I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14162

Do Non-tariff Barriers to Trade Save American Jobs and Wages?

Marco Leonardi
Elena Meschi

MARCH 2021

DISCUSSION PAPER SERIES

IZA DP No. 14162

Do Non-tariff Barriers to Trade Save American Jobs and Wages?

Marco Leonardi
Universita' degli Studi di Milano and IZA

Elena Meschi
Universita' degli Studi di Milano-Bicocca

MARCH 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Do Non-tariff Barriers to Trade Save American Jobs and Wages?*

Before the recent rebound due to the US–China trade war, tariffs on international trade were being progressively reduced over the last decades and advanced countries increasingly relied on non-tariff measures (NTMs) to protect their industries from foreign competition. In this paper, we exploit a novel database on NTMs to test their role in shaping the labour market effects of exposure to Chinese import competition over the 2000–2015 period. We relate changes in manufacturing employment to the share of employed workers protected by NTMs across US local labour markets and we instrument NTMs using the industry share of employment in swing states during presidential elections. Our results indicate that NTMs mitigate the negative employment effect of exposure to Chinese imports and have a positive effect on manufacturing wages (especially for the unskilled).

JEL Classification: E24, J23, J31

Keywords: import competition, non-tariff barriers, labour market, Chinese imports

Corresponding author:
Marco Leonardi
Department of Economics
University of Milan
Via Conservatorio 7
I-20122 Milan
Italy
E-mail: marco.leonardi@unimi.it

* We thank Giulia Vattuone for outstanding research assistance, David Dorn for excellent comments, 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, Giovanni Facchini, Lionel Fontagne, Mahdi Ghodsi, Gianluca Orefice, Giovanni Pica, Lorenzo Trimarchi and all the participants to the Vienna ”Pronto” conference, the Milan 'Trade and Labour Market' workshop and the EALE Conference 2017 and the 'Labour Market Challenges' workshop in Prague. This paper 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.

1 Introduction

The rapid increase in manufacturing exports from low-wage countries and in particular from China has raised concerns about its impact on employment in high-income countries. China's export surge in manufacturing especially accelerated after 2001, the year the country entered the WTO. From 2001 to 2015, US imports from China increased dramatically, rising from about $102 billion in 2001 to about $483 billion in 2015. The negative effect of such an increase in import competition on manufacturing employment has been extensively documented in the economic literature (see for example for Autor et al. 2013a, 2013b and 2016).

Different countries have reacted in different ways to protect domestic industries from import competition. Since tariffs on international trade have been progressively liberalized over the last decades, countries have increasingly relied on non-tariff measures (NTMs) to restrict their market access and pursue their policy objectives (UNCTAD, 2013). Gourdon (2014) reports that the use of NTMs to regulate trade has been rising since the 1990s, both in terms of the number of countries adopting these measures as well as in their variety. Up until very recently (2018 and the Trump administration's policy reversal on tariffs), reducing non-tariff barriers was a key part of transatlantic liberalization (Francois et al. 2013).

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.[1] We focus on Sanitary and Phytosanitary Standards (SPS) which include quality and hygienic requirements, as well as production and conformity assessments regarding food and beverages and on Technical Barriers to Trade (TBT) which 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, a number of papers have attempted to quantify the effect of NTMs on countries' and firms' international trade flows (see for example Kee et al., 2009; Fontagne et al., 2015). However, to the best of our knowledge, there are no studies that investigate the impact of NTMs on the labour market.[2]

[1] UNCTAD 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

[2] An exception is Trimarchi (2020) who studied the impact of anti-dumping measures on Chinese import competition and on manufacturing employment in the US

This is what we do in this paper in the context of the US manufacturing sector.

In particular, we look at the role of NTMs in mitigating the effect of Chinese imports on the decline of manufacturing employment in the US. In a series of papers, Autor and co-authors have documented the effect of the rise in Chinese imports on various dimensions of the US economy (Autor et al. 2013a, 2013b and 2016). Autor et al. (2013a) show that rising Chinese import competition between 1990 and 2007 significantly contributed to the aggregate decline in US manufacturing employment. This impact is greater in the local labour markets in which the industries exposed to foreign competition are more concentrated. Adjustment is typically slow and manufacturing employment and wages remain depressed for a long time after the rise of Chinese trade (Autor et al., 2016).

All these papers assume that the surge in Chinese imports is driven by Chinese supply shocks and falling trade tariffs rather than increased demand in the US. In this paper, we rely on the same assumption and deepen the analysis, looking at the role of NTMs, which in many cases have replaced tariffs in manufacturing industries: it is therefore possible (but not yet proven) that they have mitigated the effect of the China shock on various local labor market outcomes.

