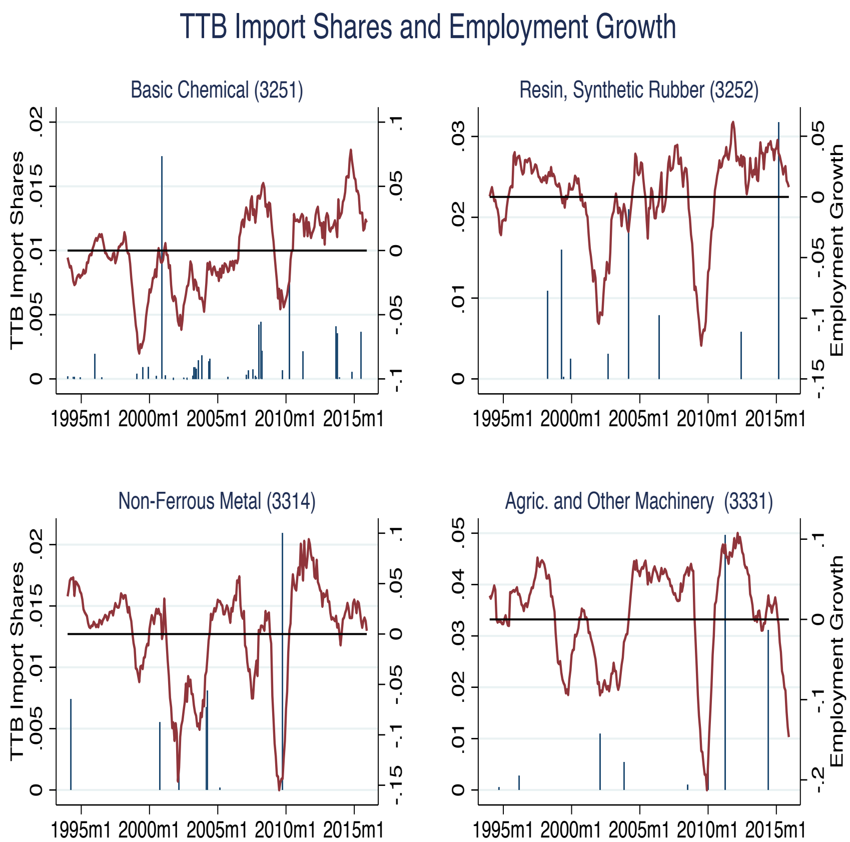

Figure A.1: Share of imports subject to new TTB investigations in selected NAICS-4 industries (histograms) and employment growth (continuous line).

codes and construct the median market-to-book ratio for each industry.[38]

At the firm level, we construct the price-to-earnings ratio as the ratio between the price of a share (the variable *prc* in CRSP) on the last trading day of the month and earnings per share from operations (the variable *oeps12*).

Share of Imports Subject to New TTBs

Figure A.1 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.

[38] We rely on the 2002 concordance table from the Census Bureau (available at url-https://www.census.gov/eos/www/naics/concordances/concordances.html) and conversion tables from Pierce and Schott (2009).

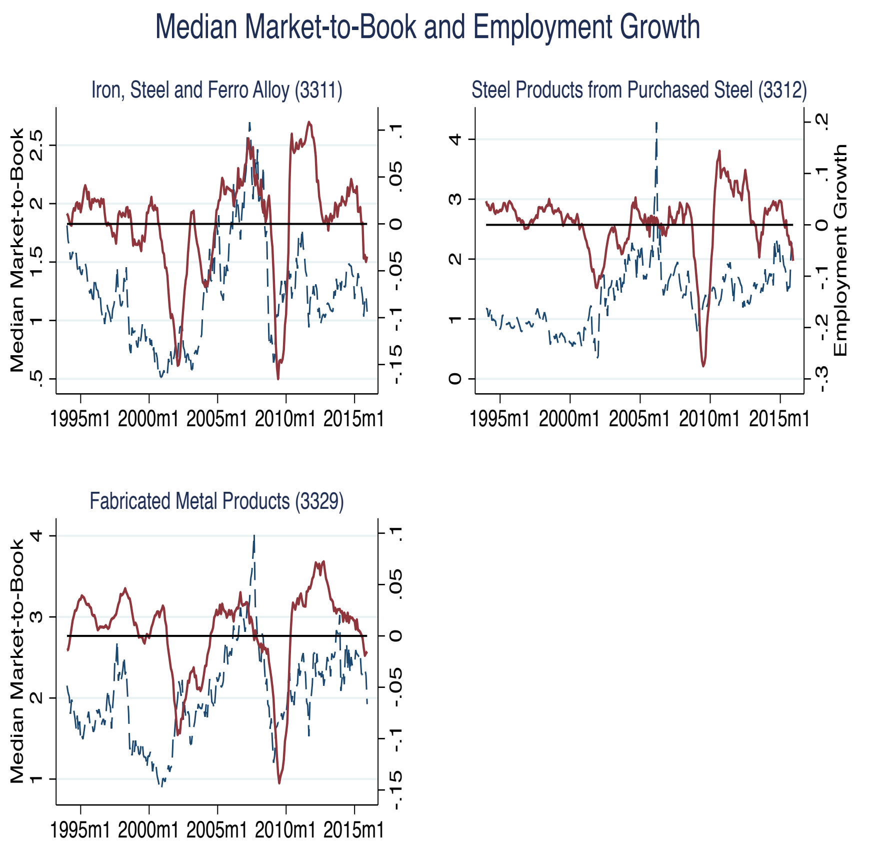

Figure A.2: Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuos line).

Market-to-Book Ratio

Figures A.2 and A.3 plot the market-to-book ratio and employment growth for the industries in Table 1. The figure shows that movements in MB_{it} lead movements in ΔL_{it}. Figure A.4 shows the market-to-book ratio also contains information about TTB petitioners' expected profitability. To illustrate this result, we construct a petitioner-specific market-to-book ratio for the most important TTB user, industry 3311 ("Iron, Steel, and Ferro-Alloy"). For each of the 60 U.S. TTB episodes in that industry, we identify the petitioners present in Compustat and CRSP through a manual match by company name. In industry 3311, about 20% of firms are also TTB petitioners in our sample period. We use those firms to compute the petitioner-specific median market-to-book ratio, $MBP_{3311,t}$. Figure A.4 plots $MBP_{3311,t}$ against the market-to-book ratio for the whole industry, $MB_{3311,t}$. The figure shows a very high correlation (approximately equal to 0.95).

