The Journal of Law, Economics, and Organization, 2026, **42**, 188–220
https://doi.org/10.1093/jleo/ewae023
Advance access publication September 5, 2024
Article

Non-tariff barriers to trade

Marco Leonardi[1,*], Elena Meschi[2]

[1]Department of Management and Economics, DEMM, University of Milan, Milan, 20122, Italy
[2]Department of Economics, DEMS, University of Milan—Bicocca, Milan, 20126, Italy

*Corresponding author. E-mail: marco.leonardi@unimi.it

ABSTRACT

Prior to the recent resurgence prompted by the US–China trade war, tariffs on international trade had been consistently diminishing over the past few decades. In response, advanced countries increasingly turned to non-tariff measures (NTMs) to protect their industries from foreign competition. In this article, we exploit a novel database on NTMs to investigate their impact on the labor market in the United States. We use the political importance of an industry, measured by its employment share in swing states during presidential elections, as an instrumental variable for NTM protection. Our results suggest that NTMs mitigate the adverse employment effects resulting from exposure to Chinese import competition, but exert a negative influence on manufacturing wages, particularly for skilled workers.

1. INTRODUCTION

The surge in manufacturing exports from low-wage countries, particularly from China, has sparked concerns about its impact on employment in high-income countries. China's manufacturing exports notably escalated after its entry into the WTO in 2001. From 2001 to 2015, US imports from China increased dramatically, rising from about \$102 billion in 2001 to about \$483 billion in 2015.

The adverse effects of this import competition on manufacturing employment have been extensively documented in the economic literature (Autor et al. 2013a, 2013b, and 2016). In response, countries have taken diverse measures to shield domestic industries from import competition. As tariffs on international trade have been progressively liberalized in recent decades, countries have increasingly relied on non-tariff measures (NTMs) to restrict their market access and pursue their policy goals (UNCTAD 2013). Gourdon (2014) has observed a growing trend in the adoption and variety of NTMs since the 1990s, indicating a shift in how countries regulate trade.

NTMs can be broadly defined as policy measures other than ordinary customs tariffs that can have an economic effect on international trade in goods, changing the quantities traded, or prices, or both. For practical purposes, NTMs are categorized depending on their scope and design and are generally divided into technical measures (Sanitary and Phytosanitary Standards [SPS] and Technical Barriers to Trade [TBT]) and non-technical measures (see UNCTAD 2013).[1] We focus on SPS, which include quality and hygienic requirements, as well as production and conformity assessments regarding food and beverages and on TBT, that refer to technical regulations that set out specific characteristics of a product, and procedures for assessment of conformity with technical regulations and standards.

Given the central role that NTMs have taken in the international trade agenda, several papers have investigated their impact on the trade flows of countries and firms (see, e.g., Kee et al. 2009; Fontagné et al. 2015). However, to the best of our knowledge, no studies investigate the impact of NTMs on labor market outcomes, except Bown et al. (2021 and 2023), who study the impact of antidumping measures on manufacturing employment in the United States. We bridge this gap by investigating the influence of NTM protection on the US labor market. In particular, we relate changes in local manufacturing employment and wages for the 2000–2015 period to an index of NTM protection at the local level. The mechanism that we have in mind is that NTM protection affects the labor market by reducing imports from China. Therefore, in some specifications, we condition our basic regression on changes in local exposure to Chinese import competition (Autor et al. 2013a, 2013b, and 2016).

To construct the index of NTM protection, we exploit the recently released WTO database on Specific Trade Concerns (STC), which records NTMs at the six-digit product level. STC refer to the concerns raised by WTO members in specific committees to complain about NTMs taken by other members. Rather than simple notifications, STC identify measures that exporters and/or governments perceive as major obstacles to trade. Based on this dataset, we compute a measure of NTM protection at the local area level (defined as a Public Use Microdata Area, PUMA). We define a product as *protected* by an NTM if it is subject to an STC. We compute the intensity of NTM protection of a specific industry by calculating the (weighted) sum of protected products in each industry. We then translate this measure of protection from the industry level to the local area level, using the employment composition of the area at the beginning of the period. The final measure at the PUMA level, our 'NTM index of protection', is essentially the share of employed workers that work in protected industries weighted by the share of protected products in each industry and their incidence in trade flows.

Our empirical strategy addresses the potential endogeneity of NTM protection to labor market conditions by using an instrumental variable approach. Specifically, following Bown et al. (2023), we use the industry share of employment in swing states during presidential elections as an instrument for the NTM protection index. The identification assumption is that NTMs are imposed on industries deemed crucial in swing states for political reasons, and this is orthogonal to other variables that may directly affect the local levels of employment and wages. We discuss the credibility of this assumption and provide the results of some falsification tests in Section 4.

Our article relates and contributes significantly to different strands of literature. First, we expand the extensive body of literature on the labor market consequences of trade competition from China (Autor et al. 2013a, 2013b; Acemoglu et al. 2016; Pierce and Schott 2016), by focusing on how non-tariff protection can shape the effects of the exposure to import competition. Second, we contribute to the research on the employment effects of NTMs,

[1] UNCTAD established the Multi-Agency Support Team to work on the taxonomy of NTMs and classifies NTMs in: Sanitary and Phytosanitary Measures; Technical Barriers to Trade; Pre-shipment Inspection and Other Formalities; Contingent Trade-protective Measures; Non-automatic Licensing, Quotas, Prohibitions and Amp, Quantity-control Measures; Price-control Measures; Export-related Measures

using new WTO-STC data and constructing a novel NTM protection index at the local level. This is not the first paper using WTO-STC data. For example, Fontagné et al. (2015) use the STC dataset to test the effect of NTMs on French firms' exports. Beverelli et al. (2014) and Orefice (2015) use these data to test the trade policy substitution between tariffs and NTMs, whereas Ghodsi (2016) studies the determining factors of STCs raised on TBT notifications. Barba Navaretti et al. (2023) use WTO-STC data combined with matched employer-employee data for the population of French exporters to study the impact of TBT on the workforce composition of French firms. To our knowledge, we are the first to use these data to study the labor market impact of NTMs. The most closely related work is Bown et al. (2023), which investigates the impact of antidumping measures on US manufacturing employment. We borrow from them the identification strategy based on instrumenting the protection with the political importance of an industry, measured by its employment share in swing states. However, a key distinction lies in the focus and methodology. Bown et al. (2023) concentrate on antidumping duties (non-technical NTMs) imposed by the United States against China, relying on industry-level analysis. In contrast, our study focuses on technical NTMs such as TBT and extends the analysis to the local level, building upon the literature initiated by Autor et al. (2013a).

Our article makes several findings. Our results indicate that an increase in the (instrumented) NTM index leads to an increase in manufacturing employment at the PUMA level. Specifically, an average five-year increase of the NTN index (0.5 of a standard deviation) leads to an increase in the share of manufacturing in total employment by 0.4 percentage points, corresponding to about one-fourth of the average five-year decline in the share of manufacturing employment.

A rise in the NTM index is also associated with a significant decrease in manufacturing wages, especially for skilled workers, potentially stemming from lower productivity resulting from heightened protective measures. We investigate this explanation by building an NTM index adjusted to consider the protection of intermediate inputs, utilizing input-output tables. Finally, we do not find any effect of NTMs on non-manufacturing employment and labor market participation, indicating that NTMs affect the manufacturing sector only.

The rest of this article proceeds as follows. Section 2 describes the STC dataset and the construction of the NTM protection index. In Section 3, we present the data and the empirical specification. Section 4 discusses our identification strategy and instrumental variable approach. In Section 5, we present and comment on the results, and we report a number of robustness and sensitivity checks. Finally, in Section 6, we provide some concluding remarks.

2. THE WTO STC DATABASE ON NTMS

NTMs constitute a very diverse array of policies that countries apply to imported and exported goods and that typically have restrictive and distortionary effects on international trade: they include all policy-related trade costs incurred from production to final consumer, with the exclusion of tariffs (Nicita and Gourdon 2013). NTMs are increasingly shaping trade, affecting the quantity and the types of traded goods and the direction of trade flows. Although many NTMs aim primarily at protecting public health or the environment, they substantially affect trade through information, compliance, and procedural costs. The main problem with the study of NTMs has been the scarcity so far of reliable databases on these measures, due to the difficulty of collecting and assembling this type of data. In fact, unlike tariffs, NTM data are not merely numbers and are not subject to comprehensive reporting requirements, so the relevant information is often hidden in legal and regulatory documents that are typically not centralized and often reside in different regulatory agencies (UNCTAD 2013; Gourdon 2014).

In this article, we rely on the recently released WTO database on STC, which records the concerns raised by WTO members in the dedicated committees of the WTO to complain and discuss specific measures taken by other members that are perceived as obstacles to trade.[2] The I-TIP database provides comprehensive information on NTMs applied by WTO members in merchandise trade. It includes members' notifications of NTMs[3], such as TBT, sanitary and phytosanitary measures, and antidumping and countervailing measures, as well as information on STC raised at WTO committee meetings.

We focus on STC regarding SPS and TBT, which are the most commonly used regulatory measures. SPS measures include all measures that are applied to protect human or animal life from risks arising from additives, contaminants, toxins, or disease-causing organisms in food (for example, a requirement limiting the use of hormones and antibiotics in the production of meat or a sample test on imported oranges to check for the residue level of pesticides). TBT refer to technical regulations and standards that set out specific characteristics of a product, such as its size, shape, design, functions, and performance, or stipulate the way a product is labeled or packaged before it enters the marketplace (for example, a restriction on toxins in children's toys or a label for refrigerators indicating their size, weight, and electricity consumption level).

The advantage of STC over traditional information on the existence of regulations on product standards is that the former identify measures that exporters and/or governments truly perceive as major obstacles to trade (i.e. they are important enough that countries whose exports are affected raise a concern to the WTO committees). As such, the information they provide relates to restrictive trade measures only (See also Fontagné et al. 2015).[4] However, we acknowledge that focusing solely on the subset of TBT and SPS measures that were discussed in specific committees at the WTO (Specific Trade Concerns) implies a potential selection and may exclude restrictive NTMs that were not raised in these committees, possibly due to various reasons such as retaliation. Therefore, as a robustness check, we build an index measure named *NTMALL*, which also includes the universe of TBT and SPS measures that were notified to the WTO secretariat and are reported in the Integrated Trade Intelligence Portal (I-TIP). Only a small fraction of NTMs notified to the WTO are subject to STC. Specifically, in our sample, on average across all years, only 18% of HS six-digit products with a reported NTM also receive a STC.

Overall, the dataset provides information on the 317 STC raised in the TBT Committee and the 312 concerns raised in the SPS Committee between January 1995 and June 2015. For each concern, we have information on: (a) the country or countries raising the concern and the country imposing the measure, (b) the product codes (HS 2002 at the six-digit level) involved in the concern, (c) the year in which the concern was raised with the WTO, and (d) whether it has been resolved and how (see WTO 2012 for more details).

Our analysis focuses on a sub-sample of the 41 concerns raised by China or the rest of the world against the United States over the period 1995–2015. Based on these concerns,

[2] The data are made accessible from the Integrated Trade Intelligence Portal (I-TIP), and are available at $http : //www.wto.org/english/res_e/publications_e/wtr12_dataset_e.htm$ in a quantitative format and in a searchable format at $http : //spsims.wto.org/web/pages/search/stc/Search.aspx$. In particular, we exploit the dataset constructed by Ghodsi et al. (2017), which is a compilation of NTM notifications to the WTO for the period 1995-2019, enriched by matching HS 6-digit product codes. See Ghodsi et al. (2017) for more details.

[3] To increase the transparency of governments' trade policies, the WTO obliges member states to notify their imposed policy instruments.

[4] This is not the case for other datasets, such as TRAINS, which only records whether a country has imposed an NTM, without indicating whether the measure constitutes a trade barrier.

we build a panel dataset tracking the presence of an ongoing STC against the United States on HS six-digit products over time.

Figure 1 plots the 41 STCs over time against a measure of the incidence of tariffs in the UNITED States and reveals that the strong decline in tariffs that occurred over the last decades has been associated with a significant increase in NTMs.

For the purposes of this article, the idea is that the imposition of NTM increases (or slows the reduction of) manufacturing employment growth, reducing imports from China in the following years.[5] Of course, there are potential issues of endogeneity of NTMs and employment changes at the PUMA level that will be treated afterward (see Section 4). Here, as a motivation exercise, we show that—at the HS four-digit product level—NTMs are correlated with future changes in imports from China. In particular, we estimate the equation:

$$\Delta log(ChinaImport)_{ht} = \beta NTM_{h(t-i)} + \alpha_t + \alpha_j + \varepsilon_{ht} \tag{1}$$

where h represents the product, defined at the four-digit HS level, and t the year, from 1995 to 2015. The dependent variable, $\Delta log(ChinaImport)$, is the annual percentage change in US imports from China in product h at time t. NTM is a dummy indicating whether product h is subject to any STC at time $(t-i)$ (we consider the lags up to five years, as shown in the five columns of Table 1). α_t are time-fixed effects that control for macroeconomic dynamics and α_j are industry-fixed effects (four-digit SIC codes) to account for unobserved product-specific characteristics that might affect the likelihood of imposing an NTM. Standard errors are clustered at the same industry level (four-digit SIC codes).