We exploit the recently released WTO database on Specific Trade Concerns, which records NTMs (TBTs and SPSs) at the 6-digit product level to construct an index of non-tariff protection of US manufacturing industries over time. We then translate the measure of NTM protection of an industry into a measure at the local area level (defined as a Public Use Microdata Area, PUMA), using the industrial composition of the area. We proceed as follows. First, we define a product to be *protected* if it is subject to a Specific Trade Concern ('Specific Trade Concerns' refer to the concerns raised by WTO members in specific committees in order to complain about NTMs taken by other members).[3] Secondly, we create a measure of industry protection, based on the number of products protected in each industry, weighted by the importance of each product in the total trade of the industry. Thirdly, we define a PUMA's degree of protection as the share of the total number of workers in that area that work in protected industries. The final measure at the PUMA level is basically the share of employed workers that work in protected industries weighted by the share of protected products in each

[3]Specific Trade Concerns (rather than simple notifications) identify measures that are perceived by exporters and/or governments as major obstacles to trade.

industry and their incidence in trade flows: we call this the 'NTM index of protection' (because it measures the intensity of protection) and we standardize it to have mean 0 and standard deviation 1 for ease of interpretation.

We then investigate whether NTM protection affects employment, by relating changes in local manufacturing employment for the 2000–2015 period across US labor markets to the (weighted) share of local employment protected by NTMs, conditional on changes in local exposure to Chinese import competition (we use Chinese exports to the EU to build a potential exposure measure for the US). A concern for our analysis is that NTMs may be endogenous to changes in employment: imagine that a decline in manufacturing employment due, for example, to increasing imports of a specific product from China is the cause of the imposition of an NTM. In this case, there would be a reverse causality problem: it is not NTMs that affect employment (reducing imports) but the other way around. Or think of the case of unobservable import shocks (not captured by our measure of imports from China) which drive both the decline of manufacturing and the imposition of NTMs: we would still have an endogeneity issue. To address this endogeneity issue, we instrument the (weighted) share of NTM-protected employment in a PUMA (our NTM protection index) with the industry share of employment in swing states during presidential elections (see Conconi et al. 2017): the idea is that if a PUMA has a high incidence of employment in industries that are popular in swing states, then that PUMA is also more likely to have a high share of employed workers protected by NTMs. The identification assumption is that NTMs are raised for industries that are more important in swing states for political reasons, and this is orthogonal to other variables that may affect directly the local levels of employment and wages. We discuss the credibility of this assumption and provide the results of some falsification tests.

This paper makes four key findings. First, our results indicate that an increase in the NTM index – instrumented by the industry share of employment in swing states – leads to an increase in the share of employment in manufacturing at the PUMA level. A one standard deviation increase in the NTM index (which corresponds to a PUMA moving from the 50th percentile of NTM protection to the 80th percentile) increases by 1.3% the share of employed workers in manufacturing. This means that PUMAs that have seen a large increase in the NTM index – because they have a similar industrial composition of swing states during presidential elections

– have offset the declining trend in manufacturing employment (on average 1% every five years between 2000 and 2015). Second, an increase in the NTM index is also related to an increase in manufacturing wages, especially for unskilled workers. Third, we find a negative effect on unemployment (i.e. PUMAs with higher NTMs have lower unemployment) but we do not find any effect on non-manufacturing employment, confirming that NTMs have an effect on manufacturing sector only. A fourth finding is that while TBT protection has a stronger effect on PUMAs more exposed to Chinese import competition (thus reinforcing the argument that NTMs mitigated the effect of a potential China shock), the opposite is true for SPSs, probably because SPSs on agricultural goods are very correlated across countries and Chinese exports to the EU provide a potential exposure measure for the US only to the extent that the EU does not use similar NTMs (furthermore the US does not import agricultural goods from China but rather from closer countries).

These results enrich the analysis in Autor et al. (2013a) and at the same time contribute to the literature on NTMs, uncovering their role in the labour market beyond trade-protection measures. Of course, these results do not imply that trade protection is beneficial for the manufacturing sector. They capture only the partial-equilibrium effects of NTM on protected industries and do not take into account the potential benefits of trade for consumers. However, they show that NTMs may have an effect through protecting employment in the industries (and in the PUMAs) that are the most hit by the displacing effects of Chinese imports.