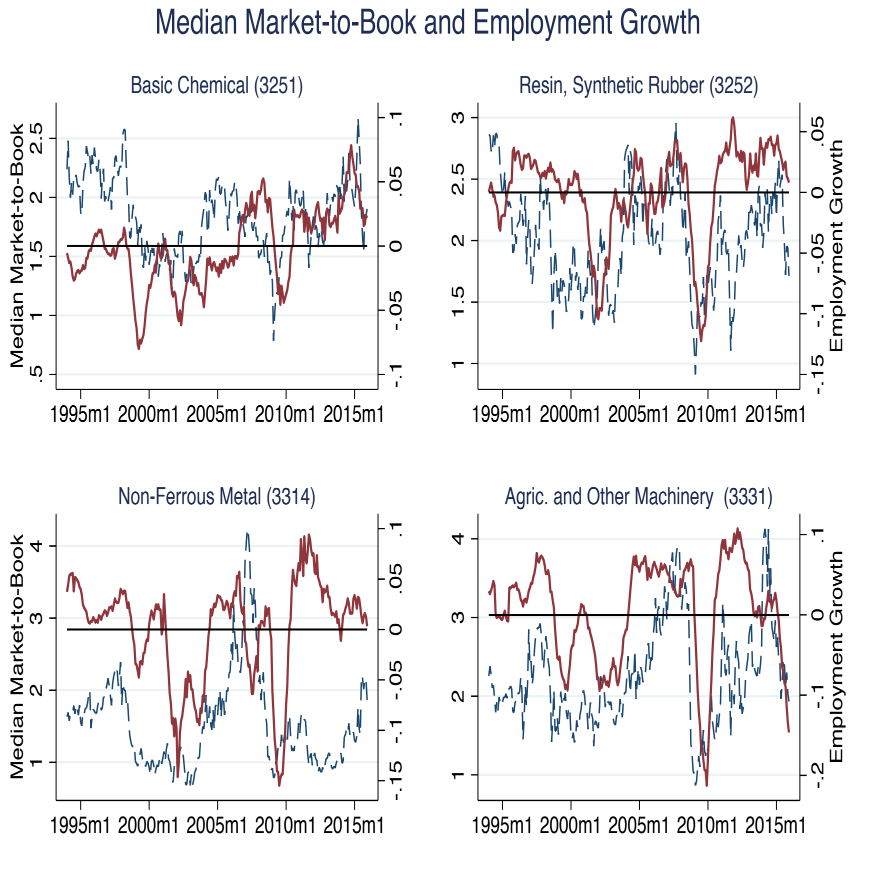

Figure A.3: Market-to-book ratio in selected NAICS-4 industries (dashed line) and employment growth (continuos line).

B First-Stage Regression

Figure A.5 plots the predicted values implied by the fractional-response model against the data for the industries appearing in Table 1 that are not plotted in the main text.

C Additional Outcome Variables

Here we present the response of additional outcome variables following TTB shocks.

Bilateral Imports

We first investigate the response of bilateral, industry imports following TTBs. We construct a dummy variable, d_{ict}, that takes value one when industry-i in country c faces new U.S. TTBs in month t. We then construct a dummy variable, $\tilde{d}_{ict}$, that is equal to one if country c does not face

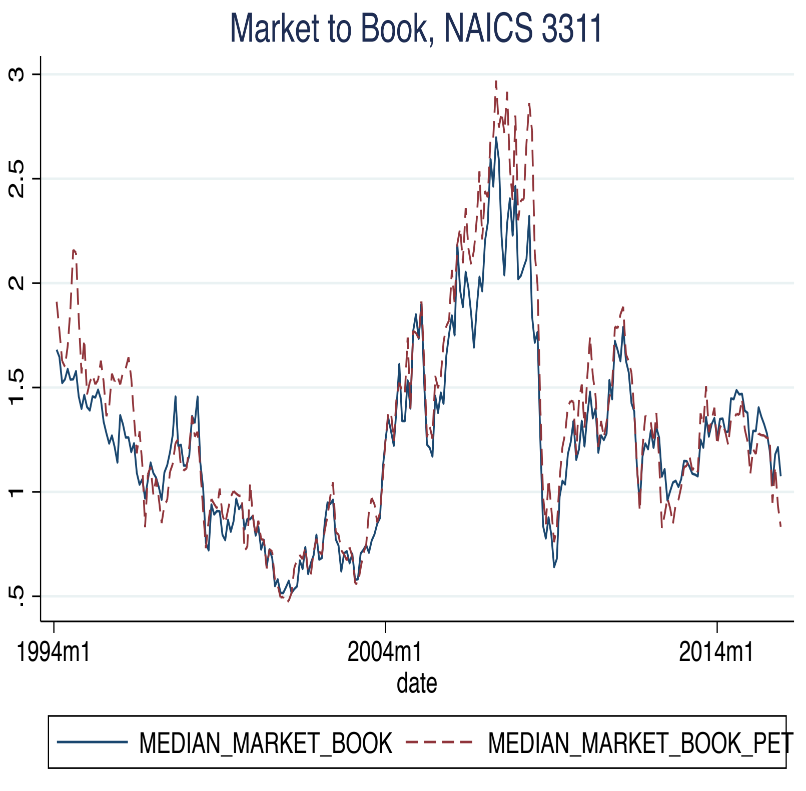

Figure A.4: Market-to-book ratio: median for the industry 3312 (continuous line) and median for TTB petitioners in industry 3312 (dashed line).

new TTBs in industry i while the U.S. imposes TTBs against other countries in the same month and industry. For example, suppose that in January 2000, the U.S. imposes new TTBs in the industry 3311 against Brazil. In this case, $d_{3311,Brazil,2000:1} = 1$ and $\tilde{d}_{3311,Brazil,2000:1} = 0$. At the same time, $d_{3311,China,2000:1} = 0$ and $\tilde{d}_{3311,China,2000:1} = 1$. The use of d_{ict} and $\tilde{d}_{ict}$ avoids endogeneity concerns associated with the baseline measure used in the paper—τ_{it} already uses (lagged) imports data.

We then estimate the following set of h-steps ahead local projections:

$$\begin{aligned}\Delta IMP_{ict+h} = \nu_{ih} + \nu_{ch} + \beta_h d_{ict} + \tilde{\beta}_h \tilde{d}_{ict} + \sum_{s=1}^{p_{IMP}} \phi_{sh} \Delta IMP_{ict-s} \\ + \sum_{s=1}^{p_L} \varsigma_{sh} \Delta L_{it-s} + \sum_{s=1}^{p_{L^{DI}}} \varsigma_{sh}^{DI} \Delta L_{it-s}^{DI} \\ + \sum_{s=1}^{p_{MB}} \varphi_{sh} MB_{it-s} + \sum_{s=1}^{p_{MB^{DI}}} \varphi_{sh}^{DI} MB_{it-s}^{DI} + \psi_{t+h} + \epsilon_{ict+h},\end{aligned}$$

where $\Delta IMP_{ict} \equiv \log IMP_{ict} - \log IMP_{ict-1}$ is the log-difference of bilateral U.S. imports in

Figure A.5: Share of imports subject to new TTB investigations in selected NAICS-4 industries (light histograms) and predicted values from the fractional-response model (dark histograms).

industry i from country c, ν_{ih} is an industry fixed effect, ν_{ch} is a country fixed effect, and ψ_{t+h} is a time fixed effect. The coefficient β_h measures the response of imports subject to TTBs h periods after the shock. The coefficient $\tilde{\beta}_h$ measures the response of imports not subject to TTBs in the same industry.