The table clearly shows that NTMs are negatively correlated with future US imports from China: in particular, the imposition of an NTM on a specific product h has a negative significant effect on the change in imports in the following three years (each cell of the table shows the result of a separate regression). As a check, in Panel B, we also show that the same regression with the change in Chinese imports in the rest of the world yields insignificant results, that is, we can conclude that NTMs (of the United States toward Chinese or other countries' products) are associated with lower Chinese exports toward the United States but not toward other countries.[6] This evidence is consistent with other papers showing that NTMs constitute an effective trade barrier. For example, Chen et al. (2022) find that non-tariff barriers were responsible for 50% of the overall reduction in Chinese imports from the United States during the height of the US–China trade war in 2018 and 2019.

2.1 Index of NTM protection

Starting from the 41 STCs raised by China or the rest of the world against the United States, we first build a measure of NTM protection at the industry level, based on the share of protected products in each industry, and then we compute a measure of protection at the local PUMA level, based on the share of total employment in protected industries.

We define a product (a six-digit HS code) as "protected" if it is subject to an STC. One STC may apply to more products, and one product may be subject to more than one

[5] In principle, the effects of standard-type NTMs on import competition are ambiguous because of heterogeneity across foreign and domestic producers (Marette and Beghin 2010). The evidence on the effects of NTMs on trade flows is, in fact, mixed: NTMs enhance or restrict trade depending on the country pairs, the sectors, and the specific measure considered (Beghin et al. 2015; Cadot and Gourdon 2016).

[6] The results hold if we use the instrumented NTM variable at the industry level (our instrument, which will be introduced later in Section 4, is the share of each industry in the total employment of swing states in presidential elections. We exploit the exogenous variation in these shares due to changes in the identity of swing states). The IV coefficient on NTM at one lag is -0.292(0.166) when the dependent variable is the change in Chinese imports in the US and is 0.113(0.088) when the dependent variable is the change in Chinese imports in the rest of the world.

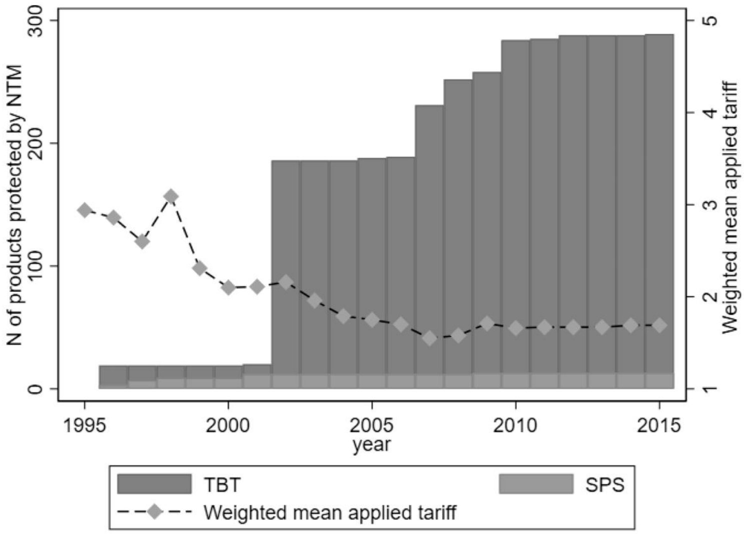


Figure 1. Evolution of tariff (right axis) and NTMs (left axis). Non-tariff is the number of HS four-digit products targeted by SPS/TBT concerns against the United States (source: WTO-STC database). Tariff is the weighted mean applied tariff.

Table 1. NTMs and changes in Chinese imports in the United States and in the rest of the world.

	1 lag	2 lags	3 lags	4 lags	5 lags
Panel A. Dep Var: Delta Chinese Imports in the United States					
NTM_{ht-i}	−0.018*	−0.025***	−0.024***	−0.016*	−0.013
	(0.009)	(0.008)	(0.009)	(0.009)	(0.013)
Observations	40,145	40,145	38,471	36,714	34,906
Panel B. Dep Var: Delta Chinese Imports in the Rest of the World					
NTM_{ht-i}	−0.01	−0.009	−0.002	0.000	0.003
	(0.007)	(0.008)	(0.009)	(0.010)	(0.015)
Observations	43,302	43,302	40,920	38,540	36,170

Each cell is the estimated coefficient of a separate regression on various lags of NTM_{ht-i} taken one in turn. Year and industry (four-digit SIC codes) fixed effects are always included. In Panel A, the dependent variable is $\Delta log(ChinaImport)$, and in Panel B, the dependent variable is the change in Chinese exports to the rest of the world (except the United States) of product h at time t. Robust standard errors, clustered at the sector (SIC four-digit) level, are in parentheses.

*** Significant at the 1% level.

* Significant at the 10% level.

concern. In our sample, 41 concerns affect 1433 products out of a total of 6292 products (six-digit HS codes) in 21 manufacturing industries (i.e., 29% of all manufacturing products are subject to an STC). We define a dummy $HSp_{it} = 1$, which indicates that product i is protected by an NTM if the product is subject to a concern in year t. Since we have the year of the beginning and the year of the end of each STC, we are able to build a time-varying measure of HSp_{it}. Appendix Figure A1 shows the products with the longest STCs (distinguishing between Technical Barriers in Panel A and Sanitary and Phytosanitary in Panel B). The figure indicates that protected products by TBT measures are especially concentrated in some manufacturing industries, such as food processing, apparel, and chemical manufacturing. SPS measures are instead concentrated in the animal production and agriculture sectors.

HS-coded products are allocated to industry j with crossover HS six-digit-NAICS 2002 at the three-digit level.[7] Each industry has N_j HS products. The incidence of NTMs in each sector is measured by looking at the percentage of products that are subject to one or more NTMs, weighted by the share of each product in the overall imports of the industry, measured at the beginning of the sample period (i.e., 2000) to avoid endogeneity.[8] The idea is that some products may be more important than others in the composition of total trade flows of each industry, and NTMs may thus have a differential impact on the overall level of trade protection of a given industry, according to the trade share of the product covered by an NTM.[9]

In formal terms, our measure of protection of industry j in year t is given by

$$NTM_{jt} = \frac{\sum_{i=1}^{N} HSp_{it}(imp)_{i2000}}{(imp)_{j2000}} \qquad \forall i \in j \tag{2}$$

where HSp_{it} indicates whether an NTM is in place for product $i \in j$ in year t. Each product i is weighted by its share in the total imports of industry j. In Section 5.3, we try different weights for robustness.

Table 2 shows the total number of HS products allocated to each industry (first column) and the number of protected products in each industry at three points in time (2000, 2005, and 2010), with their relative weighted shares. It is clear from the table that many industries are never protected by NTMs, while other industries vary their degree of protection over time according to the number of products that become progressively subject to STCs.

The measure of protection at the PUMA level reflects the share of the employed population that works in a protected industry. Therefore, the index of NTM protection for each PUMA m is given by

$$NTM_{mt} = \sum_{j} \frac{L_{mj2000}}{L_{m2000}} \times NTM_{jt} \tag{3}$$

where $\frac{L_{mj2000}}{L_{m2000}}$ is the share of workers of PUMA m employed in industry j in year 2000. NTM_{mt} is the (weighted) share of workers in a PUMA that are protected by an NTM (the weights are the intensity of protection of each industry measured by the number of NTM-protected products). NTM_{mt} changes over time because of the variation in the intensity of industry protection (NTM_{jt}). In the regression specification, we use the variable in five-year differences ΔNTM_{mt}.

NTMs are increasingly important over time, and their geographic incidence is very diverse. Appendix Figure A2 shows the distribution across PUMAs of the measure of NTM protection in various years, which ranges from zero to more than 20% of workers working in protected industries. The figure indicates that the distribution of NTM protection shifts to the right over time, confirming their growing incidence.

[7] In particular, we first use a cross-walk between HS02-6 digit and ISIC Rev 3.1 and then a cross-walk between ISIC Rev. 3.1 and NAICS 2002.

[8] The data on trade flows by product (HS classification) in the year 2000 used to construct the weights are taken from COMTRADE.

[9] This measure is similar to the coverage ratio computed by UNCTAD (see Disdier and Fugazza 2020, for more details), which measures the percentage of trade subject to NTMs for an importing country.

Table 2. Number and weighted share of HS products protected in each NAICS sector.

Year		N of HS (4digit)	Index of NTM protection		
			2000	2005	2010
311	Food Manufacturing	115	20.63	84.65	84.65
312	Beverage and Tobacco Product Manuf	10	0.00	75.36	96.78
313	Textile Mills	68	0.00	0.00	0.00
314	Textile Product Mills	33	55.51	10.52	55.51
315	Apparel Manufacturing	41	48.84	0.00	94.25
316	Leather and Allied Product Manuf	23	0.00	0.00	0.00
321	Wood Product Manufacturing	23	96.71	96.71	96.71
322	Paper Manufacturing	28	0.00	0.00	0.00
323	Printing and Related Support Activities	11	0.00	0.00	0.00
324	Petroleum and Coal Products Manuf	6	0.00	0.00	0.00
325	Chemical Manufacturing	198	0.01	6.03	5.53
326	Plastics and Rubber Products Manuf	24	0.00	18.43	0.00
327	Nonmetallic Mineral Product Manuf	58	0.00	0.00	0.00
331	Primary Metal Manufacturing	96	0.00	0.00	0.00
332	Fabricated Metal Product Manuf	70	0.00	0.00	1.39
333	Machinery Manufacturing	96	21.68	0.00	6.73
334	Computer and Electronic Product Manuf	53	0.00	0.80	3.29
335	Electrical Equipment and Component Manuf	31	0.00	0.00	10.09
336	Transportation Equipment Manuf	31	51.45	42.05	0.00
337	Furniture and Related Product Manuf	3	0.00	0.00	0.00
339	Miscellaneous Manufacturing	76	0.59	2.10	15.38

Source: WTO-STC data. Manufacturing industries only. The table shows the index NTM_{jt} where each protected product is weighted by its import share in total industry imports.

Appendix Figure A3 shows the geographic pattern of NTM protection (average value of the index 2000–2015) across the whole country. The figure highlights the significant variability in the intensity of NTM protection across different PUMAs, with the most protected areas mainly concentrated in the mid-west, California, and some PUMAs in the northwestern states.

2.2 Alternative NTM indexes

Our main NTM index, NTM_{mt}, is constructed using only STCs because we believe that only STCs indicate a serious obstacle to trade. This index can be disaggregated according to the type of regulatory measure adopted: in Appendix Table A3, we distinguish between the NTM index constructed using only Sanitary and Phytosanitary Standards (*NTMSPS*) and using only *Technical Barriers to Trade* (*NTMTBT*) in order to identify the impact of the two components separately.

As mentioned before, we also build an index (called *NTMALL*) that takes into account all notifications, not only those that sparked an STC. In this way, we consider a broader set of NTM, including potentially restrictive measures not raised in STC committees, which are not accounted for in our main measure.

To test the robustness of our results to the inclusion of antidumping measures, we consider all antidumping measures notified to the WTO, which account for about 10% of all notifications in the I-TIP dataset (see Ghodsi et al. 2017, for more details).[10] Following the

[10] I-TIP covers all measures notified to the WTO (as required by the antidumping Agreement to WTO Members), which are in force or initiated since December 2000. For each notification of antidumping, we know the product affected (at four-digit HS code) and the country imposing the measure.

procedure described above for NTMs, we define an index of sectoral protection by antidumping measures (ADP), by computing the weighted share of products protected by ADP in each industry (NAICS 3 digit); we then project the industry-level index to each PUMA according to its employment composition at the beginning of the period (ADP_{mt}). We use ADP_{mt} as a control variable and to build a comprehensive index of protection that includes both technical NTMs (TBT and SPS) and non-technical antidumping measures ($NTMADP_{mt}$).

Finally, we compute an NTM protection index based on supply chains ($NTMIO$), that is, we adjust the NTM index of protection for the protection of intermediate inputs using input–output tables from the Bureau of Economic Analysis (BEA) in the year 1995 (we use only 1995 tables before the period of analysis for all years). We use their concordance guide to convert six-digit BEA industry codes into three-digit NAICS codes to combine input–output tables with industry-level data. We account for NTM protection in intermediate inputs because it is difficult to attribute the employment effects to the protected industry only, when many products are used as intermediate goods in other productions.