The rest of this paper proceeds as follows. Section 2 describes the Specific Trade Concern dataset on NTMs. In Section 3 we present our empirical specification and discuss the construction of our key variables of interest: Section 3.1 describes how we compute the novel measure of NTM protection at the local area level and Section 3.2 describes the measure of local exposure to Chinese import competition. We discuss our identification strategy and our instrumental variable approach in Section 4. In Section 5 we present and comment on the results, and in Section 6 we provide some concluding remarks.

2 The Specific Trade Concerns 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. NTMs 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. In fact, though many NTMs aim primarily at protecting public health or the environment, they substantially affect trade through information, compliance and procedural costs.

For practical purposes, NTMs are categorized depending on their scope and design and are generally divided into technical measures (Sanitary and Phytosanitary Standards and Technical Barriers to Trade) and non-technical measures (see UNCTAD, 2013).[4]

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. This makes the collection of NTM data a very resource-intensive task (Gourdon, 2014; UNCTAD, 2013).

In this paper, we rely on the recently released WTO database on Specific Trade Concerns (STC) [5], which records the concerns raised by WTO members in the dedicated committees of the WTO in order to complain and discuss specific measures taken by other members that are perceived as obstacles to trade.

We focus on concerns regarding Sanitary and Phytosanitary Standards (SPS) and Technical Barriers to Trade (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 labelled 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).

[4]These are further divided into hard measures (e.g. price and quantity control measures), threat measures (e.g. anti-dumping and safeguards) and other measures, such as trade-related finance and investment measures.

[5]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 $http://spsims.wto.org/web/pages/search/stc/Search.aspx$.

The advantage of specific trade concerns over traditional information on the existence of regulations on product standards is that the former identify measures that are truly perceived by exporters and/or governments 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.[6]

When a country raises a concern over a measure, it specifies the product of concern, the type of concern regarding the measure, and the objective of the measure concerned (see WTO, 2012 for more details).

Overall, the dataset provides information on the 317 Specific Trade Concerns raised in the TBT Committee and the 312 concerns raised in the SPS Committee between January 1995 and June 2014. For each concern, we have information on: (i) the country or countries raising the concern and the country imposing the measure, (ii) the product codes (HS 2002 at the 6-digit level) involved in the concern, (iii) the year in which the concern was raised with the WTO, and (iv) whether it has been resolved and how.

Our analysis focuses on a sub-sample of the 41 concerns raised by China or the rest of the world against the US over the period 1995–2014. Based on these concerns, we build a panel dataset tracking the presence of an ongoing STC against the US on HS 6-digit products over time.

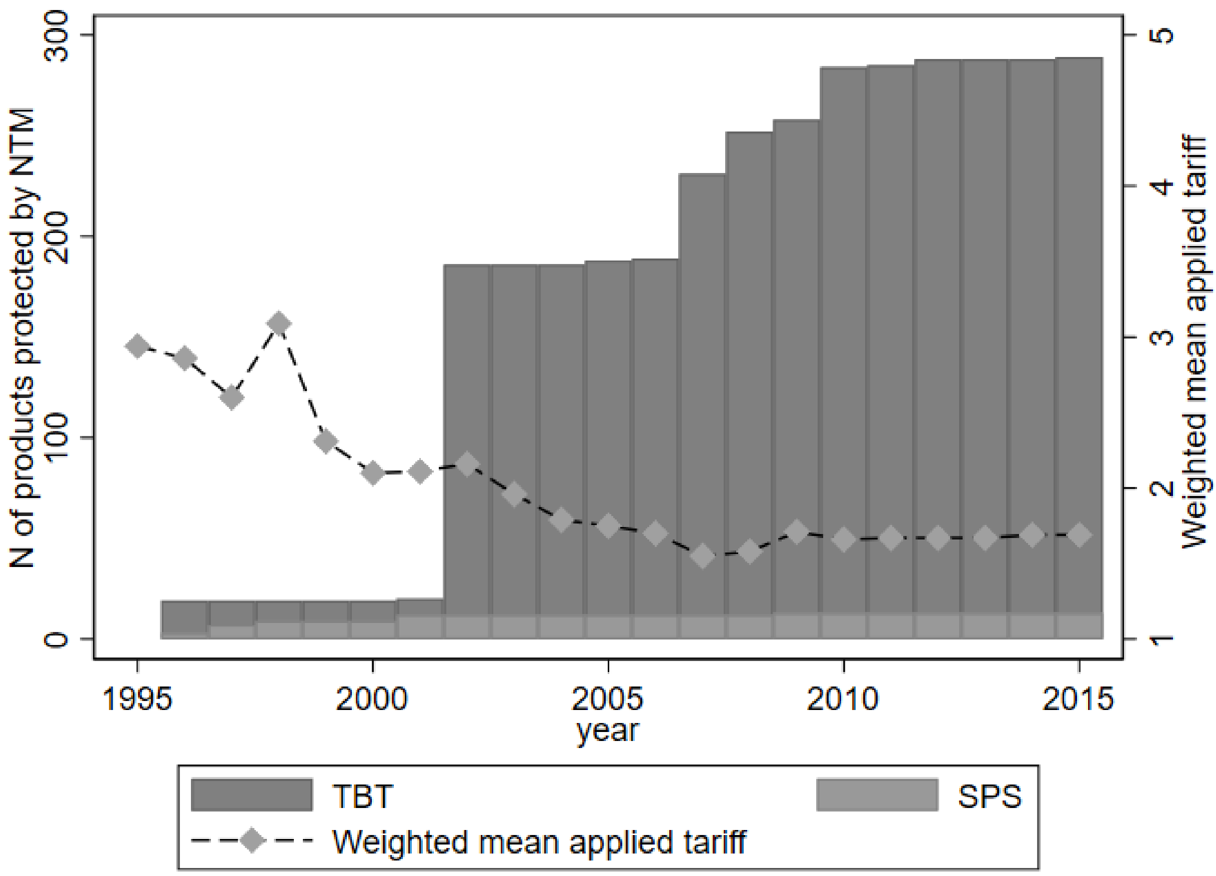
Figure 1 plots the 41 STCs over time against a measure of the incidence of tariffs in the US and reveals that the strong decline in tariffs occurred over the last decades has been associated to a significant increase in NTMs.