We control for the lagged log-difference of bilateral imports, lags of the employment log-difference ($\Delta L_{it} \equiv \log L_{it} - \log L_{it-1}$), lags of the industry market-to-book ratio (MB_{it}), and their downstream counterparts (ΔL_{it}^{DI} and MB_{it}^{DI}). We do so since variation in d_{ict} and $\tilde{d}_{ict}$ may partly reflect an endogenous response to past or expected industry dynamics. We include twelve lags for the growth rate of employment and three lags for ΔIMP_{ict}, ΔL_{it}^{DI}, MB_{it}, and MB_{it}^{DI}.

Figure A.6 shows a statistically significant decline in bilateral imports subject to U.S. TTBs. In addition, bilateral imports increase when considering countries that do not face U.S. protectionism. These results provide additional support to the main results of the paper. In addition, they suggest

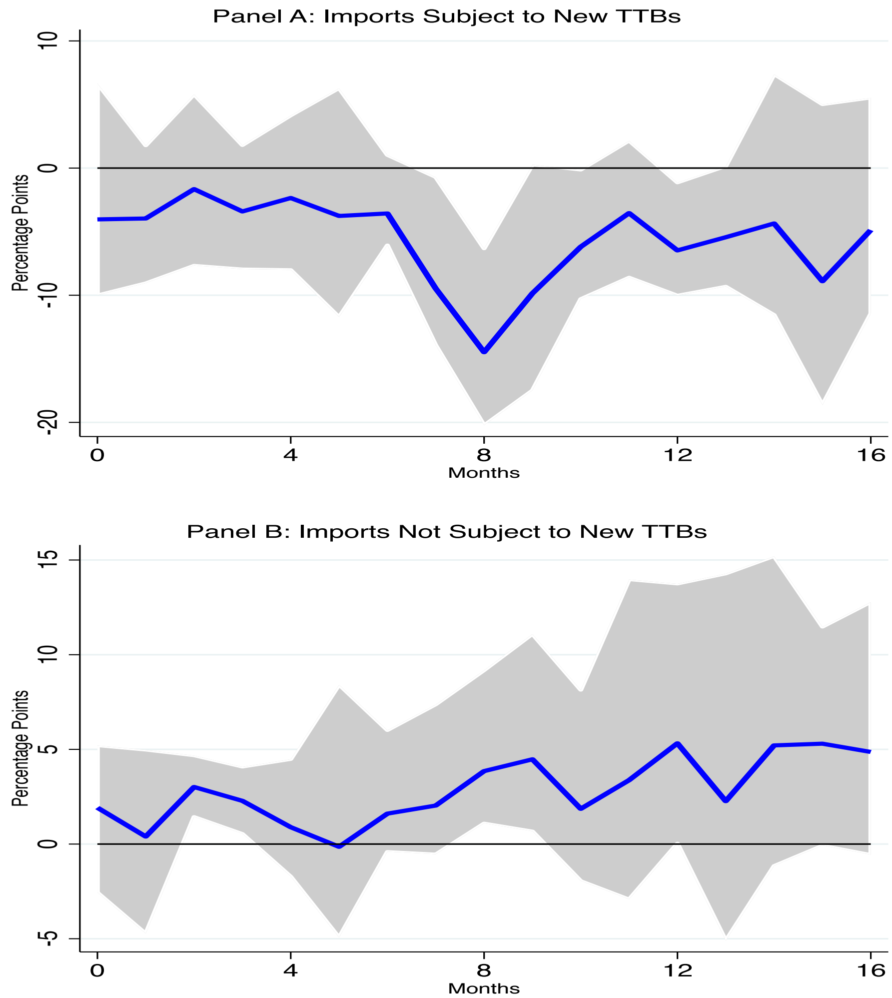

Figure A.6: Impulse responses following a U.S. protectionism shock, average bilateral U.S. imports response. *Panel A*: Bilateral imports in industries subject to new TTBs. *Panel B*: Bilateral imports in industries not subject to new TTBs when other countries face TTBs in the same industry.

that U.S. TTBs trigger some imports substitution, contributing to explain the absence of positive employment effect in protected industries.

Custom Unit Values

We also investigate the response of custom unit values (which exclude tariffs), exploring the extent to which foreign producers absorb TTB tariffs. The U.S. Census provides data only at the HS 10-digit level. As a result, we must aggregate unit values to the NAICS 4-digit level—the most disaggregated level at which it is possible to identify TTB shocks. We use HS 10-digit product shares over the whole sample and apply the conversion table constructed by Pierce and Schott

(2009). Figure A.7 plots unit values dynamics in the eight NAICS 4-digit upstream industries considered in the analysis. We then estimate the following panel local projection for $h = 0, .., H$:

$$\Delta UV_{it+h} = \nu_{ih} + \chi_h \hat{\varepsilon}_{it} + \sum_{s=1}^{p} \phi_{sh} \Delta UV_{it-s} + \psi_{t+h} + \epsilon_{it+h},$$

where ΔUV_{it+h} denotes the log-change in unit values between time t and $t+h$, ν_{ih} is an industry fixed effect, and ψ_{t+h} is a time fixed effect. We include three lags of ΔUV_{it} to control for TTB variation potentially correlated to past unit-value dynamics. The coefficient χ_h measures the response of unit values h periods after the shock. Figure A.8 shows the effect of TTBs on unit values is not statistically significantly different from zero. This finding is consistent with recent evidence that documents full tariff pass-through (Cavallo, Gopinath, Neiman, and Tang, 2021). However, we warrant caution in interpreting the evidence in Figure A.8 as conclusive. The reason is that aggregating HS 10-digit unit values unavoidably introduces noise in the measure (unit values are not summable quantities like imports). As a result, unit values' response at the NAICS 4-digit level may not be tightly estimated.

Profits in Downstream Industries

We construct quarterly industry-level profits using Compustat data. We consider the difference between net sales and the cost of goods sold. We obtain quarterly TTB shocks by aggregating monthly TTB shocks.

We estimate the following set of h-steps ahead predictive panel regressions, for $h = 0, .., H$:

$$\Delta \pi_{it+h} = \nu_{ih} + \gamma_h \hat{\varepsilon}_{it}^{IO} + \psi_{t+h} + \epsilon_{it+h},$$

where $\Delta \pi_{it+h} \equiv \log \pi_{it+h} - \log \pi_{it-1}$ denotes the cumulative profit difference between time t and $t+h$, ν_{ih} is an industry fixed effect, ψ_{t+h} is a time fixed effect, $\hat{\varepsilon}_{it}^{IO}$ is the upstream TTB shock, and ϵ_{it+h} is the prediction error term.

Figure A.9 below shows a statistically significant decline in downstream profits following an increase in upstream TTBs, consistent with the results of the paper.