The input-adjusted index of protection of final product j is calculated as $NTMIO_j = \sum_i \frac{I_{ij}}{\Sigma_i I_{ij}} NTM_i$, where NTM_i is the index of protection of intermediate industry i (STC only). The weights $\frac{I_{ij}}{\Sigma_i I_{ij}}$ indicate the industry's i input contribution to produce one unit of product in industry j (including the diagonal of the matrix, i.e., own industry as input).

This allows us to build a NTM measure at the PUMA m level:

$$NTMIO_{mt} = \sum_j \frac{L_{mj2000}}{L_{m2000}} \times NTMIO_{jt} \tag{4}$$

3. DATA AND EMPIRICAL STRATEGY

To analyze the local labor market effect of NTMs, we regress a measure of change in local labor market outcomes, such as manufacturing employment or wages, on the index of NTM protection plus a set of location-specific controls.

We use data from the 5% sample of the decennial census in 2000 and the 1% sample of the American Community Survey (ACS) in 2005, 2010, and 2015 Integrated Public Use Microsample Series (IPUMS) files. Our analysis requires a time-consistent definition of regional economies in the US: following Hakobyan and McLaren (2016), we define local labor markets by the Census Consistent PUMAs. PUMAs cover the entire United States, do not cross state lines, and are consistently defined over time. They are a slightly smaller geographic unit than the Commuting Zones (CZs) used in Autor et al. (2013a) and related papers.[11] We keep only manufacturing sectors (21 sectors at three-digit level) and a balanced sample of 1078 PUMAs, which are present in all years. The units of observations in the analysis are PUMA-year weighted averages (using IPUMs personal weights): the final dataset contains 4,312 observations (1078 PUMAs times four years). The regressions are in differences (3,234 observations).

[11] Unlike CZs, PUMAs are not specifically designed to outline the boundaries of local labor markets, but they have been used in the literature to define local labor markets (see Hakobyan and McLaren 2016; Lake and Millimet 2016)) and we do not expect our results to be significantly affected by the choice of the geographic unit.

Table 3. Effect of NTMs on manufacturing employment, controlling for antidumping measures. IV estimates.

	(1)	(2)	(3)	(4)
Dep var: Δ log manuf. employment				
ΔNTM_{mt}	0.121***	0.115***		
	(0.029)	(0.030)		
ΔADP_{mt}	0.010	0.007		
	(0.008)	(0.008)		
$\Delta NTMADP_{mt}$			0.114***	0.105***
			(0.024)	(0.025)
$\Delta Impexposure_{mt}$		−0.023***		−0.029***
		(0.005)		(0.004)
F stat.	259.7	267.4	742.7	738.8

$N = 3234$ (1078 PUMAs, three 5-year changes). ΔADP_{mt} is a measure of antidumping regulations; *NTMADP* is the index constructed using both STCs and antidumping measures (see text for details). The dependent variables are five-year differences in log manufacturing employment. All regressions control for PUMAs' share of college-educated, female, and foreign-born population, all measured at the beginning of each period, and swing state and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA. See the description of the Table in Section 5.1.1.

*** Significant at the 1% level.

Appendix Table A1 in the provides some descriptive statistics of the main variables included in the analysis and computed from CENSUS and ACS data and from the WTO-STC database for NTMs.

More specifically, we estimate the following equation:

$$\Delta Y_{mt} = \beta \Delta NTM_{mt} + \gamma \Delta Impexposure_{mt} + \delta X_{mt} + \alpha_t + \varepsilon_{mt} \tag{5}$$

where ΔY_{mt} is the five-year change (between 2000 and 2015) in various labor market outcomes of PUMA m. The main outcome of interest is the five-year change in the share of the working-age population employed in manufacturing (or the change in log manufacturing employment) and the change in log hourly manufacturing wages, but we also look at employment and wages of skilled and unskilled workers, non-manufacturing employment, labor force participation, and reallocation of workers across PUMAs.

ΔNTM_{mt} is the five-year change of our index of NTM protection at the PUMA level. We standardize the NTM index to have a mean of 0 and a standard deviation of 1 for ease of interpretation.

The vector X_{mt} contains a set of controls for the PUMA's labor force and demographic composition that might independently affect manufacturing employment (share of females, share of college-educated, share of whites, average age, all measured at the initial year of the five-year change to avoid simultaneity).

All estimates are in five-year differences and therefore control for PUMAs' time-invariant unobservable characteristics. α_t are time dummies for the three five-year changes considered in the analysis (2000–2005, 2005–2010, and 2010–2015) and absorb a common non-linear trend. Standard errors are clustered at the PUMA level.[12]

[12] In the robustness section, we show that our main results hold if we estimate the same equation clustering the standard errors at the state level to account for spatial correlations between PUMAs.

Our variable of interest is ΔNTM_{mt}. This specification identifies the effect of NTM protection if workers' mobility across local areas is limited and if local labor markets differ in their level of protection only because of their employment structure. Even though our equation controls for time-invariant unobserved heterogeneity across PUMA, estimates based on equation 5 may still be biased if NTM is endogenous to PUMA's demand conditions. We discuss the potential endogeneity of NTM protection and explain our identification strategy based on the exogenous variation of swing states in presidential elections in Section 4.

In some specifications, also control for PUMAs' differential exposure to import competition from China: $\Delta Impexposure_{mt}$ measures the increase (five-year change) in exposure to competition from Chinese imports faced by a location m. Similarly to Autor et al. (2013a), the measure is computed as follows:

$$\Delta Impexposure_{mt} = \sum_j \frac{L_{mj2000}}{L_{j2000}} \frac{\Delta Imp_{jt}^{EU}}{L_{mt}}. \tag{6}$$

For each PUMA m and each time period t, $\Delta Impexposure_{mt}$ is the sum across all industries j of the five-year changes in per capita EU imports from China $\frac{\Delta Imp_{jt}^{EU}}{L_{mt}}$, weighted by the industry share of local manufacturing employment at the beginning of the period (year 2000) $\frac{L_{mj2000}}{L_{j2000}}$. In contrast to Autor et al. (2013a), who employ this measure as an instrumental variable for actual Chinese imports in the United States, we directly incorporate it into the main equation. Actual US imports would be an obvious bad control in equation 5 because the presence of NTMs affects the level of US imports. Therefore, we want a measure of *potential* exposure to Chinese imports rather than *actual* exposure.[13] Chinese exports to the EU provide such a measure of potential exposure because they are not affected by US trade policy and depend only on Chinese supply shocks in each industry and on the industry mix in each PUMA. According to this definition, the most exposed areas are the PUMAs in which a larger share of workers are employed in industries in which (potential) Chinese exports have experienced the largest increase due to the rising competitiveness of Chinese manufacturers. For this variable to be considered exogenous, it must depend only on Chinese supply shocks in each industry (and on the industry mix in each PUMA) and that import demand shocks in high-income countries are not the primary cause of China's export growth. This assumption seems plausible in our case, considering that during the 1990s and early 2000s, China's export growth was largely the result of internal supply shocks and falling global trade barriers (see Autor et al. 2013a). Imports to Europe as a proxy for import pressure from China would still be a bad control in equation 5 if the industries where China exports large quantities to the EU are precisely those where NTMs are imposed because Chinese production is very competitive. We show that this is not necessarily true by regressing Chinese imports in the EU on NTMs imposed by the United States. The coefficient is close to zero and not statistically significant (P-value = 0.375).[14]

[13] Chinese exports to the EU grew even more than exports to the US in the period 2000 to 2015: the increases were 350% and 230%, respectively.

[14] Furthermore, Chinese imports into the EU provide a measure of potential trade exposure for the US to the extent that the EU does not use similar NTMs, otherwise a high(low) level of imports may indicate low(high) NTM protection in Europe rather than a Chinese supply shock. At the product level h (43,302 products), the correlation between NTMs imposed in the United States and NTMs imposed in the EU is 0.56; however, when dividing the sample in TBT and SPS measures, the correlation is 0.19 between TBTs in the US and the EU and 0.64 between SPSs, that is, Sanitary and Phytosanitary Standards (which are imposed on agricultural goods) are more similar across countries. Notice, for instance, in Table 2 that food and beverages (the first two entries in the table)—which are sectors with little Chinese exports—have high NTMs (SPSs); therefore, the low level of Chinese exports in these categories may result from Europe also protecting its market. In alternative,

4. IDENTIFICATION AND IV

Identifying the causal impact of trade protection through NTMs is challenging, given the plausible endogeneity of NTM to local labor market conditions. Many factors could bias OLS estimates: in general, the error term in equation 5 may reflect unobserved PUMA-specific differences in economic performance that may correlate with the share of workers protected by NTMs. For example, if NTMs were predominantly concentrated in a PUMA that experienced significant employment loss, then the OLS estimates would be downward biased. Conversely, a positive bias in OLS estimates would occur if a PUMA with the most robust manufacturing employment also tended to have a higher prevalence of NTMs.

To address this problem, we follow an instrumental variable approach and adapt the IV strategy based on swing states in presidential elections used in Bown et al. (2021 and 2023). They claim that members of the US Department of Commerce and the US International Trade Commission can be captured by political power as they are appointed by the Congress and the US President and are more likely to put NTMs (in their papers, they focus on antidumping measures) on products from industries that are important in swing states. This is in line with the growing literature on the political economy of trade protection, which shows that NTMs are driven not only by economic but also by political motivations. Conconi et al. (2017) show that the importance of an industry in a swing state affects the initiation of WTO disputes by the United States, while others have emphasized that trade policy in the United States is biased toward the interests of swing states (see for example Muuls and Petropoulou 2013; Ma and McLaren 2018). Recent papers suggest that governments tend to grant more NTM protection to industries that are politically important and are more represented by lobbies (see, for example, Maggi and Goldberg 1999; Lee and Swagel 2000; and Herghelegiu 2018).

Swing states are identified based on the narrow margin of victory in various presidential elections: a state is considered a 'swing state' if the difference in the average vote shares of the two parties is less than 5% (see Conconi et al. 2017, and Bown et al. 2023, for more details). To capture an industry's political importance, we use its percentage share of employment in all swing states at the beginning of the period. Our instrument thus varies over time due to changes in the identity of the swing states (and their industrial composition), which is arguably exogenous to demand shocks.

More specifically, the IV for NTM_{mt} is first defined at the sectoral level and then projected to each PUMA m according to its employment composition. The IV is thus constructed as follows:

$$indswing_{jt} = \frac{\sum_{i=swing} L_{ijt}}{\sum_{i=swing} \sum_{j} L_{ijt}} \tag{7}$$

where $indswing_{jt}$ is the employment share of each industry j in total employment of states that are classified as swing in presidential term t. In particular, we consider swing states in four presidential elections in 2000, 2004, 2008, and 2012. Therefore, within an industry j, variation in $indswing_{jt}$ comes from changes in the identity of swing states across four electoral terms[15].

SPSs may shield US industries from import competition from countries other than China (for instance, agricultural goods are more likely to come from Canada or Mexico, and in this case, our measure of NTMs based on STC raised by China would not be a good measure of protection).

[15] In 2000, the swing states were Florida, Iowa, Minnesota, Missouri, Nevada, New Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, Tennessee, and Wisconsin. In 2004, they were Florida, Iowa, Michigan, Minnesota, Nevada, New

Then, the projection at the PUMA level is:

$$indswing_{mt} = \sum_j \frac{L_{mj2000}}{L_{m2000}} \times indswing_{jt} \tag{8}$$

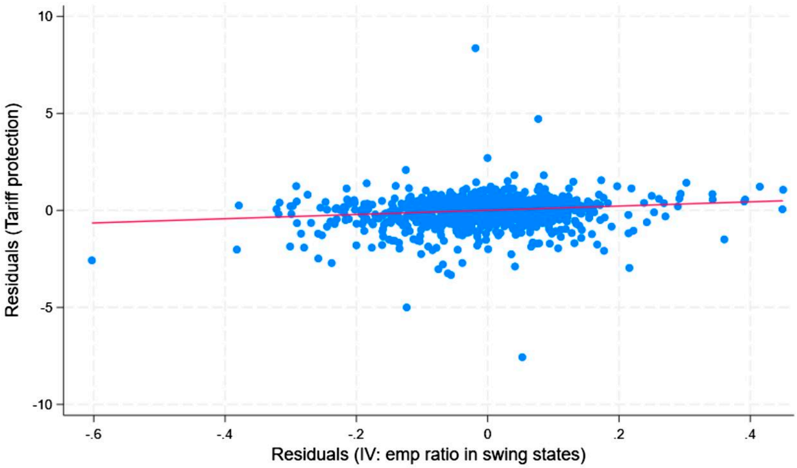
where $indswing_{jt}$ is weighted by the employment share of each industry j in total manufacturing employment of PUMA m at the beginning of the period (in the year 2000). The IV is in five-year differences $\Delta indswing_{mt}$ as the endogenous variable ΔNTM_{mt}.