This is not the first paper using WTO-STC data. For example, Fontagne et al. (2015) use the STC dataset to test the effect of NTBs 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 and confirms the complex nature of TBT, which are found to be affected by economic, technological, institutional, and health and environmental issues.[7] Barba Navaretti et al. (2019) use WTO-STC data combined with matched employer–employee data for the

[6]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 barrier to trade or not.

[7]Beverelli et al. (2014) find clear evidence of trade policy substitutability, showing that countries impose NTMs to compensate for reductions in imposed applied tariffs. Similarly, Orefice (2015) shows that SPS and TBT concerns are raised by exporting countries as a consequence of an importer's tariff cut.

FIGURE 1. Evolution of tariff and non-tariff measures over time



Notes: Left axis – the number of HS 4-digit products targeted by SPS/TBT concerns against US by at least one country (source: WTO-STC database). Right axis – the weighted mean applied tariff. Weighted mean applied tariff (source: World Development Indicators) is the average of effectively applied rates on all products weighted by the product import shares corresponding to each partner country. Import weights were calculated using the United Nations Statistics Division's Commodity Trade (Comtrade) database.

population of French exporters to study the impact of TBT on the workforce composition of French firms.

To the best of our knowledge, we are the first to use these data to study the labour market impact of NTMs (through their effect on imports). 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). For the purposes of this paper, 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. Of course there are potential issues of endogeneity of NTMs and employment changes at the PUMA level that will be treated afterwards (see Section 4). Here, as a motivation exercise, we show that – at the HS 4-digit product level – NTMs are correlated with future changes in imports from China. In particular, we estimate the equation

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

where h represents the product, defined at the 4-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 5 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 (at the 4-digit NAICS level) for unobserved product specific characteristics that might affect the likelihood of imposing an NTM.

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 3 years. As a check in Panel B we also show that the same regression (each cell of the table shows the result of a separate regression) with the change in Chinese imports in the rest of the world yields insignificant results i.e. we can conclude that NTMs are associated with lower Chinese exports towards the US but not towards other countries.

3 Data and Empirical Strategy

The typical empirical specification in the literature analysing the local labour market effect of trade exposure consists in regressing a measure of change in local labour market outcomes, such as manufacturing employment, on a measure of trade exposure faced by a specific location, plus a set of location specific controls (Autor et al. 2013a). We build on this specification and add our variable of interest, which is the measure of NTM protection of specific sectors in specific areas as described below. Our analysis requires a time-consistent definition of regional economies in the US: following Hakobyan and McLaren (2016) we define local labour markets by the Census Consistent Public Use Microdata Area (PUMAs hereafter). More specifically,

Table 1. NTMs and Changes in Chinese Imports in the US 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 US					
NTM_{ht-i}	-0.018***	-0.018***	-0.012**	-0.005	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
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)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	43,302	43,302	40,920	38,540	36,170