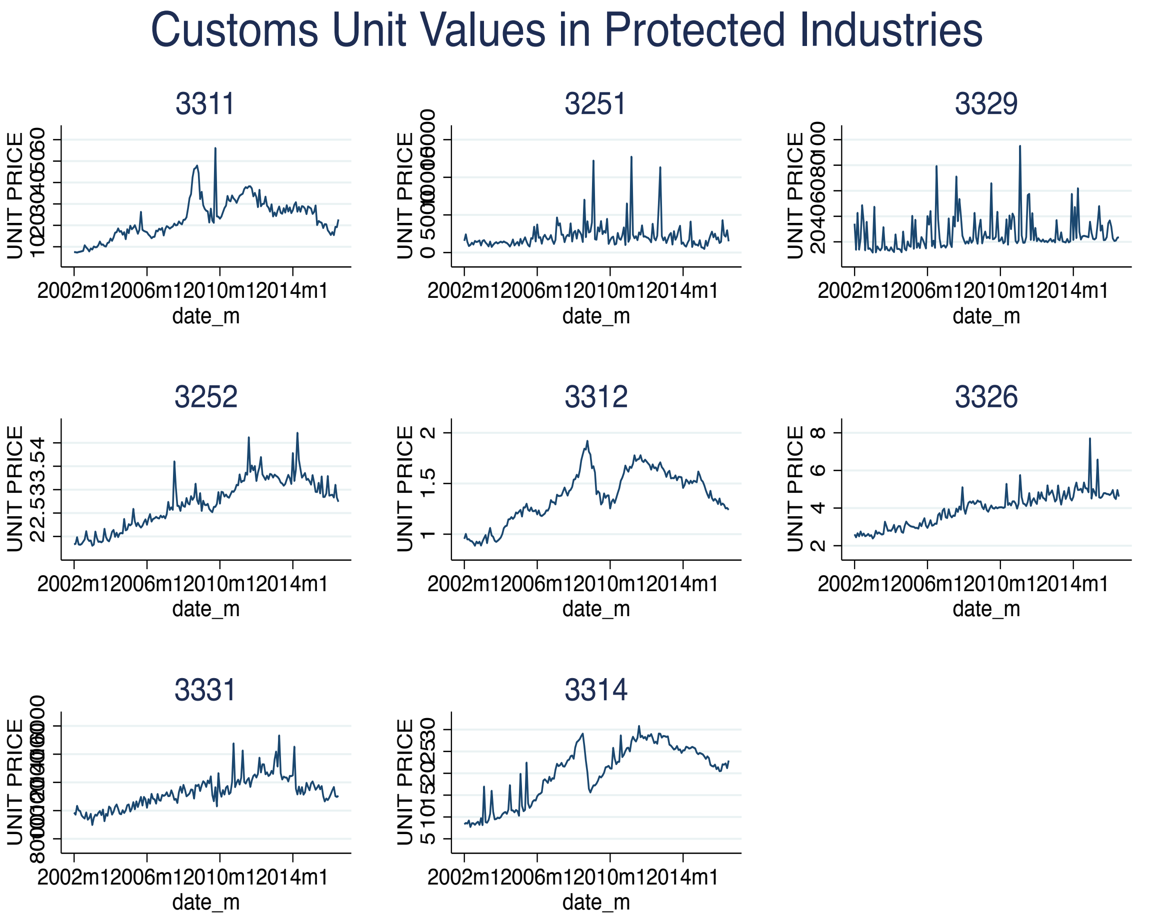

Figure A.7: Import unit values in upstream NAICS 4-digit industries.

Prices in Upstream Industries

We estimate the following set of h-steps ahead predictive panel regressions, for $h = 0, .., H$:

$$\Delta P_{it+h} = \nu_{ih} + \gamma_h \hat{\varepsilon}_{it} + \psi_{t+h} + \epsilon_{it+h},$$

where $\Delta P_{it+h} \equiv \log P_{it+h} - \log P_{it-1}$ denotes the cumulative producer price difference between time t and $t+h$ in industry i; $\hat{\varepsilon}_{it}$ denotes the trade-policy shock for the same industry; ν_{ih} is an industry fixed effect; ψ_{t+h} is a time fixed effect; and ϵ_{it+h} is the prediction error term.

As in the paper, we consider a uniform 1 percentage-point increase in the share of imports subject to TTBs. Figure A.10 shows that the peak in upstream producer prices precedes the peak of the price increase in downstream industries. This finding provides additional evidence to the loss of competitiveness triggered by upstream protectionism.

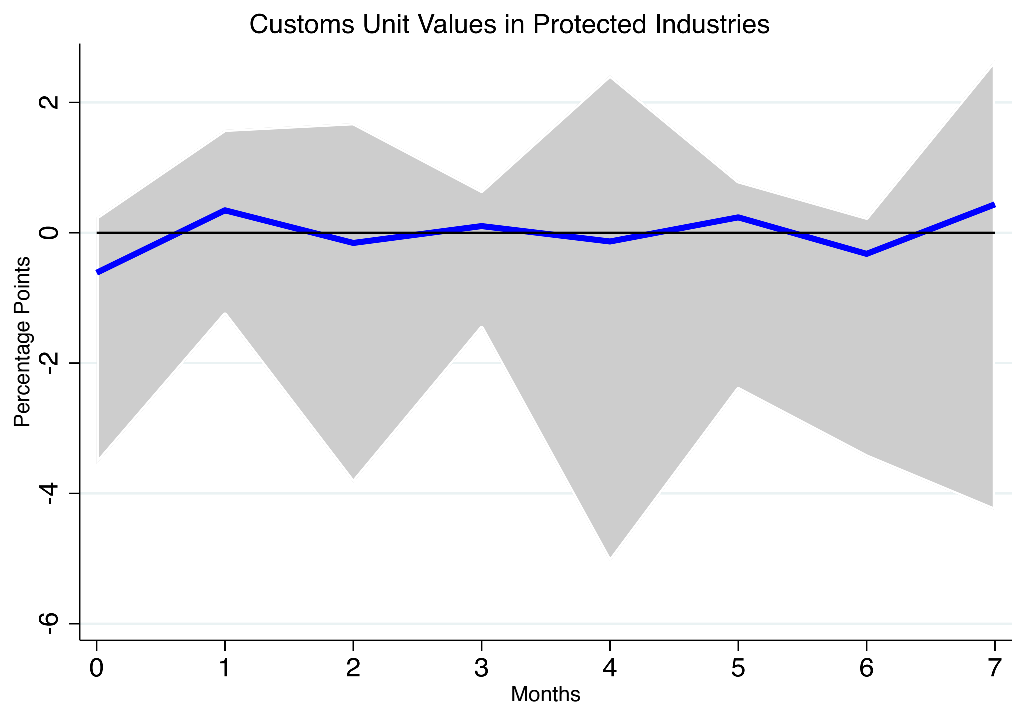

Figure A.8: Impulse responses following a U.S. protectionism shock, import unit-values response.

D Tariff-Equivalent

Figure A.11 plots the total sectoral imports share subject to TTB tariffs in each month. Figure A.12 plots the corresponding tariff series. In the industry that uses TTBs more intensively ("Iron, Steel, and Ferro-Alloy," industry 3311), the uniform-tariff equivalent reaches up to 22%. The series displays substantial persistence in all industries, reflecting that TTB tariffs remain in place for several years (ten on average). The tariff increase can be as high as 50%.