To satisfy the exclusion restriction, the instrument must affect the outcome only through its effect on the endogenous variable. In this setting, it must be that the PUMA's share of employment in industries important in swing states affects employment and wages only through its effect on NTMs. Otherwise, the coefficient may capture the effect of other factors similarly triggered by political pressure in swing states. The most obvious policy that may violate the exclusion restriction is tariffs. In Figure 2, we show an empirical exercise ruling out that the most important alternative policy (i.e., tariffs) has similarly been adopted in PUMAs with a high value for the instrument. It is reassuring that the figure shows no correlation between (the residuals of) tariffs and (the residuals of) the instrument, while the correlation is positive and significant between NTM and the instrument, both in five-year differences.

There is also a concern that our instrument might also capture the influence of other policies implemented to support crucial industries in swing states (e.g., antidumping measures), thus potentially violating the exclusion restriction. Indeed, Bown et al. (2021 and 2023) have used the same instrument to predict industries' antidumping protection against China. Therefore, we know that our instrument may affect employment not only via NTMs but also via the imposition of antidumping duties. To assuage the possibility that our instrument picks up the impact of both measures on employment, as a robustness check, we add to our estimating equation a control for antidumping protection (see the description of Table 3 in section 5.1.1), computed as described in Section 2. This approach enables us to isolate the specific effect of NTMs, distinct from the impact of antidumping measures. In addition, to account for other policy changes, apart from NTM, that might occur in swing states for political reasons and could potentially impact labor markets, we incorporate an indicator for whether a PUMA belongs to a swing state (swing state dummy) into all specifications.

Table 4 reports the results of the first stage regressions for different types of NTMs (*NTM*, *NTMTBT*, *NTMSPS*) measures in five-year differences. The estimates confirm that $\Delta indswing_{mt}$ has a large and significant impact on NTM protection. The estimated first-stage coefficient is about twice as large for TBT than for Sanitary and Phytosanitary measures (SPS), suggesting that the determinants of NTMs differ across the two measures. In fact, while SPS measures are usually introduced for genuine health and safety reasons, TBT are frequently also used as protectionist tools to limit the competition faced by domestic industries (Ghodsi 2016). The table confirms that our IV is highly predictive of NTM, even after controlling for the index of ADP protection in columns (4)–(6). This finding suggests that our instrument affects NTMs, over and above its impact on other polices, such as antidumping measures. The table also reports the Kleibergen-Paap F-statistics, a version of the Cragg-Donald statistic adjusted for clustered robust standard errors. We see that the F-statistic is always highly significant and well above the critical value of 10, which confirms that our

Hampshire, New Mexico, Ohio, Oregon, Pennsylvania, and Wisconsin. In 2008, they were Florida, Indiana, Missouri, Montana, North Carolina, North Dakota, and Ohio. In 2012, they were Colorado, Florida, Iowa, Nevada, New Hampshire, North Carolina, Ohio, Virginia, and Wisconsin.



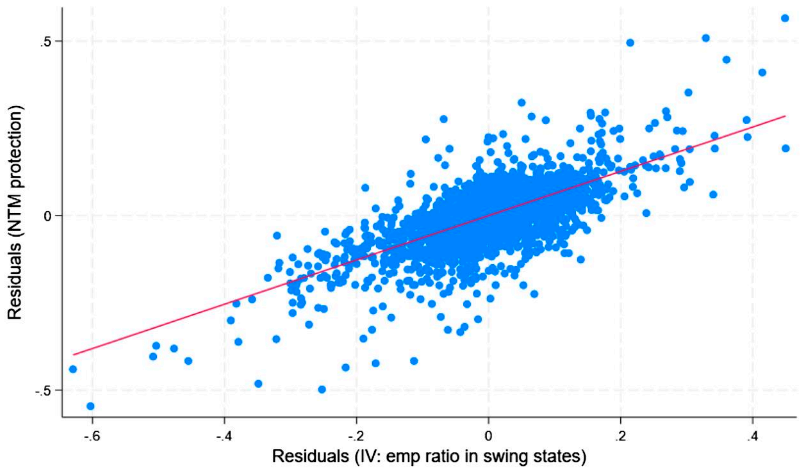


Figure 2. First stage relationship between (residual) tariffs (Top) and NTM (Bottom) and the incidence of swing states' industries in the employment composition of PUMAs (the IV).

instrument is informative and relevant. Finally, columns (7) and (8) report the estimated impact of our instrumental variable $indswing_{mt}$ on PUMAs' manufacturing employment share (reduced form equation), with and without the control for antidumping measures, respectively. We observe that the instrumental variable has a direct positive effect on manufacturing employment.

4.1 Instrument Validity

Our identification is based on the assumption that the political importance of a PUMA (i.e., belonging to a swing state during a presidential election) is not influenced by the demand shocks (local or national) that also affect local employment changes. Therefore, the identifying assumption for using our instrument is that the variation in NTMs due to the similarity of the industrial composition of a PUMA with swing states' industrial structure must be

Table 4. First stage and reduced form. Controls for antidumping measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First stage						Reduced form	
	ΔNTM	$\Delta NTMTBT$	$\Delta NTMSPS$	ΔNTM	$\Delta NTMTBT$	$\Delta NTMSPS$	Δ *man emp sh*	
$\Delta indswing_{mt}$	1.987***	1.984***	0.949***	1.993***	1.991***	0.942***	1.036**	1.100*
	(17.17)	(16.52)	(11.78)	(17.16)	(16.51)	(11.77)	(0.520)	(0.567)
Control for ADP	*no*	*no*	*no*	*yes*	*yes*	*yes*	*no*	*yes*
Kleibergen-Paap F test	294.8	272.9	138.8	294.4	272.7	138.4	.	.

Each cell in columns (1)–(6) reports the first-stage estimated coefficient of $\Delta indswing_{mt}$ on changes in *NTM*, *NTMTBT*, and *NTMSPS*. Columns (3)–(6) add the control for the five-year change in the index of ADP protection. All regressions control for time-fixed effects and for all variables in the vector X_{mt} described in equation (2). Columns (7) and (8) report the OLS coefficients of our instrument $\Delta indswing_{mt}$ on five-year changes in manufacturing employment share (reduced form regression). T-statistics in parentheses (columns (1)–(6)). Robust standard errors in parentheses (columns (7)–(8)).

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level

independent of unobservable factors that affect changes in manufacturing employment and wages.

As it is not possible to directly test this identifying assumption, we present suggestive evidence by examining the correlation between the pre-trends and our instrument. To this extent, we estimate the following equation:

$$indswing_{mt} = \beta \Delta Manufempl_{mt-1} + \gamma X_{mt} + \alpha_t + \alpha_m + \varepsilon_{mt} \tag{9}$$

where $\Delta Manufempl_{mt-1}$ is lagged change in manufacturing employment share on working age population, X_{mt} are the same controls of equation 5 and α_t and α_m are time and PUMA fixed effects. If our instrument is credible, we expect to see a weak correlation between the instrument and the pre-trends. The results are presented in column (1) of Table 5 and reassuringly indicate that the instrument does not predict the pre-trends in employment, which is consistent with the instrument being uncorrelated with unobserved and persistent economic factors affecting employment trends. Another possible test of the instrument validity is the following: the mechanism that we have in mind is that politicians decide first to put NTMs on products/industries that are important in swing states for political reasons, and then NTMs affect future employment growth nationwide (in different PUMAs according to their specific industrial composition) through their restrictive effects on import growth. Our identifying assumption, therefore, is that states become "swing" during a presidential election for reasons that are independent of their past economic performance so that we can use their industrial structure to identify the effects of NTMs on employment growth. In other words, the exclusion restriction implies that, conditional on the control variables, the identity of swing states should not be correlated with unobserved PUMA-level demand shocks. To this extent, similarly to Bown et al. (2023), we show in column (2) of Table 4 the results of a linear probability model of being a PUMA in a swing state in year t on past employment trends (the specification is the same as in equation 9, but the dependent variable is $Pr_t(m = swing)$, that is, PUMA m belongs to a swing state in year t). As expected, the coefficient is again insignificant.[16]

[16] As in Bown et al. (2023), we also tested that the identity of swing states is uncorrelated to other PUMA-level characteristics, such as previous exposure to NTM protection and import competition.

Table 5. Instrument validity checks.

Dep. Var:	$indswing_{mt}$ (1)	PUMA of swing state (2)
$\Delta Manufempl_{mt-1}$	−0.000	0.006
	(0.001)	(0.006)
Observations	2156	2156
Number of PUMA	1078	1078

Each cell reports the estimated coefficient of the change in manufacturing employment share in period t-1 on $indswing_{mt}$ (column (1)) and on the probability that a PUMA belongs to a state that is classified as a swing in period t (column (2)). All regressions control for time and PUMA fixed effects and for all variables in the vector X_{mt} described in equation (2). Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by state.

We conduct an additional test to assess the validity of our IV. We separately regress the instrument and the instrumented variable on the controls, and we plot the residuals in Appendix Figure A4. In particular, the figure reports on the X-axis the quantiles of the residuals of a regression of the instrument $indswing_{mt}$ on the controls and on the y-axis the corresponding average residuals of a regression of the instrumented variable (NTM) on the controls. The figure reassuringly shows that the relationship between the instrumented variable and the instrument is monotonic.

Since our empirical strategy follows a shift-share design, we also present a test proposed by Borusyak et al. (2022) to assess the instrument's validity.[17] The shift-share design studies the impact of a set of shocks on units differentially exposed to them, with the exposure measured by a set of weights. In our setting, this means combining industry-specific changes in NTM protection induced by changes in the identity of swing states (the shocks) with local exposure given by the lagged industrial composition of each PUMA (the exposure shares). As extensively discussed in Borusyak et al. (2022) and Borusyak and Hull (2023), a key assumption for instrument validity in shift-share instrumental variable regressions is that shocks' assignment is as good as random. This condition captures the orthogonality of the shift-share instrument with the second-stage residuals: initial shares and intensity of shocks may, in fact, be confounded with other unobserved industry characteristics. To test the plausibility of this assumption, we perform the balance checks proposed by Borusyak et al. (2022) and regress potential industry-level confounders directly on the shocks. If industry-level shocks are, in fact, as good as random, they should be uncorrelated with industry characteristics and pre-shock weighted sums of outcomes. In particular, in Panel A of Table 6, we first provide an industry-level balance test, performed by regressing each potential confounder on the shocks (normalized to have a unit variance) and period fixed effects, weighting by average industry employment shares.[18] In panel B, we show the estimated regional balance coefficients obtained by regressing each potential confounder (regional controls included in our main specification) on the shift-share instrument (normalized to have a unit variance) and the share weighted average of period effects (i.e., the period-interacted sum of shares). We find no statistically significant relationships between most of these variables and the shift-share instrument. Locations differently exposed to shocks tend to have similar

[17] See Borusyak et al. (2022), Borusyak and Hull (2023), and Goldsmith-Pinkham et al. (2020) for recent contributions on the validity of shift-share instruments.

[18] As in Borusyak et al. (2022), we use the industry-level production controls included in Acemoglu et al. (2016).

Table 6. Shock balance tests.

Balance variable	Coeff	SE
Panel A: Industry-level balance		
Prod. workers' share of employment, 2000	0.032	(0.025)
Ratio of capital to value-added, 2000	0.053	(0.034)
Log real wage 2000	−0.016	(0.046)
No. of industry-periods	63	
Panel B: Regional balance		
Share of females	−0.031	(0.006)
Average age	−0.013	(0.122)
Share of college-educated	−0.063	(0.047)
Share of white	0.046	(0.01)
No. of puma-periods	3234	

Panel A of this table reports coefficients from regressions of the industry-level covariates in Acemoglu et al. (2016) on the shocks, controlling for period indicators and weighting by average industry exposure shares. Standard errors are reported in parentheses and allow for clustering at the level of three-digit NAICS codes. Panel B reports coefficients from regressions of PUMA-level covariates on the shift-share instrument, controlling for period indicators interacted with the lagged manufacturing share. NAICS-clustered exposure-robust standard errors are reported in parentheses and obtained from equivalent industry-level IV regressions as described in Borusiak et al. (2022). Independent variables in both panels are normalized to have a variance of one in the sample.

characteristics in terms of workforce composition, although we find that areas with greater exposure tend to have slightly lower concentrations of females and non-white workers. However, this correlation should not pose a problem in our context, as we include these variables as controls in all specifications to residualize their impact on labor market outcomes.