Notes: Each cell is the estimated coefficient of a separate regression on various lags of NTM_{ht-i} taken one in turn. Year and industry (NAICS 4 digit) fixed effects are always included. In Panel A the dependent variable is $\Delta log(ChinaImport)$, as indicated in regression 1, in Panel B the dependent variable is the change in Chinese exports to the rest of the world (except the US) of product h at time t. Robust standard errors in parentheses. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

we estimate the following equation:

$$\Delta Y_{mt} = \beta_0 \Delta Impexposure_{mt} + \beta_1 NTM_{mt} + \gamma X_{mt} + \alpha_t + \alpha_m + \varepsilon_{mt} \tag{2}$$

where ΔY_{mt} is the 5-year change (between 2000 and 2015) in various labour market outcomes of PUMA m . The main outcome of interest is the 5-year change in the share of the working-age population employed in manufacturing and the change in log hourly manufacturing wages, but we also look at employment and wages of skilled and unskilled workers, non-manufacturing employment, unemployment rate and labour force participation. $\Delta Impexposure_{mt}$ is a measure of exposure to Chinese import competition faced by location m at time t, while NTM_{mt} is our new measure of NTM protection at the PUMA level in the initial year of the 5-year change. We will explain in detail how we construct these measures in paragraphs 3.1 and 3.2.

The vector X_{mt} contains a set of controls for the PUMA's labour 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 5-year change to avoid simultaneity).

We choose to carry out all our estimates in first differences since in this way we control for PUMAs' time-invariant unobservable characteristics. In addition, to control for PUMA-specific trends, in our main results we also add PUMA fixed effects α_m to the first-difference estimates. 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.

This specification identifies the effect of trade exposure and trade protection if workers' mobility across local areas is limited and if local labour markets differ in their exposure to import competition and in their level of protection only due to their industrial structure. Even though we control for time invariant unobserved heterogeneity and possible linear PUMA-specific trends, estimates based on Equation 2 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.

We use data from the 5 percent sample of the decennial census in 2000 and the 1 percent sample of the American Community Survey (ACS) in 2005, 2010 and 2015 Integrated Public Use Microsample Series (IPUMS) files. As mentioned above, we define local labour markets by PUMAs. PUMAs cover the entire US, 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.[8] We keep only manufacturing sectors (21 sectors at 3-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).

We merge the Census data, at the PUMA-year level, with: (1) the measure of NTM protection, illustrated in Section 3.1, and (2) the measure of exposure to Chinese imports (from COMTRADE data), described in Section 3.2. Both these measures are initially computed at the sectoral level, and then projected to each PUMA according to the sectoral composition of their employment at the beginning the sample period.

[8]Unlike CZs, PUMA are not specifically designed to outline the boundaries of local labour markets, but they have been used in the literature to define local labour 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 2 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.

Table 2. Descriptive Statistics

	2000		2005		2010		2015		Total	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Share employed in manuf.	0.12	(0.06)	0.10	(0.05)	0.09	(0.04)	0.09	(0.04)	0.10	(0.05)
Share employed in manuf. – skilled	0.05	(0.02)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)	0.04	(0.02)
Share employed in manuf. – unskilled	0.07	(0.04)	0.06	(0.04)	0.05	(0.03)	0.05	(0.03)	0.05	(0.04)
Hourly wage	15.75	(2.89)	19.32	(4.73)	21.73	(5.14)	24.79	(8.70)	20.34	(6.63)
Hourly wage – unskilled	14.00	(2.38)	16.20	(3.34)	17.46	(3.66)	18.32	(5.39)	16.46	(4.17)
Hourly wage – skilled	19.90	(3.60)	24.50	(5.50)	27.71	(6.31)	31.92	(10.72)	25.93	(8.28)
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	0.26	(0.06)	0.26	(0.05)	0.26	(0.06)	0.28	(0.06)	0.27	(0.06)
Share female	0.30	(0.06)	0.29	(0.10)	0.29	(0.10)	0.28	(0.09)	0.29	(0.09)
Age	40.25	(1.78)	42.22	(2.67)	43.38	(2.59)	43.87	(2.71)	42.40	(2.84)
Share college educated	0.39	(0.13)	0.44	(0.17)	0.47	(0.16)	0.49	(0.16)	0.44	(0.16)
Share white	0.76	(0.20)	0.77	(0.21)	0.77	(0.20)	0.77	(0.20)	0.77	(0.20)
NTM_{mt}	0.004	(0.005)	0.022	(0.019)	0.036	(0.027)			0.026	(0.026)
$Indswing_{mt}$	0.16	(0.08)	0.14	(0.08)	0.14	(0.09)			0.14	(0.08)
$Impexposure_{mt}$	1.63	(1.03)	3.89	(2.75)	6.60	(4.70)	6.54	(4.67)	4.63	(4.16)

Notes: N=1078 PUMAs. Shares are intended as shares of the working age population to avoid having the PUMA employment on both sides of the regression. Decennial census in 2000 and American Community Survey (ACS) in 2005, 2010 and 2015. NTM data from WTO database on Specific Trade Concerns. Data on exposure to import competion from COMTRADE data. *Impexposure* is the Dollar value of (imports from China to Europe) per worker.