E Abnormal Returns

We first calculate "normal" (i.e., expected) returns using the standard "market model." Motivated by the CAPM, the model imposes the market portfolio return R_d^m as the only systematic factor affecting firms' returns:

$$R_{id} = \alpha_i + \beta_i R_d^m + \varepsilon_{id},$$

where the median return for industry i and the market portfolio return, R_{id} and R_d^m, are expressed as excess returns with respect to the risk-free rate, i.e., the one-month T-bill. The estimated

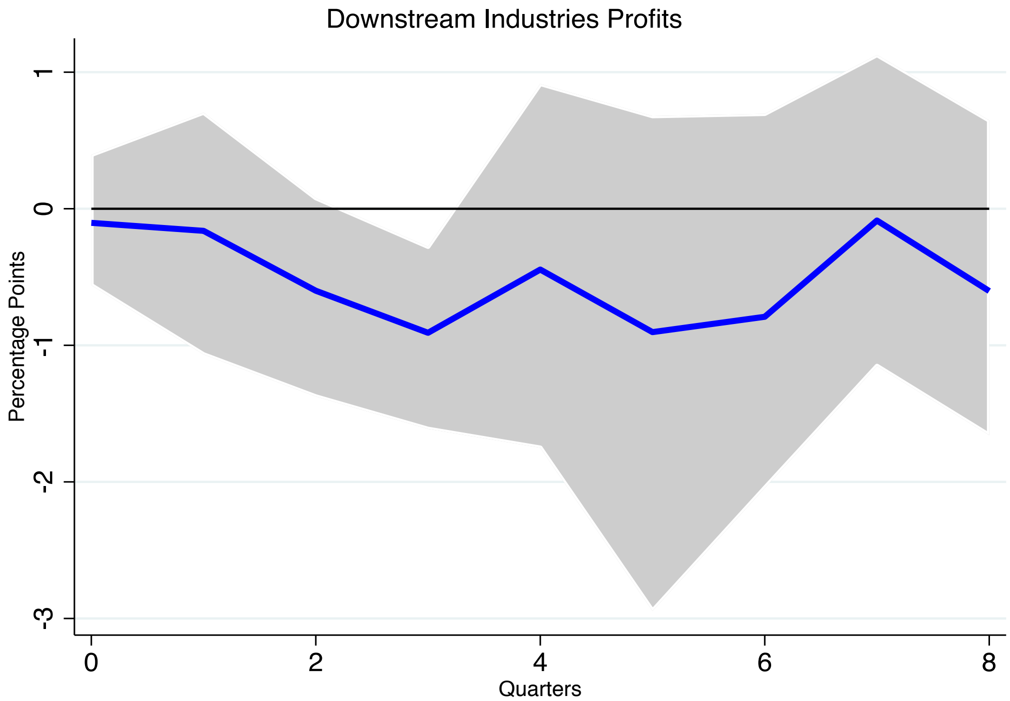

Figure A.9: Impulse responses following a U.S. protectionism shock, profits in downstream industries.

"normal" return at date d is $\hat{\alpha}_i + \hat{\beta}_i R_d^m$, which yields the standard estimate for abnormal returns:

$$R_{id}^A \equiv R_{id} - \left(\hat{\alpha}_i + \hat{\beta}_i R_d^m\right).$$

We then estimate the following panel local projection:

$$\Delta R_{id+h}^A = \nu_{ih} + \gamma_h^{IO} \hat{\varepsilon}_{id}^{IO} + \epsilon_{id+h},$$

where $\Delta R_{id+h}^A \equiv R_{id+h}^A - R_{id}^A$. Figure A.13 shows the results are very similar to Panel C in Figure 6.

F Aggregate Effects

Figure A.14 plots impulse responses for the log-difference of aggregate employment.

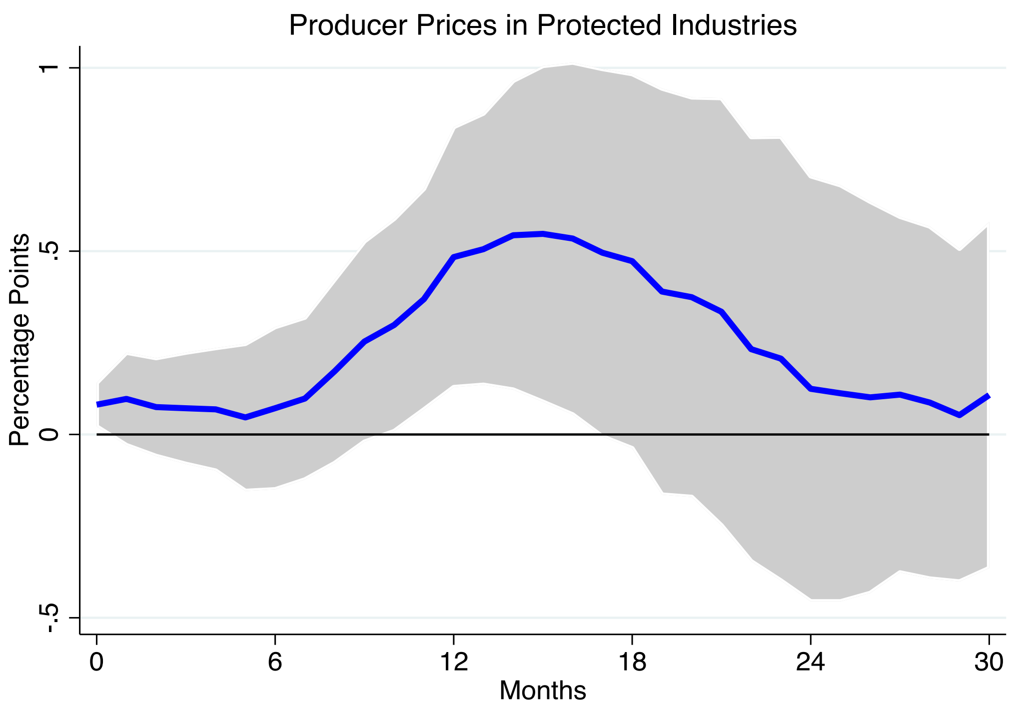

Figure A.10: Impulse responses following a U.S. protectionism shock, prices in upstream industries.

G Additional Aensitivity Analysis

Additional Controls in the First-Stage Regression

As discussed in Section 3, we consider four additional industry-level controls in the first-stage regression: the growth rate of hourly earnings, imports, sales, and industry-specific commodity prices.

For the NAICS codes 3311, 3312, 3314, and 3326, hourly earnings are not available. For these industries, we use NAICS 3-digit data. When including imports, 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 sectoral import share over the entire sample for each product under investigation.