Before getting to the main results, it is important to understand better the characteristics of the local labor markets most affected by the instrument, that is, the compliers PUMAs, those that have NTM protection because they have industries that are important in swing states, and that would not have those NTMs if they had zero employment in those industries. In Appendix Table A2, we show the first stage separately for the division in quartiles of PUMAs with a higher initial share of manufacturing employment (panel A), higher initial share of blue-collar workers (panel B), and higher initial level of Chinese imports (panel C, not the China shock exposure measure but the actual imports). Each table cell shows the coefficient on the instrument $indswing_{mt}$ from a different regression. The coefficients are significant everywhere but are higher in PUMAs with an initial (i.e., in the year 2000) lower share of manufacturing employment and lower imports per capita, while there is little difference across groups with different shares of blue-collar workers. PUMAs in the first quartile of the distribution of manufacturing employment (panel A) and of import penetration (panel C) have a coefficient three times larger than PUMAs in the fourth quartile of the distribution; the results for NTMs and TBTs are similar, while for SPSs the coefficients are up to seven times larger in the first rather than in the fourth quartile of the distribution. We conclude that the IV-induced variation is concentrated in PUMAs with an industrial structure initially less intensive in manufacturing and less impacted by Chinese imports (those PUMAs have NTMs due to external factors, and they would not have if their industrial structure had not been similar to swing states). This is reassuring for the exogeneity of the instrument.

5. RESULTS

This section reports our results on the causal effect of NTMs on local labor market outcomes at the PUMA level. Section 5.1 presents our estimates on the impact of NTM on manufacturing employment, while Section 5.2 investigates the impact of NTM on wages of skilled and unskilled workers and other outcomes, such as non-manufacturing employment, labor market participation, and population growth. Finally, in Section 5.3, we present several robustness tests.

5.1 Impact of NTMs on manufacturing employment

Table 7 presents the IV estimates of the relationship between NTM protection and US manufacturing employment. The dependent variables are the five-year change in the share of manufacturing employment in the working-age population in PUMA m (Panel A) and the five-year change in log employment in manufacturing (Panel B). Each model is weighted by the PUMA's share in the national population in the initial period. All specifications include controls for a set of PUMA demographic characteristics at the beginning of each period to eliminate potential confounders (PUMA's share of females, college-educated, whites, and average age). The first two columns refer to all NTMs notified to the WTO (*NTMALL*), while columns (3) and (4) refer to our standard index of NTMs subject to STCs (*NTM*). In columns (2) and (4), we augment our main specification by adding the measure of exposure to import competition. The last row of each panel report the *F*-tests of the joint significance of the excluded instruments in the first stage (Kleibergen-Paap F statistic), which reveal that our instruments are informative and valid: the *F*-test is, in fact, always highly significant.

Our estimates indicate that NTMs significantly increase both manufacturing employment share (Panel A) and the growth rate of manufacturing employment (Panel B). In column (1) of Panel A, a one-standard-deviation increase in *NTMALL* results in a 0.63 percentage point rise in the share of manufacturing in total employment over a five-year period. This effect becomes more pronounced when focusing on STCs, which are more effective trade-restricting measures (Fontagné et al. 2015). In column (3), a one-standard-deviation increase in *NTM* increases the share of manufacturing in total employment by 0.85 percentage points. To gauge the significance of these effects, consider that over the sample period, the share of manufacturing employment declined by 1.57 percentage points every five years in the average PUMA. Therefore, the increase of 0.85 percentage points implies that the declining trend would be slightly more than halved. Given that the average five-year increase in the *NTM* index is 0.5 of a standard deviation (see the desciptive statistics in Appendix Table A1), our estimates suggest that the average surge in NTMs offsets approximately one-fourth of the overall decline in the share of manufacturing employment.[19] Keep also in mind that the standard deviation and the mean value of the *NTM* index are, respectively, equal to 0.10 and 0.12, and, therefore, a one-standard-deviation increase in the *NTM* index is almost equivalent to doubling the mean of the index. In other words, one standard deviation is a big change for a PUMA: this is like moving from a PUMA at the 50th percentile (NTM index = 0.108) of the NTM protection distribution, such as for example, Minneapolis (Minnesota), to a PUMA at the 90th percentile (NTM index = 0.24), such as Santa Rosa (California), both measured in 2005.

[19] These IV estimates are larger than the OLS results, not reported here, according to which a one standard deviation increase in the NTM-protection index increases the share of workers employed in manufacturing by 0.2 percentage points. This indicates a downward bias of OLS estimates, possibly due to unobservable shocks affecting the changes in NTMs and employment shares of manufacturing workers in opposite ways. For instance, unobservable import shocks, not captured by our measure of imports, might increase NTMs, while diminishing the share of manufacturing employment. Or alternatively, politicians may implement NTMs in industries where manufacturing is already declining, which would also induce a negative correlation between NTM and the outcome. Our identification strategy would instead isolate variations in NTMs that are orthogonal to the performance of the manufacturing sector (the variation essentially comes from the change in the identity of swing states).

Table 7. Effect of NTMs on manufacturing employment. IV estimates.

	(1)	(2)	(3)	(4)
Panel A: Δ manuf. employment share				
$\Delta NTMALL_{mt}$	0.626***	0.364**		
	(0.215)	(0.178)		
ΔNTM_{mt}			0.851***	0.518**
			(0.280)	(0.254)
$\Delta Impexposure_{mt}$		−0.983***		−0.917***
		(0.084)		(0.080)
F stat.	722	840	288.4	292.4
Average dep. var.		−1.573 (sd = 2.57)		
Panel B: Δ log manuf. employment				
$\Delta NTMALL_{mt}$	0.096***	0.086***		
	(0.020)	(0.020)		
ΔNTM_{mt}			0.131***	0.122***
			(0.028)	(0.029)
$\Delta Impexposure_{mt}$		−0.038***		−0.022***
		(0.005)		(0.005)
F stat.	722	840	288.4	292.4
Average dep. var.		−0.059 (sd = 0.231)		

$N = 3234$ (1078 PUMAs, three 5-year changes). Dependent variables are five-year changes in the percentage of the working-age population employed in manufacturing (Panel A) and five-year differences in log manufacturing employment (Panel B). *NTMALL* indicates that in constructing the NTM measure, we use all notifications, while in *NTM* we use only STC (see text for details). All regressions control for PUMAs' share of college-educated, female, and foreign-born population, all measured at the beginning of each period, and swing state and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA.

*** Significant at the 1% level.

** Significant at the 5% level.

Examining Panel B, we observe that NTMs also significantly increase the growth rate of manufacturing employment. Specifically, focusing on the specification that controls for exposure to Chinese import competition, a one standard deviation increase in *NTMALL* (*NTM*) raises manufacturing employment growth by 8.6 (12) percentage points. Hence, an average increase in *NTM* (equivalent to 0.5 standard deviation every five years) would result in a 6 percentage point increase in the growth rate of manufacturing employment, explaining approximately one-third of the standard deviation of employment growth (see last row in Table 7).

In columns (2) and (4), we add a control for PUMAs' exposure to import competition to account for PUMAs' differential exposure to Chinese imports due to their industrial structure and to Chinese supply shocks in particular industries. We find that our results hold, although the coefficients of NTM slightly shrink. Our estimates also reveal that increasing the exposure to Chinese import competition reduces manufacturing employment, and reassuringly, our results are comparable in magnitude with the estimates reported in the literature (see Acemoglu et al. 2016 and Autor et al. 2013a). In particular, we find that an increase of 1000 dollars in per-worker exposure to import competition reduces manufacturing employment shares by about 0.98 percentage points in five years (Panel A, column 4, in Table 7).

To test whether the impact of NTMs varies according to PUMAs' exposure to Chinese import competition, we augment our baseline specification and introduce an interaction term between *NTM* and five quintiles of $\Delta Impexposure_{mt}$. The results are reported in Figure 3 and suggest that NTMs have mitigated the effect of the China shock. The impact of NTM is, in fact, non-significantly different from zero in PUMAs that are not exposed to

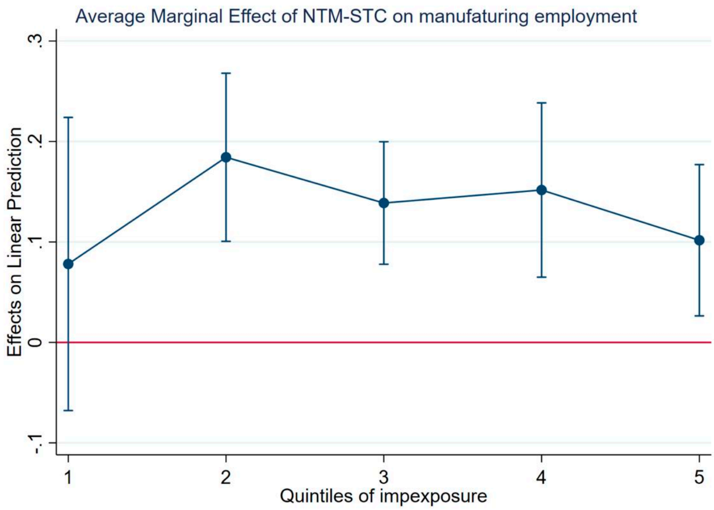


Figure 3. Interaction between NTM and import exposure. The figure reports the estimated coefficients (average marginal effects) of ΔNTM_{mt} on $\Delta Log(manufacturingemployment)_{mt}$ across different quintiles of the $\Delta Impexposure_{mt}$ distribution.

Chinese competition, while it is positive and significant in PUMAs with higher exposure. However, the impact of NTM is homogeneous across PUMAs in the second, third, fourth, and fifth quintiles of the $\Delta Impexposure_{mt}$ distribution.

Finally, in Appendix Table A3, we investigate whether our results change when considering different types of NTM. We replicate the estimates reported in Table 7, distinguishing between TBT and SPS. The estimates reveal that the impact of the two types of measures is qualitatively similar, although significantly larger for TBT measures, which account for most of the STC received by the United States. SPS measures primarily affect the agricultural sector and appear to have a lesser impact on local manufacturing employment. In the subsequent sections of the article, we focus solely on the comprehensive measure of *NTM*, without differentiating between TBT and SPS.

5.1.1 Accounting for antidumping measures

As discussed in Section 4, we know from Bown et al. (2021 and 2023) that our instrument also predicts antidumping measures. Therefore, in Table 3, we augment our baseline estimates conditioning on a measure of antidumping protection at the local level (*ADP*), as described in Section 2. The Table reports only the specification where the dependent variable is the five-year changes in log manufacturing employment (as in Panel B of Table 7), but our results are also confirmed when using changes in manufacturing employment share as the outcome variable. In columns (1) and (2), we add as a control variable the index of antidumping protection (*ADP*), while in columns (3) and (4), we use an alternative measure of protection computed by summing up all STCs and antidumping measures (the measure is called *NTMADP*).[20] Columns (2) and (4) control for the local exposure to import competition, while columns (1) and (3) do not. The estimates reveal that adding the controls for

[20] This measure is constructed by computing the weighted share of products protected by Antidumping or NTM in each NAICS three-digit industry, and we then project the industry protection to each PUMA according to its employment composition at the beginning of the period. The data comes from the WTO database on notification, available at https://i-tip.wto.org/goods/default.aspx

antidumping measures does not change our results substantially, which suggests that our findings hold after taking out part of the effect of NTMs on employment that operates via antidumping duties. Our main findings are also confirmed when using the comprehensive index of protection that includes both technical NTM (sanitary and phytosanitary and TBT) and non-technical antidumping measures.

Our results indicate that NTMs increase manufacturing employment in local labor markets even after accounting for antidumping measures. Although we differ from Bown et al. (2023) because we look at the effects of NTMs at the local labor market level, while they look at the effects of antidumping measures at the industry level, our results are comparable in magnitude. They obtain that 'one standard deviation increase in Direct Tariff Exposure (their antidumping measure), increases the growth rate of employment in protected industries by 3 percentage points, explaining around 14% of the standard deviation of employment growth in those industries'. Our estimates indicate that one-standard-deviation increase in the NTM protection index accounts for approximately half of the standard deviation in employment growth.[21] This effect appears more pronounced than Bown et al. (2023), possibly because our analysis captures the overall impact on the local labor market rather than focusing solely on protected industries.

5.2 Impact of NTMs on employment composition, wages, and other outcomes

In the following tables, we further investigate the effects of NTMs, looking at their impact on employment composition and wages (see Table 8), and on other outcomes, such as non-manufacturing employment, labor force participation, and outmigration (see Table 9).

The total effect of NTM on manufacturing employment may mask differences between skilled (i.e., with college education) and unskilled workers. We present the results on employment (columns (1) and (2)) and wages (columns (1), (4), and (5)) by education in Table 8.