3.1 NTM protection

Starting from the 41 STCs raised by China or the rest of the world against the US, 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 PUMA level, on the basis of the share of total employment in protected industries.

In particular, we define a product (a 6-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 concern. In our sample, 41 concerns affect 1433 products over a total number of 6292 products (6-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 the 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}. Figure 2 shows the products with the longest STCs (distinguishing between Technical Barriers in Panel A and Sanitary and Phytosanitary in Panel B). The table 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 animal production and agriculture sector.

Figure 2. Products subject to STCs

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 Tea	0204, 0206, 0210, 2004, 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

Notes: Source: WTO-STC data

HS products are allocated to industry j with crossover HS 6-digit-NAICS 2002 at the 3-digit level.[9] 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 trade of the industry, measured at the beginning of the sample period (i.e. 2000) to avoid endogeneity.[10] 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.[11]

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

$$NTM_{jt} = \sum_{i=1}^{N} \frac{HSp_{it}}{N_j} \frac{(imp + exp)_{i2000}}{(imp + exp)_{j2000}} \tag{3}$$

where N_j is the total number of products produced in industry j and $\frac{(imp+exp)_{i2000}}{(imp+exp)_{j2000}}$ is the weight in terms of imports plus exports of product i in the total trade of industry j.

Table 3 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 and some 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. The intensity of protection of different industries is measured by NTM_{jt} as described above. Therefore the index of NTM protection for each PUMA m is given by

$$NTM_{mt} = \sum_{j} \frac{L_{mjt}}{L_{mt}} \times NTM_{jt} \tag{4}$$

where $\frac{L_{mjt}}{L_{mt}}$ is the share of workers of PUMA m employed in industry j. Therefore NTM_{mt} is the (weighted) share of workers in a PUMA that are protected by an NTM (the weights are the

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

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

[11] This measure is similar to the coverage ratio computed by UNCTAD (2000), which measures the percentage of trade subject to NTMs for an importing country.

Table 3. Number and weighted share of HS products protected in each NAICS sector

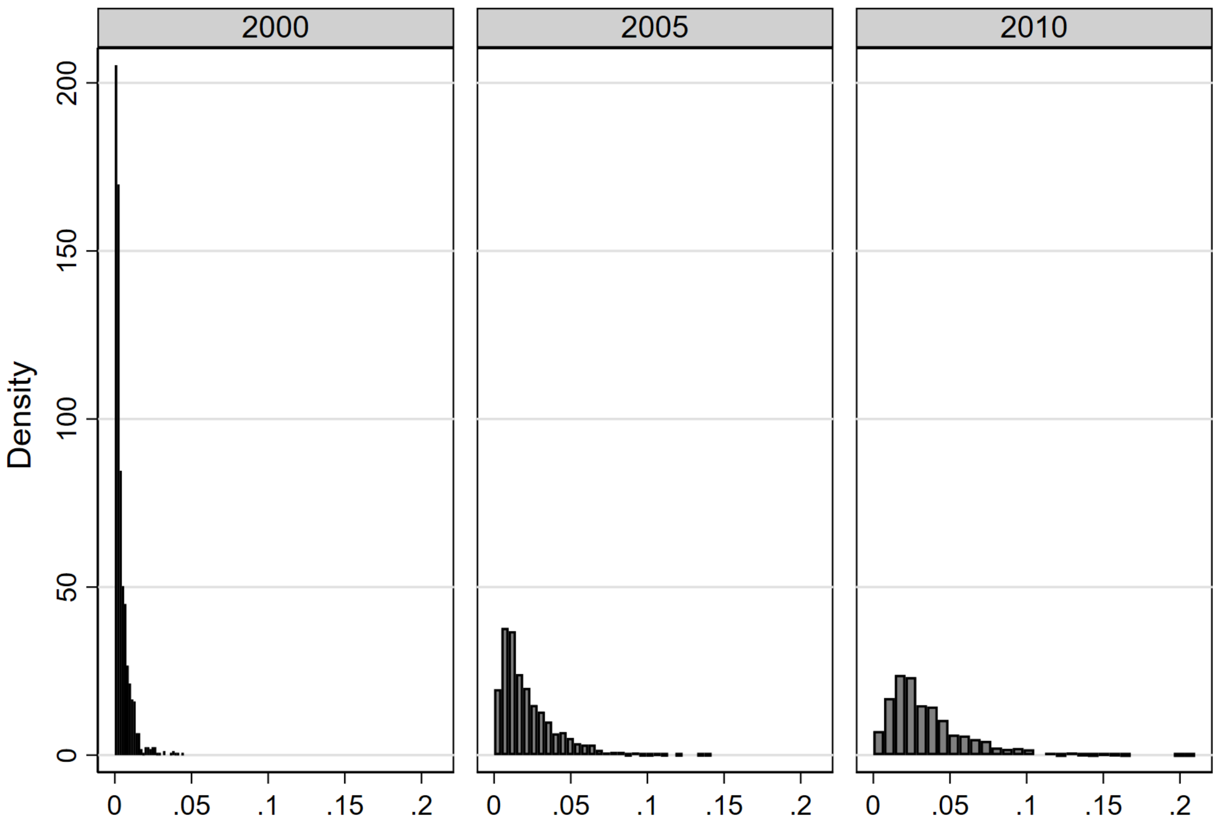
		N of HS (4digit)	Index of NTM protection		
Year			2000	2005	2010
311	Food Manufacturing	115	20.63	84.65	84.65
312	Beverage and Tobacco Product Manuf	10	0.00	75.36	96.78
313	Textile Mills	68	0.00	0.00	0.00
314	Textile Product Mills	33	55.51	10.52	55.51
315	Apparel Manufacturing	41	48.84	0.00	94.25
316	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