Concerning sales, we use quarterly data from Compustat (net sales), aggregating firm-level data

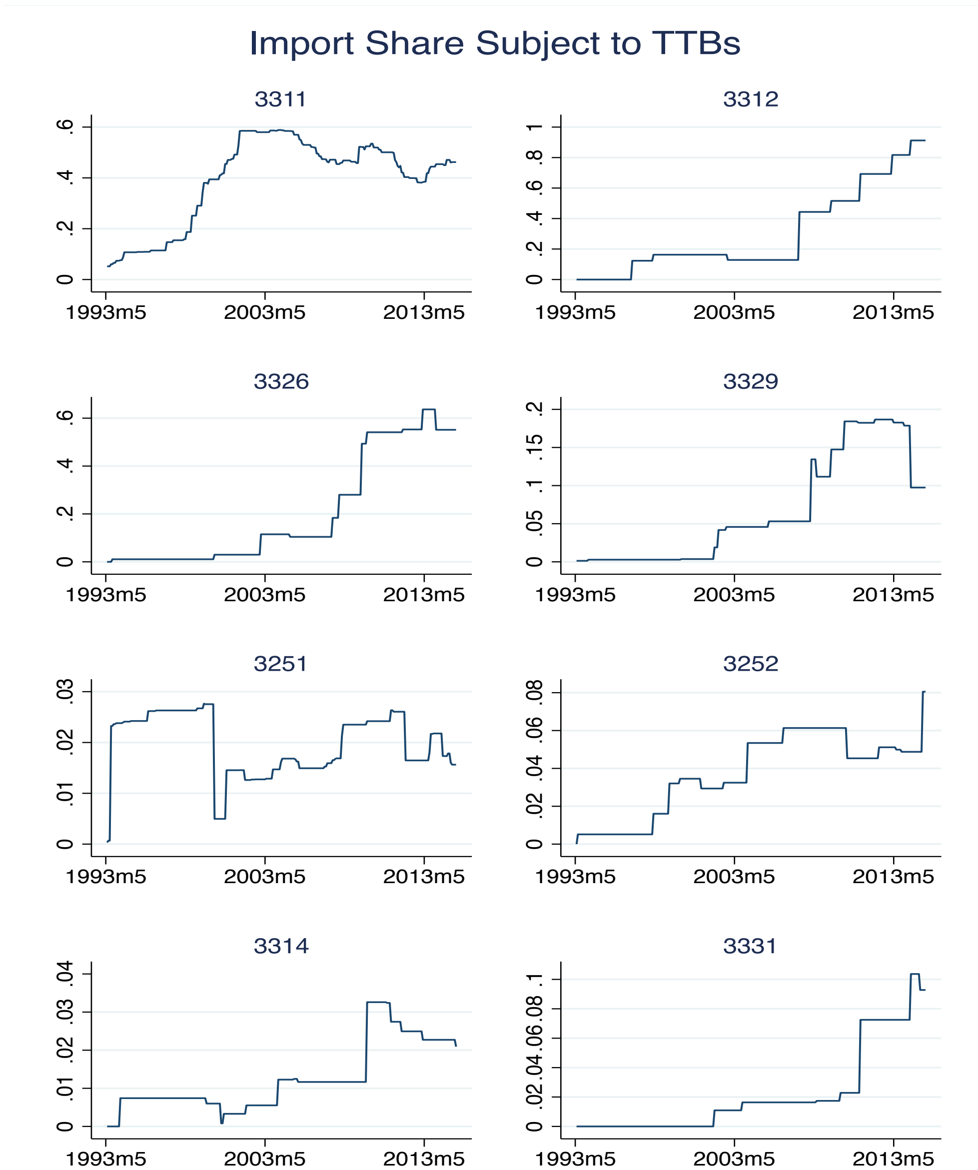

Figure A.11: Share of imports subject to TTBs.

within each NAICS code. Finally, for commodity prices, we consider lags of aggregate and industry-specific series. Aggregate series include the oil price and a global price index of all commodities. In addition, for the commodity-producing industries appearing in Table 1—industries 3331, 3312, 3329, 3252, and 3314—we also control for lags of their commodity price growth rate.

Figure 7 shows the results are not affected by the inclusion of hourly earnings (Panel A), imports (Panel B), net sales (Panel C), and commodity prices (Panel D).

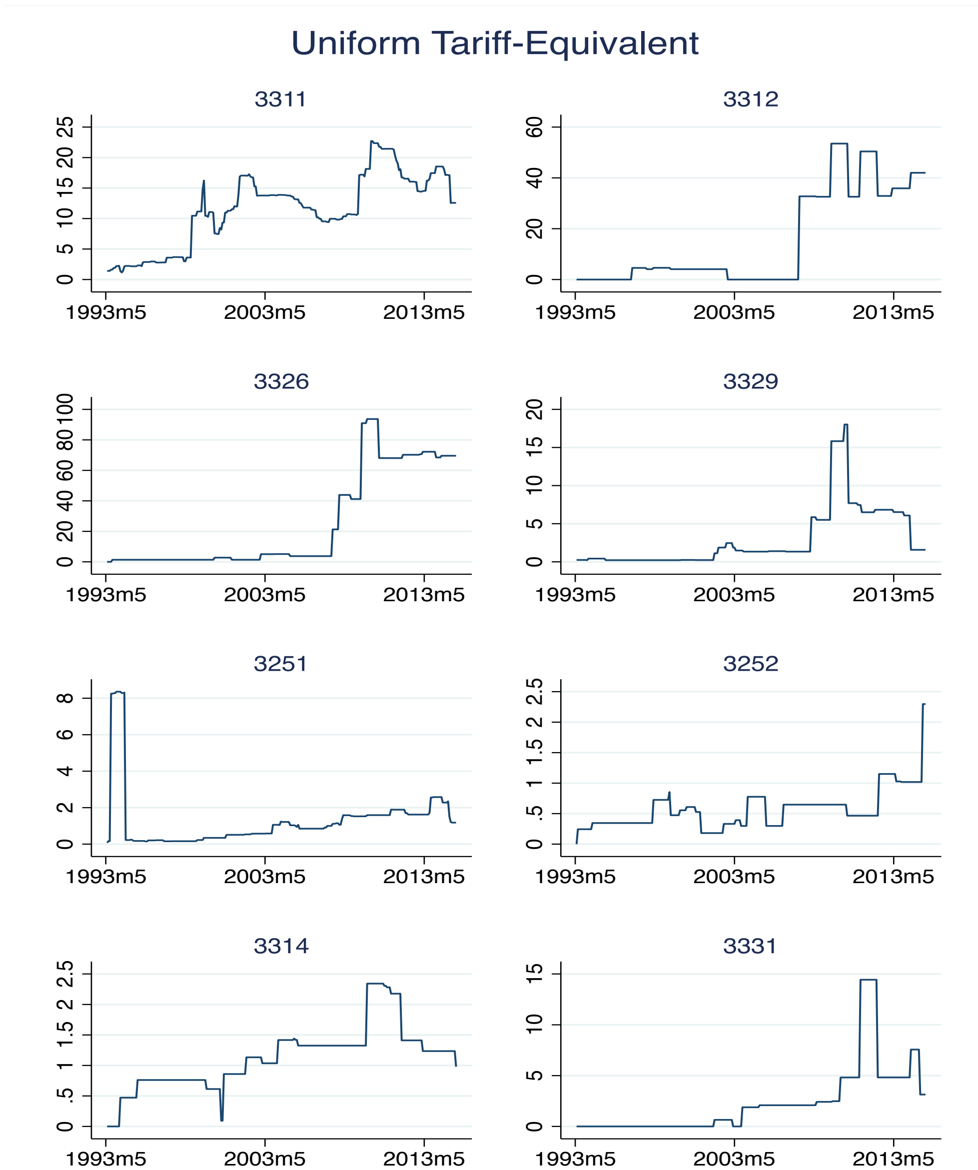

Figure A.12: TTB-implied uniform tariff equivalent.