Our estimates suggest that NTMs increase manufacturing employment of both skilled and unskilled workers, albeit more for the latter. In particular, a one-standard-deviation increase in *NTM* increases skilled employment by 0.071% and unskilled employment by 0.23%. Considering that employment of unskilled workers in manufacturing declined by 0.9% over five years in an average PUMA (see Appendix Table A1), an increase by 0.23% offsets one-fourth of the total decline.

Our result of NTMs protecting the employment of the unskilled is partially in contrast with Barba Navaretti et al. (2023), who find that exporting firms in France respond to the increased complexity associated with a restrictive NTM by raising the share of skilled workers at the expense of blue collars and white collars. That article, however, looks at the substitution of workers within (exporting) firms rather than at the overall effect at the local labor market level. At the local level, the positive effect of NTMs on the employment of the unskilled is coherent with a skill-biased impact of the China shock to the detriment of the unskilled.[22]

In the same table (columns (3)–(5)), we see that a one standard deviation increase in the NTM index is also associated with 0.05% decrease in the hourly wages of manufacturing workers. Skilled workers drive the negative and statistically significant coefficient on wages.

We interpret the negative impact of NTM on wages, considering that protectionism tends to decrease the competitiveness of domestic firms and may reduce labor productivity and

[21] The coefficient of ΔNTM_{mt} in column (1) of Table 7 is 0.12, which corresponds to about half of the standard deviation of employment growth (0.23).

[22] Autor et al. (2013a) find a skill-biased effect only in the non-manufacturing sector: in their paper, an additional 1,000 dollars of per-worker exposure to imports from China was associated with lower non-college employment of 0.53 percentage points and higher employment of college graduates of 0.17 percentage points (although the latter estimate was not significantly different from zero).

Table 8. Effect of NTMs on manufacturing employment composition and wages. IV estimates.

	(1)	(2)	(3)	(4)	(5)
	Δ log manuf. employment		**Δ log hourly manuf. wages**		
	Unskilled	***Skilled***	***All***	***Unskilled***	***Skilled***
ΔNTM_{mt}	0.231***	0.071*	−0.052***	−0.011	−0.040**
	(0.047)	(0.040)	(0.015)	(0.024)	(0.018)
$\Delta Impexposure_{mt}$	−0.008	−0.022***	−0.009***	−0.004	−0.007***
	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)
Kleibergen-Paap F stat	292.2	292.4	292.4	286.3	291.9

Dependent variables are five-year changes in the log employment in manufacturing and in log hourly wages. Skilled are defined as workers with at least a college degree. Employment, population, and income data are based on US Census and American Community Survey data. All regressions control for PUMAs' shares of college-educated, female, and foreign-born population, all measured at the beginning of each period, and swing state and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA.

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level.

Table 9. Effect of NTMs on non-manufacturing employment, labor force participation, and outmigration. IV estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log non-manuf empl.		*Δ share out of LF*		*Δ log population*	
ΔNTM_{mt}	0.005	0.002	0.184	0.293	0.013	0.009
	(0.011)	(0.011)	(0.284)	(0.290)	(0.009)	(0.009)
$\Delta Impexposure_{mt}$		−0.006***		0.301***		−0.010***
		(0.002)		(0.060)		(0.002)
Kleibergen-Paap F stat	288.4	292.4	288.4	292.4	288.4	292.4

$N = 3234$ (1078 PUMA, three 5-year changes). The dependent variables are five-year changes in the percentage of the working-age population employed in the non-manufacturing sector (columns (1) and (2)), out of labor force (columns (3) and (4)) and in log of the working-age population. Employment, population, and income data are based on US Census and American Community Survey data. All regressions control for PUMA shares of college-educated, females, and foreign-born population, all measured at the beginning of each period, and for swing state and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA.

*** Significant at the 1% level.

wages. Other papers have shown that higher tariffs reallocate domestic market share toward less-efficient domestic producers, lowering aggregate productivity and wages (Amiti and Konings 2007; Furceri et al. 2018). The same mechanism may apply to NTMs. For example, Shepotylo et al. (2022) show that NTMs applied to imported intermediate inputs lower firms' productivity by restricting the variety of available imported inputs and distorting the efficient input mix toward domestic producers. Moreover, since trade barriers on intermediate products raise prices, workers employed in sectors other than the protected ones may see a decrease in their real wages. This explanation is consistent with Bown et al. (2023), who find that antidumping duties foster employment growth in protected industries but decrease employment growth rate and wages in downstream industries that use the protected goods as inputs. They also provide evidence of the mechanisms behind the negative effects of tariffs along supply chains: antidumping duties against China decrease US imports of targeted products and raise the prices charged by foreign and domestic producers of these products, increasing production costs for firms in downstream industries.

Table 10. Impact of input-adjusted NTM on manufacturing employment and wages. IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log manufacturing employment			Δ log hourly wages in manufacturing		
	All	*Unskilled*	*Skilled*	*All*	*Unskilled*	*Skilled*
ΔNTMIO_{mt}	0.154***	0.283***	0.096*	−0.069***	−0.021	−0.051**
	(0.036)	(0.059)	(0.050)	(0.020)	(0.031)	(0.023)
$\Delta Impexposure_{mt}$	−0.023***	−0.010	−0.021***	−0.009***	−0.005	−0.007**
	(0.005)	(0.007)	(0.006)	(0.003)	(0.004)	(0.003)
Kleibergen-Paap F stat	244.1	242.5	244.1	244.1	236.3	243.6

$N = 3234$ (1078 PUMAs, three 5-year changes). Dependent variables are five-year changes five-year differences in log manufacturing employment (columns (1)–(3)) and log hourly manufacturing wages (columns (1)–(3)). All regressions control for PUMA share of college-educated population, females, and foreign-born population, all measured at the beginning of each period, and swing state and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA.

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level.

As discussed above, differently from Bown et al. (2021 and 2023), our analysis identifies the overall effect of NTM on local labor markets. In the same local labor market, the final good industry and the input-producing industries coexist. Therefore, we observe a net impact resulting from the direct effect of NTMs and the indirect effect through the rising costs of inputs, which increases prices and decreases real wages. In Table 10, we consider the supply chain effects of NTMs using the measure adjusted for NTM in inputs (*NTMIO*), and we confirm all results obtained with *NTM*.

So far, we have focused solely on NTMs' impact within the manufacturing sector. However, it's conceivable that a shock in the manufacturing sector could also influence the aggregate labor market. Hence, in Table 9, we investigate the broader effects of NTMs on local labor markets. Specifically, we explore their effects on non-manufacturing employment (columns (1) and (2)), labor market participation (share of working-age population out of the labor force, columns (3) and (4)), and the reallocation of workers across PUMAs (log of the working-age population, columns (5) and (6)).

Our results indicate that NTMs do not significantly affect employment in the non-manufacturing sector, labor force participation, and mobility across PUMA. This latter result is reassuring, as a large mobility response would make it difficult to find effects of a trade shock on *local* labor market, given that initial local impacts would spread across regions (see also Autor et al. 2013a, who similarly find that shocks to local manufacturing do not induce substantial changes in population).

Overall, our findings suggest that the impact of NTM is limited to the manufacturing sector, where NTMs belong.

5.3 Robustness checks

This section presents a set of robustness checks of our main findings. All tests use the baseline IV specification on manufacturing employment, as reported in column (2) of Table 7. First, we assess the sensitivity of our results to alternative definitions of NTM protection. In our main specification, NTM protection at the industry level was measured by computing the percentage of products subject to NTMs, weighted by each product's share in total imports of the industry in 2000. As a robustness check, we now compute this measure by changing the weights and using the share of each product in total trade (imports + exports) rather than in total imports *NTM*(*TW*). The results are reported in column (2) of Table 11 and

Table 11. Robustness checks: impact of NTM on change in manufacturing employment.

	(1) *Baseline*	(2) *NTM(TW)*	(3) *NTM(CH)*	(4) *State FE*	(5) *PUMA FE*
ΔNTM_{mt}	0.122***			0.125***	0.148***
	(0.029)			(0.035)	(0.037)
$\Delta NTM(TW)_{mt}$		0.103***			
		(0.024)			
$\Delta NTM(CH)_{mt}$			1.134*		
			(0.587)		
$\Delta Impexposure_{mt}$	−0.022***	−0.026***	−0.016	−0.028***	−0.034***
	(0.005)	(0.004)	(0.015)	(0.009)	(0.008)
State fixed effects	-	-	-	*Yes*	-
Puma fixed effects	-	-	-	-	*Yes*
Kleibergen-Paap F stat	292.4	518.4	4.962	88.07	227.8

$N = 3234$ (1078 PUMA, three 5-year changes). The dependent variable is five-year changes in log manufacturing employment. Employment, population, and income data are based on US Census and American Community Survey data. All regressions control for PUMA share of college-educated population, foreign-born population, females, average age, and swing state and time dummies. Models are weighted by the start of the period PUMA share of the national population. Column (1) reports baseline estimates from Table 7; in column (2), NTM weights the share of each product in total trade rather than in total imports; in columns (3) NTM protection is computed using STC raised by China only; in column (4) and (5) we add to the baseline specification state and PUMA dummies respectively. Robust standard errors in parentheses are clustered by PUMA.
*** Significant at the 1% level.
* Significant at the 10% level.

reveal that our main findings are robust to this alternative definition of NTM protection: the coefficient of the new NTM measure is similar in magnitude and significance to the baseline specification from Table 7, also reported in column (1) for ease of comparison. Second, in column (3), we compute NTM protection, considering only STC raised by China, rather than by all US trading partners $NTM(CH)$. The estimates suggest that NTMs toward China significantly increase US employment in manufacturing, with a coefficient substantially larger than that of NTMs toward any country, likely reflecting a clearer protectionist intent of NTMs against China. In columns (4) and (5), we include respectively state and PUMA fixed effects to account for state- and PUMA-specific differential trends in labor market outcomes. Once again, we find that our results are remarkably stable across different specifications.

Finally, we test whether our results are robust to alternative econometric specifications. Specifically, Appendix Table A4 presents the estimated impact of NTMs on all outcomes with standard errors clustered at the state level (instead of PUMA) to address potential spatial correlations between PUMAs within the same state. The estimates reveal that all coefficients remain statistically significant. Additionally, in Appendix Table A5, we show that our findings hold when considering the correlation of error terms across geographic areas due to industry-specific shocks (Adao et al. 2019). A shift-share design, in fact, combines information on an aggregate shift (such as aggregate variation in NTM and changes in the political importance of specific industries) with local information on shares, and this induces a correlation of residuals across regions with similar sectoral shares. We follow Adao et al. (2019) to correct standard errors appropriately. More specifically, we use the IVREG_SS stata module proposed by Adao et al. (2020) to compute confidence intervals, standard errors and p-values in an IV regression with a shift-share structure. Appendix Table A5 reports the estimated regression coefficients, AKM[23] standard errors, and the corresponding p-values of all *NTMALL* (columns (2)–(4)) and *NTM* (columns (5)–(7)) on different dependent variables specified in each row. The AKM inference procedure described in Adao et al. (2019)

[23] AKM: Adao, Kolesar, Morales.

yields larger standard errors, but reassuringly it maintains the statistical significance of all estimated coefficients.

6. CONCLUSIONS

In this article, we study the impact of NTMs on US manufacturing employment and wages. We contribute to the literature by developing a novel index of NTM protection at the local labor market level, based on the recently released WTO database on STC. Among the different types of NTM, we focus on TBT and on Sanitary and Phytosanitary Standards, and thus, we complement work done on the effects of antidumping measures (Bown et al. 2023), which are classified as non-technical barriers.

Borrowing their identification technique, we identify the causal effect of NTMs using the political incentive to protect industries in swing states during presidential elections (this IV is arguably exogenous to local demand shocks outside swing states).

We find that PUMAs where manufacturing industries were more protected through NTMs experienced significantly higher employment growth in manufacturing. Furthermore, our estimates indicate that NTMs have a more pronounced impact on unskilled workers. This finding is consistent with the existing evidence suggesting that unskilled workers are adversely affected by import competition from low-wage countries. NTMs tend to reduce these imports because compliance with NTM regulations increases the production costs of the exporting firms, potentially leading them to serve other markets.

The estimated effect is important from the quantitative point of view: a PUMA that moves from the 50th to the 80th percentile of the NTM-protection measure offsets one-fourth of the decline in manufacturing employment share over the 2000–2015 period. Our estimates also suggest that the impact on NTMs is positive and significant in areas exposed to Chinese import competition, while it is non-significantly different from zero in PUMAs not exposed to Chinese imports (in the first quartile of the exposure distribution).