Notes: Source: WTO-STC data. Manufacturing industries only. The table shows the index NTM_{jt} described in equation (3), where each protected product is weighted by its share of imports+exports in total industry imports+exports.

intensity of protection of each industry measured by the number of NTM-protected products). NTM_{mt} changes over time both because of the changes in industrial composition of the PUMA and because of the variation in the intensity of industry protection (NTM_{jt}).

Histogram 3 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 the increasing importance of NTMs and their growing incidence.

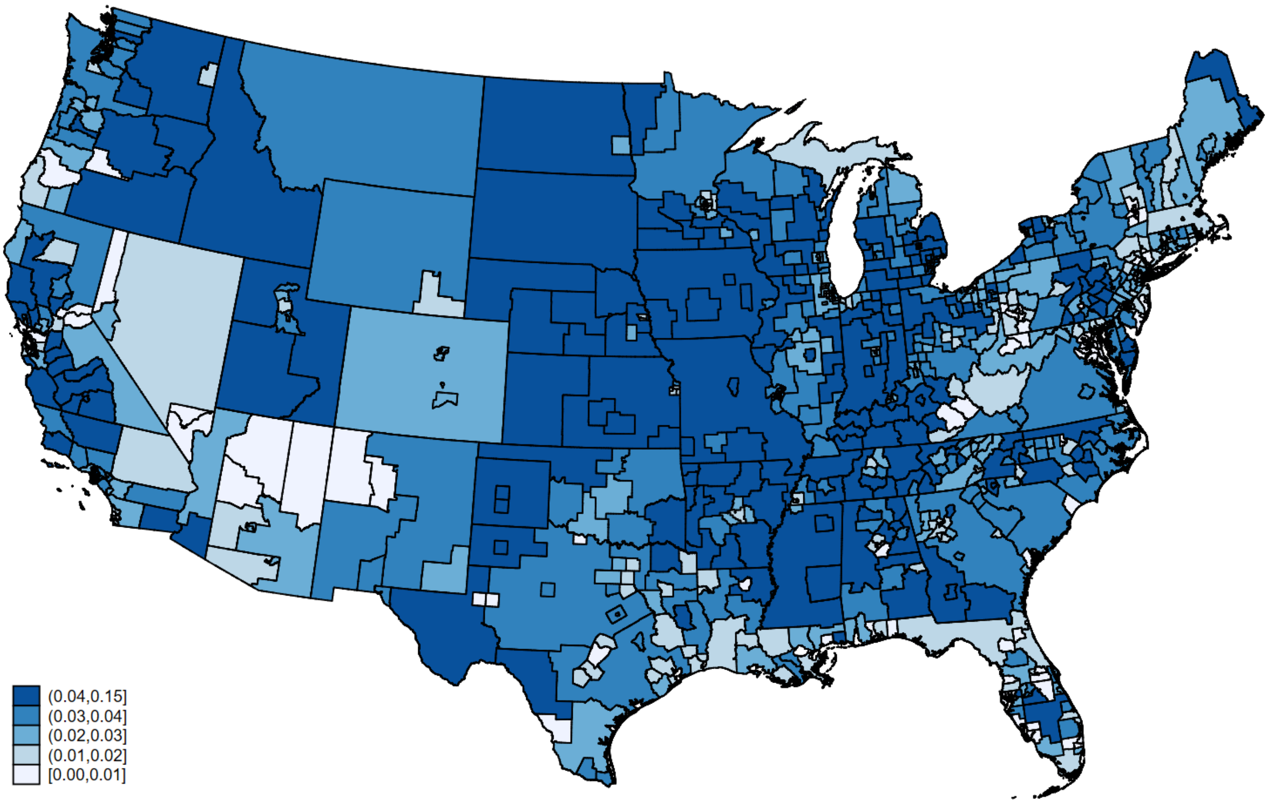
FIGURE 3. NTM index across PUMAs over time