Alternative Measures of Protectionism

Tariffs

We consider an alternative protectionism measure that uses variation in the TTB uniform-tariff equivalent, τ_{it}^U. As discussed in Section 4 and Appendix D, τ_{it}^U corresponds to a tariff rate that if applied to all sectoral imports, would result in a tariff revenue equivalent to that generated by the stock of products subject to TTB tariffs. When $\Delta\tau_{it}^U \equiv \tau_{it}^U - \tau_{it-1}^U > 0$, new TTBs are imposed within the month. As a result, we use $\Delta\tau_{it}^U$ as an alternative measure of industry protectionism.

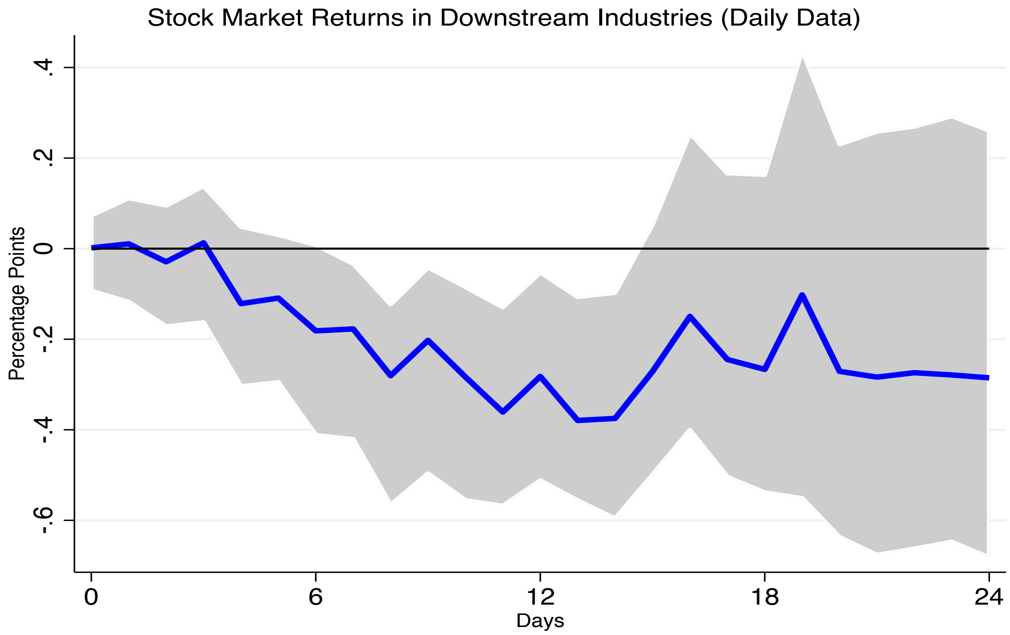

Figure A.13: Impulse responses following a U.S. protectionism shock, median cumulative downstream stock-market abnormal return (days).

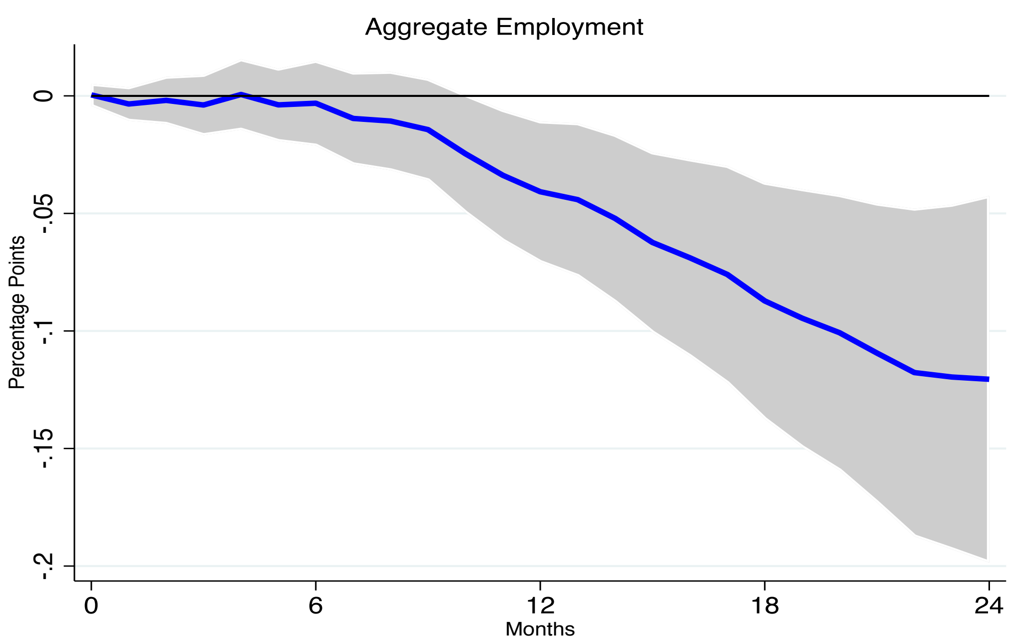

Figure A.14: Impulse responses following an aggregate TTB shock.

Panel A in Figure A.16 plots the employment response in protected industries (left panel) and downstream industries (right panel) following a uniform 1% increase in the average uniform tariff