We find a negative effect of NTMs on wages (especially for skilled workers), and we speculate that this may have to do with the effects of NTMs on intermediate inputs. We construct an NTM index (*NTMIO*) that considers the protection of intermediate inputs, and we confirm the effect found with the main index that accounts only for NTMs on final goods. Since our analysis is at the local labor market level, we cannot exclude that the estimates are picking up both direct effects on final goods and indirect effects on inputs. Although Bown et al. (2023) look at the effect on employment of a different policy (antidumping) at the industry level (rather than at the PUMA level), our results on wages are consistent with their finding that antidumping duties increase employment growth in protected industries, but decrease it in downstream industries that use the protected goods as inputs.

With the *caveat* that our analysis captures the impact of NTMs at the local level and does not account for general equilibrium effects (such as, for example, potential benefits of trade for consumers), we believe that our findings offer insights into the labor market effects of trade policy and regulation, which is particularly relevant at a time when the debate between tariffs and NTMs persists in the United States and globally.

APPENDIX

Type of measure	Product description	HS code
	Panel A: Barriers to Trade (TBT)	
Food standard, labelling and traceability requirements	Olive Oil	1509, 1510
	Dairy products	0401, 0402, 0403, 0404,
	Food Products	1601-1605, 1701-1704,
	Beef, Lamb, Pork, Perishable Agricultural Commodities, and	0204, 0206, 0210, 2004,
	Tea	0902
Labelling requirements	Motor vehicles	8702, 8703, 8704, 8705,
	Display products (computer monitors, digital picture frame); DTV	8525, 8528, 8529
Product characteristics standards	Control units for fire protective signaling systems	8530
	DTV Tuner	8529
	Air conditioning machines; Refrigerators, freezers; heat pumps;	8415, 8418, 8422, 8450
	Broadcast Services; Television Broadcast Stations; TV Transmission	8525, 8527, 8528, 8529
	Children's products: reduced-size models; puzzles of all kinds.	9403
	Refrigerators, refrigerator-freezers, and freezers.	8415, 8418
	Fibre	5503, 5504, 5506, 5507,
	Mattresses and bedding	9404
	Tyres and tyres monitoring systems	4011, 4012
	Children's products	9501, 9502, 9503, 9504
	Fuel containers of casting and fencing material	8609
Production Process standards	Pisco and cognac	2208
	Residential central air conditioners and heat pumps	8415, 8418
	High density discharge lamps, Fluorescent and incandescent lamps	9405
	Lithium Batteries	8506
	Chemicals, chemical ingredients, and products, consumer product	2801-2851, 2901-2942,
	Formaldehyde emissions; Composite wood products; Third-party	4807
	Wheat flour and foods prepared with wheat flour (with some	1901, 1904
Registration	Vegetables, fruit, nuts, fruit-peel and other parts of plants	2001, 2006, 2008
Restricted use of certain substances	Children's jewellery	7113
	Cigarettes and tobacco products containing certain additives	2401, 2402, 2403
	Panel B: Sanitary and Phytosanitary (SPS)	
Food safety, Human health	Meet of bovine animals, swine, sheep or goats, horses, asses,	0102, 0103, 0104, 0201,
	Birds' eggs, in shell, fresh, preserved or cooked.	0407
	Milk and cream	0401, 0402
	Wood products, tools and packaging	4401, 4402, 4405-4421

Figure A1. Products subject to STCs. Source: WTO-STC data.

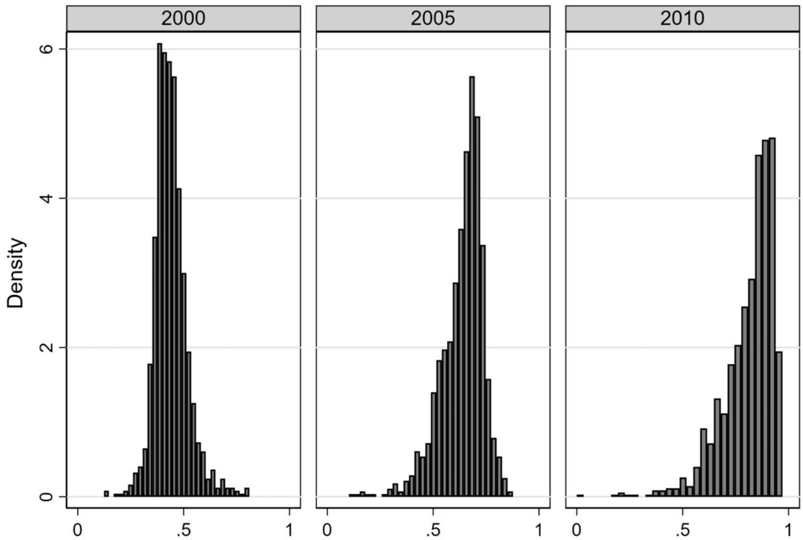


Figure A2. NTM index across PUMAs over time.

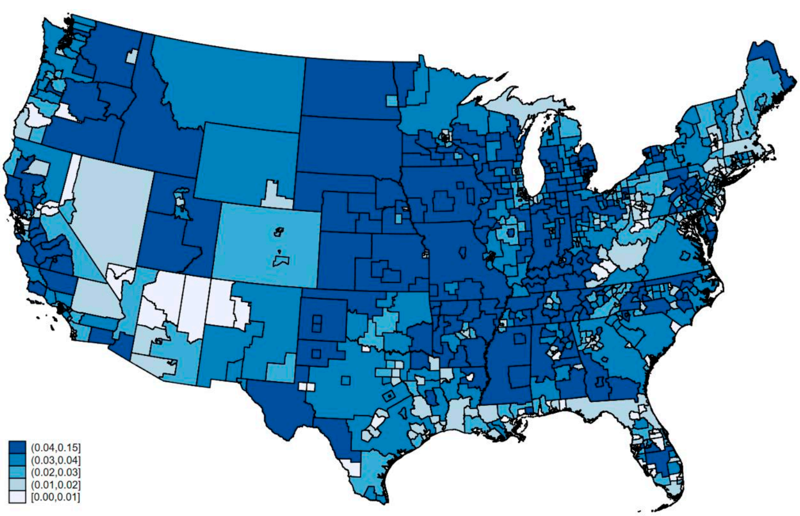


Figure A3. NTM index: share of protected employment NTM_{mt}—average across all years. Source: WTO-STC and Census-ACS data.

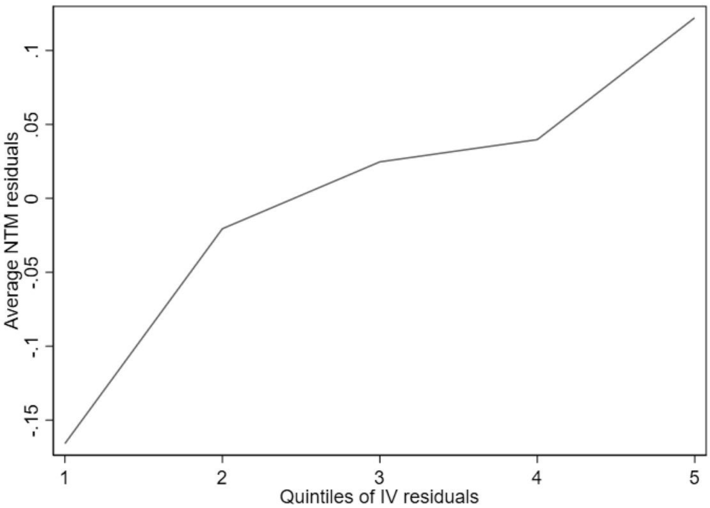


Figure A4. First stage: Monotonicity of the instrument. For each quintile of the distribution of the residuals of a regression of the instrument ($indswing_{mt}$) on all controls (in X axis), the y-axis reports the average residuals of a regression of the instrumented variable (NTM_{mt}) on the same set of controls.

Table A1. Descriptive statistics.

	2000		2005		2010		2015		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Share employed in manuf.	0.17	0.09	0.15	0.08	0.13	0.07	0.12	0.07	0.14	0.08
Log (manuf. empl.)	9.46	0.86	9.34	0.90	9.25	0.88	9.28	0.90	9.33	0.89
Log (manuf. empl.—skilled)	8.69	0.90	8.60	0.94	8.57	0.93	8.63	0.95	8.62	0.93
Log (manuf. empl.—unskilled)	8.72	1.00	8.56	1.08	8.41	1.04	8.41	1.07	8.52	1.06
Hourly wage	16.69	3.60	20.46	5.18	22.99	5.85	26.19	9.32	21.58	7.23
Hourly wage—skilled	19.38	3.57	23.86	5.40	26.97	6.22	30.98	10.41	25.30	8.08
Hourly wage—unskilled	13.65	2.37	15.72	3.26	16.88	3.66	17.71	5.44	15.99	4.14
Share employed in non-manuf.	0.56	0.08	0.57	0.07	0.56	0.07	0.57	0.08	0.57	0.07
Unemployment rate	0.04	0.02	0.05	0.02	0.07	0.02	0.04	0.02	0.05	0.02
Share out of the labour force	0.27	0.06	0.26	0.05	0.26	0.06	0.28	0.06	0.27	0.06
Log (working age population)	11.75	0.67	11.77	0.68	11.84	0.69	11.86	0.70	11.81	0.69
Age	40.46	1.54	42.15	2.38	43.39	2.43	43.72	2.49	42.43	2.58
Share of females	0.31	0.07	0.30	0.10	0.29	0.09	0.28	0.09	0.29	0.09
Share of college-educated	0.50	0.16	0.53	0.18	0.56	0.17	0.58	0.17	0.54	0.17
Share of white	0.76	0.21	0.76	0.21	0.76	0.20	0.76	0.21	0.76	0.21
Δ $Impexposure_{mt}$	.	.	1.23	0.94	1.38	1.05	−0.01	0.23	0.87	1.03
$Antidumping_{mt}$	0.05	0.02	0.09	0.03	0.10	0.03	0.14	0.05	0.10	0.05
$Impexposure_{mt}$	1.63	1.03	3.89	2.75	6.60	4.70	6.54	4.67	4.63	4.16
$NTMALL_{mt}$	0.44	0.08	0.64	0.10	0.81	0.12	0.82	0.12	0.68	0.19
NTM_{mt}	0.02	0.02	0.11	0.08	0.16	0.10	0.19	0.10	0.12	0.10
$NTMTBT_{mt}$	0.01	0.02	0.11	0.08	0.16	0.09	0.19	0.09	0.12	0.10
$NTMSPS_{mt}$	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.01	0.02
$\Delta(stdNTM_{mt})$	.	.	0.86	0.72	0.50	0.33	0.30	0.30	0.55	0.54

N=1078 PUMAs. Data source: Decennial census in 2000 and American Community Survey (ACS) in 2005, 2010 and 2015. NTM and Antidumping data from WTO database on Specific Trade Concerns. Data on exposure to import competition from COMTRADE data. *Impexposure* is the Dollar value of (imports from China to Europe) per worker.

Table A2. First stage regression by quartiles of PUMAs characteristics.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
	Share of manuf. employment in year 2000			
NTM	23.12***	13.60***	8.823***	7.517***
	(3.254)	(2.797)	(1.448)	(1.000)
NTMTBT	23.50***	13.67***	9.074***	7.788***
	(3.390)	(2.917)	(1.545)	(1.086)
NTMSPS	9.880***	7.253***	3.580***	1.433***
	(1.413)	(1.420)	(0.681)	(0.489)
Obs.	813	807	801	813
	Share of blue collars on total empl. in year 2000			
NTM	8.019***	10.51***	10.95***	8.363***
	(1.133)	(1.906)	(2.216)	(1.074)
NTMTBT	8.588***	10.77***	11.34***	8.781***
	(1.213)	(2.006)	(2.344)	(1.165)
NTMSPS	0.475*	3.542***	3.189***	1.916***
	(0.258)	(0.801)	(1.102)	(0.504)
Obs.	810	798	810	816
	Level of import penetration in year 2000			
NTM	26.43***	19.43***	12.96***	10.34***
	(4.536)	(2.029)	(1.557)	(1.009)
NTMTBT	26.66***	20.57***	13.69***	10.99***
	(4.752)	(2.171)	(1.659)	(1.099)
NTMSPS	13.38***	5.704***	1.371*	2.742***
	(1.983)	(0.948)	(0.757)	(0.429)
Obs.	813	819	786	816

Each cell shows the coefficient on $indswing_{mt}$ from a different regression of NTM, NTMTBT, and NTMSPS, respectively on $indswing_{mt}$. Quartiles of shares of manufacturing employment on working age population, of blue-collar workers on total employment, and of the initial level of import penetration (per capita US imports from China weighted by the industry share of local manufacturing employment) are computed in the year 2000, at the beginning of our sample period. All regressions control for time and PUMA fixed effects and for all variables in the vector X_{mt} described in equation (2). Robust standard errors in parentheses

*** Significant at the 1 percent level.

* Significant at the 10 percent level.