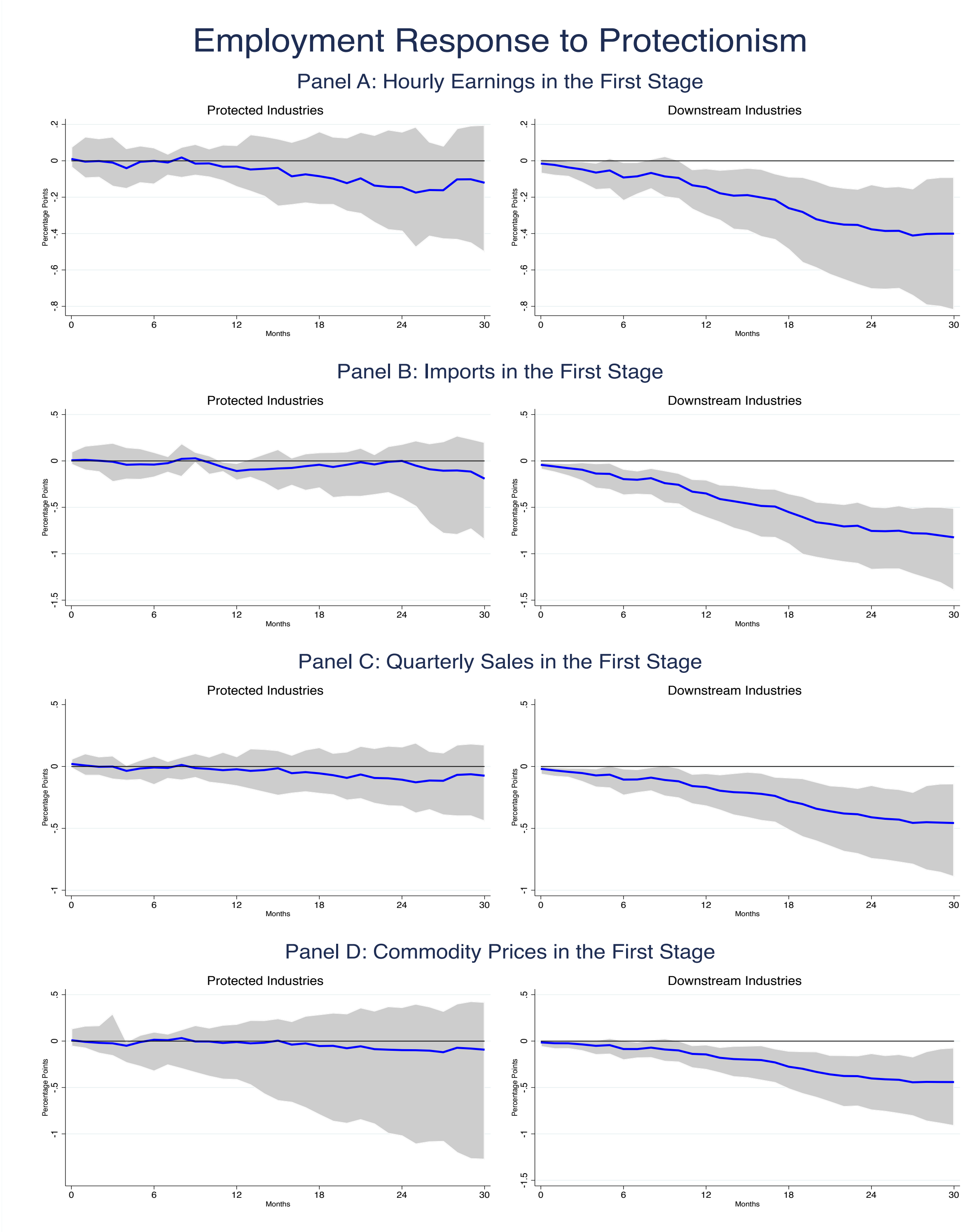

Figure A.15: Impulse responses following a protectionism shock. *Panel A*: First-stage regression includes hourly earnings. *Panel B*: First-stage regression includes imports. *Panel C*: First-stage regression includes sales. *Panel D*: First-stage regression includes commodity prices.

in the eight upstream industries. The magnitude of the shock matches the shock we consider for the baseline measure in the paper. Overall, the results remain similar to the baseline specification.

Exposure to Upstream Protectionism

We consider an alternative measure of upstream protectionism, using sectoral weights that consider upstream industries' average openness—measured by their imports over sectoral output. In this case, the upstream shock is

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

where $\tilde{s}_j$ is the average share of imports relative to output. Also in this case, we consider a uniform 1-percentage-point increase in upstream protectionism. Panel B in Figure A.16 shows that the results remain similar to the benchmark specification.

Global Safeguards

In the baseline specification, we exclude global safeguards from TTBs. Panel C in Figure A.16 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."

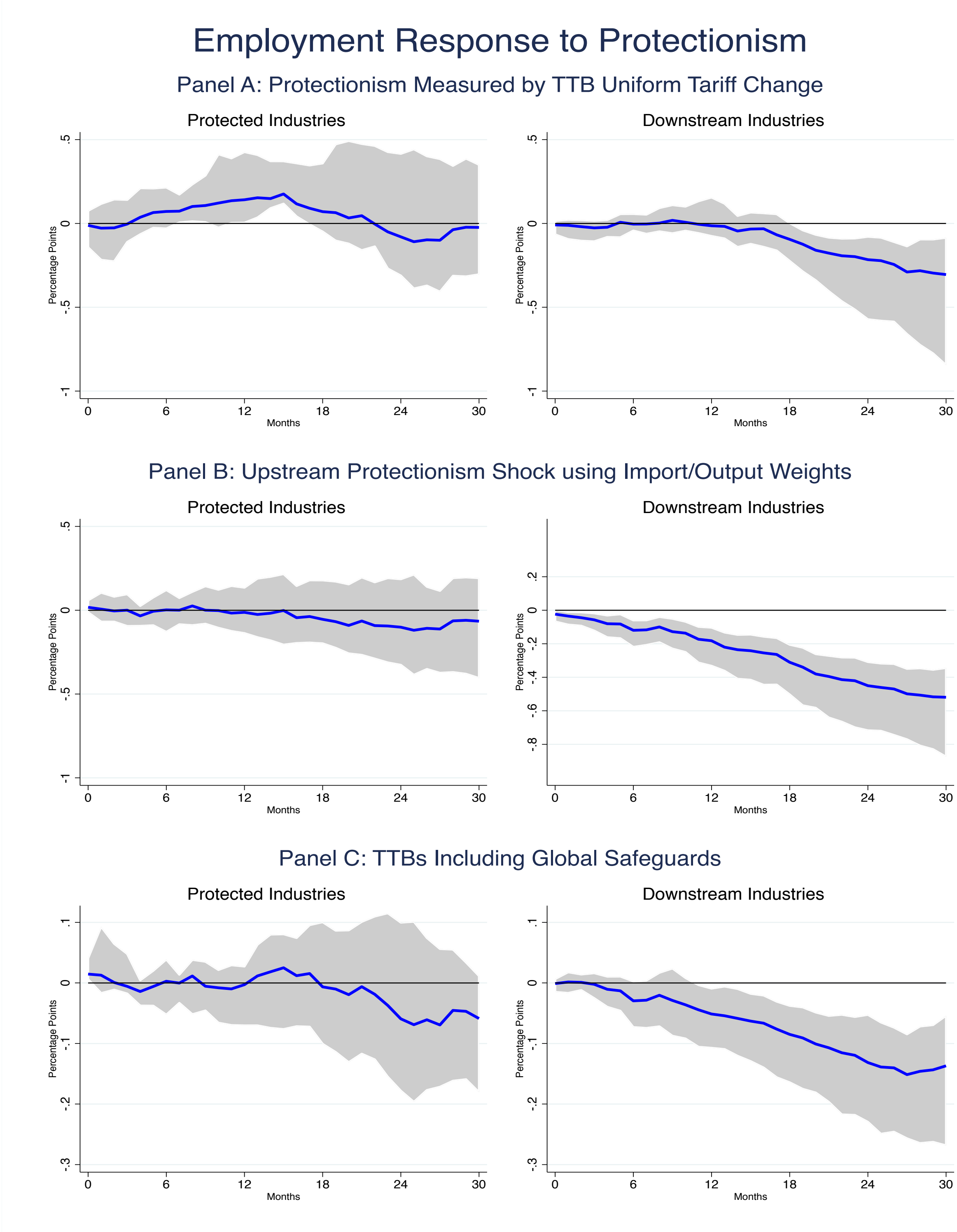

Figure A.16: Impulse responses following a protectionism shock. *Panel A*: τ_{it} measures TTB uniform tariff changes. *Panel B*: τ_{it} constructed using average shares of imports over output. *Panel C*: TTBs include global safeguards.