Table A3. Effect of NTMs on manuf. employment. IV estimates by NTM type.

	(1)	(2)	(3)	(4)
		Panel A: Δ manuf. employment share		
$\Delta NTMTBT_{mt}$	0.828***	0.522**		
	(0.285)	(0.259)		
$\Delta NTMSPS_{mt}$			1.790***	1.092**
			(0.646)	(0.547)
$\Delta\ Impexposure_{mt}$		−0.912***		−0.963***
		(0.081)		(0.080)
F stat	267.8	272.9	140.6	138.8
		Panel B: Δ log manuf. employment		
$\Delta NTMTBT_{mt}$	0.139***	0.135***		
	(0.024)	(0.025)		
$\Delta NTMSPS_{mt}$			0.301***	0.283***
			(0.056)	(0.056)
$\Delta\ Impexposure_{mt}$		−0.011***		−0.024***
		(0.004)		(0.003)
F stat	267.8	272.9	140.6	138.8

$N = 3234$ (1078 PUMAs, three 5-year changes). Dependent variables are 5-year changes in the percentage of the working-age population employed in manufacturing (Panel A) and 5-year differences in log manufacturing employment (Panel B). All regressions control for PUMA share of college-educated population, females, and foreign-born population, all measured at the beginning of each period, and year dummies. Models are weighted by the start of the period PUMA share of the national population. Robust standard errors in parentheses are clustered by PUMA.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.

Table A4. Robustness checks: standard errors clustered by state.

	(1)	(2)	(3)	(4)
	Δ log manuf employment			*Δ out of LF*
	all	*unskilled*	*skilled*	
ΔNTM_{mt}	0.122***	0.231***	0.071*	0.293
	(0.039)	(0.059)	(0.036)	(0.366)
F stat	89.85	91.80	89.85	89.85
	(5)	(6)	(7)	(8)
	Δ log hourly manuf. wages			*Δ log pop*
	all	*unskilled*	*skilled*	
ΔNTM_{mt}	−0.052**	−0.011	−0.040*	0.009
	(0.021)	(0.023)	(0.024)	(0.015)
F stat	89.85	90.79	89.89	89.85

$N = 3234$ (1078 PUMA, three 5-year changes). The table reports the estimated regression coefficients of NTM on different dependent variables specified in each column. All regressions include controls for PUMA share of college-educated population, foreign-born population, females, average age, and swing state and time dummies. Models are weighted by the start of the period PUMA share of the national population. standard errors are clustered by state.
** Significant at the 5% level.
* Significant at the 10% level.

Table A5. Robustness checks: effect of manufacturing employment and wages: standard errors computed following Adao et al. (2019)

	NTM all			NTM - STC		
	coef	*AKM se*	*P-value*	*coef*	*AKM se*	*P-value*
Dependent variables:						
Δ Manuf empl share	0.359	0.128	0.005	0.521	0.141	0.000
Δ Log manuf empl	0.084	0.016	0.000	0.122	0.017	0.000
Δ Log manuf empl—skilled	0.052	0.018	0.004	0.076	0.028	0.007
Δ Log manuf empl—unskilled	0.154	0.021	0.000	0.224	0.012	0.000
Δ Log hourly manuf wage	−0.037	0.008	0.000	−0.054	0.014	0.000
Δ Log hourly manuf wage—skilled	−0.028	0.007	0.000	−0.040	0.011	0.000
Δ Log hourly manuf wage—unskilled	−0.011	0.004	0.009	−0.016	0.008	0.033

$N = 3234$ (1078 PUMA, three 5-year changes). The table reports the estimated regression coefficients, AKM (Adao, Kolesar, Morales, 2019) standard errors, and the p-values of all NTM (columns (2)–(4)) and NTM-STC (columns (5)–(7)) on different dependent variables specified in each row. All regressions include controls for PUMA share of college-educated population, foreign-born population, females, average age, and time dummies. Models are weighted by the start of the period PUMA share of the national population.

FUNDING

Funding support for this article was provided by the project ‘Productivity, Non-Tariff Measures and Openness’ (PRONTO) funded by the European Commission under the 7th Framework Programme, Theme SSH.2013.4.3-3 ‘Untapped Potential for Growth and Employment Reducing the Cost of Non-Tariff Measures in Goods, Services and Investment’. (Grant agreement No. 613504).

Conflict of interest statement. No competing interest is declared.

ACKNOWLEDGMENTS

We thank Giulia Vattuone for outstanding research assistance and Paola Conconi and Lorenzo Trimarchi for providing data on the employment shares of swing states. We also thank Giorgio Barba Navaretti, Paola Conconi, Rosario Crino, Ron Davis, David Dorn, Giovanni Facchini, Lionel Fontagné, Mahdi Ghodsi, Gianluca Orefice, Giovanni Pica, Lorenzo Trimarchi for their comments on earlier drafts of this article. This article was produced as part of the project ‘Productivity, Non-Tariff Measures and Openness’ (PRONTO) funded by the European Commission under the 7th Framework Programme, Theme SSH.2013.4.3-3 ‘Untapped Potential for Growth and Employment Reducing the Cost of Non-Tariff Measures in Goods, Services and Investment’, Grant agreement No. 613504.

REFERENCES

Acemoglu, D., D.H. Autor, D. Dorn, G.H. Hanson, and B. Price. 2016. “Import Competition and the Great U.S. Employment Sag of the 2000s.” 34 *Journal of Labor Economics* S141–98

Adao, R. M. Kolesar, E. Morales. 2019. “Shift-Share Designs: Theory and Inference.” 134 *The Quarterly Journal of Economics* 1949–2010.

Adao, R., M., Kolesar, E., Morales and X. Zhang. 2020. “IVREG_SS: Stata Module to Compute Confidence Intervals, Standard Errors and p-Values in an IV Regression in Which the Excluded Instrumental Variable Has a Shift-Share Structure.” *Statistical Software Components* S458759, Boston College Department of Economics.

Amiti, M., and J. Konings. 2007. “Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia.” 97 *The American Economic Review* 1611–38.

Autor, D.H., D. Dorn, and G.H. Hanson. 2013a. “The China Syndrome: Local Labor Market Effects of Import Competition in the United States.” 103 *The American Economic Review* 2121–68.
Autor, D.H., D. Dorn, and G.H. Hanson. 2013b. “The Geography of Trade and Technology Shocks in the United States.” 103 *The American Economic Review* 220–25.
Autor, D.H, D. Dorn. and G.H. Hanson. 2016. “The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade.” 8 *Annual Review of Economics* 205–40.
Barattieri, A., M. Cacciatore, and F. Ghironi. 2021. “Protectionism and the Business Cycle.” 129 *Journal of International Economics* 103417.
Barba Navaretti, G., L. Fontagné, G. Orefice, G. Pica, and A. Rosso. 2023. “TBTs, Firm Organization and Labour Structure—The Effect of Technical Barriers to Trade on Skills.” 39 *Review of International Economics* 958–92.
Beghin, J.C., A.C. Disdier, and S. Marette. 2015. “Trade Restrictiveness Indices in the Presence of Externalities: An Application to Non-Tariff Measures.” 48 *Canadian Journal of Economics* 1513–36.
Beverelli, C., M. Boffa, and A. Keck. 2014. “Trade Policy Substitution: Theory and Evidence from Specific Trade Concerns.” WTO Staff Working Paper ERSD-2014-18.
Borusyak, K., P. Hull, and X. Jaravel. 2022. “Quasi-Experimental Shift-Share Research Designs.” 89 *The Review of Economic Studies* 181–213
Borusyak, K., and P. Hull. 2023. “Non-Random Exposure to Exogenous Shocks.” 91 *Econometrica* 2155–85.
Bown, C.P., P. Conconi, A. Erbahar and L. Trimarchi. 2021. “Trade Protection Along Supply Chains.” CEPR Discussion Paper No. DP15648
Bown, C.P., P. Conconi, A. Erbahar, and L. Trimarchi. 2023. “Politically Motivated Trade Protection.” *mimeo*
Cadot, O. and J., Gourdon 2016. “Non-Tariff Measures, Preferential Trade Agreements, and Prices: New Evidence.” 152 *Review of World Economics* 227–49.
Chen, T., C. Hsieh, and Z.M. Song. 2022. “Non-Tariff Barriers in the U.S.-China Trade War.” National Bureau of Economic Research (NBER) Working Paper Series, No. 30318.
Conconi, P., D. DeRemer, G. Kirchsteiger, L. Trimarchi, and M. Zanardi. 2017. “Suspiciously Timed Trade Disputes.” 105 *Journal of International Economics* 57–76.
Disdier, A.C., and M. Fugazza. 2020. “A Practical Guide to the Economic Analysis of Non-Tariff Measures. UNCTAD report.” https://unctad.org/publication/practical-guide-economic-analysis-non-tariff-measures-volume-3
Fontagné, L., G. Orefice, R. Piermartini, N. Rocha. 2015. “Product Standards and Margins of Trade: Firm-Level Evidence.” 97 *Journal of International Economics* 29–44.
Furceri, D., S.A. Hannan, J.D. Ostry, and A.K. Rose. 2018. “Macroeconomic Consequences of Tariffs.” NBER Working Paper No. w25402
Gawande, K., and U. Bandyopadhyay. 2000. “Is Protection for Sale? Evidence on the Grossman–Helpman Theory of Endogenous Protection.” 82 *The Review of Economics and Statistics* 139–52.
Ghodsi, M. 2016. “Determinants of Specific Trade Concerns Raised on Technical Barriers to Trade EU versus non-EU.” 45 *Empirica* 83–128
Ghodsi, M., J. Grübler, O. Reiter, R. Stehrer, 2017. “The Evolution of Non-Tariff Measures and their Diverse Effects on Trade.” *wiiw Research Reports* 419, The Vienna Institute for International Economic Studies, wiiw.
Goldsmith-Pinkham, P., I. Sorkin, and H. Swift. 2020. “Bartik Instruments: What, When, Why, and How.” 110 *American Economic Review* 2586–624.
Gourdon, J. 2014. “CEPII NTM-MAP: A Tool for Assessing the Economic Impact of Non-Tariff Measures.” Working Papers 2014–24, CEPII research center.
Hakobyan, S. and J. McLaren. 2016. “Looking for Local Labor Market Effects of NAFTA.” 98 *The Review of Economics and Statistics* 728–741.
Herghelegiu, C. 2018. The Political Economy of Non-Tariff Measures. 41 *The World Economy* 262–86.
Kee, H.L., A. Nicita, and M. Olarreaga 2009. “Estimating Trade Restrictiveness Indices.” 119 *Economic Journal* 172–199.
Lee, J-W., and P. Swagel 2000. “Trade Barriers And Trade Flows Across Countries and Industries.” 79 *The Review of Economics and Statistics* 372–382.
Lake, J. and D., Millimet 2016. “Good Jobs, Bad Jobs: What’s Trade Got to Do with It?” IZA Discussion Papers 9814, Institute of Labor Economics (IZA).

Ma, X. and J. McLaren. 2018. "A Swing-State Theorem, with Evidence." NBER Working Paper No. 24425.

Maggi, G. and P.K. Goldberg. 1999. "Protection for Sale: An Empirical Investigation." 89 *American Economic Review* 1135–1155.

Marette, S., and J. Beghin. 2010. "Are Standards Always Protectionist?" 18 *Review of International Economics* 179–92

Muuls, M. and D. Petropoulou. 2013. "A Swing State Theory of Trade Protection in the Electoral College." 46 *Canadian Journal of Economics* 705–24

Nicita, A. and J. Gourdon. 2013. "A preliminary analysis on newly collected data on non-tariff measures." Geneva, United Nations Conference on Trade and Development (UNCTAD), Policy Issues in International Trade and Commodities Study Series No. 53

Orefice, G. 2017. "Non-Tariff Measures, Specific Trade Concerns and Tariff Reduction." 40 *The World Economy* 1707–2030

Pierce, J.R., and P.K. Schott. 2016. "The Surprisingly Swift Decline of US Manufacturing Employment." 106 *American Economic Review* 1632–62.

Shepotylo, O., V. Vakhitov, V. Movchan, and M. Panga. 2022. "Non-Tariff Measures and Productivity of Ukrainian Food-Processing Firms." 73 *Journal of Agricultural Economics* 234–56

UNCTAD. 2013. Non-Tariff Measures to Trade: Economic and Policy Issues for Developing Countries. Developing Countries in International Trade Studies, New York and Geneva: United Nations.

WTO. 2012. *World Trade Report 2012: Trade and Public Policies: A Closer Look at Non-Tariff Measures in the 21st Century*. Geneva: World Trade Organization.

The Journal of Law, Economics, and Organization, 2026, 42, 188–220
https://doi.org/10.1093/jleo/ewae023
Article