Notes: Source: WTO-STC and Census-ACS data. The figure shows the distribution of the index NTM_{mt} described in equation (4) across PUMA over time in years 2000, 2005 and 2010 respectively.

Figure 4 shows the geographic pattern of NTM protection across the whole country. In particular, the map shows the average value of NTM protection of each PUMA over our sample period. 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, in California, and in some PUMAs in the northwestern states.

FIGURE 4. NTM index: share of protected employment – average across all years



Notes: Source: WTO-STC and Census-ACS data. The figure shows the geographical pattern of the index NTM_{mt} described in equation (4) averaged across years 2000, 2005 and 2010.

3.2 Import exposure

$\Delta Impexposure_{mt}$ measures the increase (5-year change) in exposure to competition from Chinese imports faced by a location m. As in Autor et al. (2013a), the measure is computed as follows:

$$\Delta Impexposure_{mt} = \sum_j \frac{L_{mj2000}}{L_{j2000}} \frac{\Delta Imp_{jt}^{EU}}{L_{mt}}. \tag{5}$$

For each PUMA m and each time period t, $\Delta Impexposure_{mt}$ is the sum across all industries j of the 5-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) $\frac{L_{mj2000}}{L_{j2000}}$. Unlike Autor et al. (2013a) who use this measure as an instrument for actual Chinese imports in the US, we use it directly in the main equation. The reason is that imports from China to the US may already reflect the effect of the NTMs which we want to measure; therefore we want a measure of *potential* exposure to Chinese imports rather than a measure of *actual* exposure.[12] 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 exogenous, it requires that it depends on Chinese supply shocks in each industry (and on the industry mix in each PUMA) and that import demand shocks in high-income countries (EU but also US demand shocks are probably correlated) are not the primary cause of China's export growth. However it seems plausible 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).

Furthermore, Chinese imports in the EU provide a potential exposure measure 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 US and NTMs imposed in EU is 0.56; however, when dividing the sample in TBT and SPS measures the correlation is 0.19 between TBTs in US and EU and 0.64 between SPSs i.e. Sanitary and Phyto-sanitary Standards are imposed on agricultural goods and are more similar across countries. Notice for instance in Table 3 that food and beverages (the first two entries in the table) – which are a sectors with little Chinese exports– have high NTMs: therefore the low level of Chinese exports in these categories may result from Europe also protecting its market. In alternative, NTMs 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 is not a good measure of protection). We will explore the implication of this difference between TBTs and SPSs in the results' Section 5.

[12] Imports from China to the EU grew even more than imports to the US in the period 2000 to 2015, the increases were 350% and 230%, respectively.

4 Identification and IV

Identifying the causal impact of trade protection through NTMs is challenging. Since a possible concern with our strategy is the endogeneity of NTM with respect to changes in employment (the most serious is reverse causality, i.e. that NTMs arise to protect those industries where job losses are more pronounced), we follow an instrumental variable approach, exploiting exogenous variation in NTM determinants.

Beyond reverse causality, OLS estimates could be biased by other factors: for example the error term in Equation 2 may reflect unobserved PUMA-specific differences (non-linear differences not picked up by fixed effects) in economic performance that may be positively or negatively correlated with the share of workers protected by NTMs. For example, if an NTM were especially concentrated in a PUMA that experienced the greatest employment loss, then the OLS estimates would be downward biased. In contrast, we would observe a positive bias in OLS estimates if a PUMA with the best performance in terms of manufacturing employment also tended to have more NTMs.

To solve this problem, we adapt the IV strategy based on swing states in presidential elections used in Trimarchi (2020). Trimarchi (2020) claims 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 his paper he focuses on anti-dumping 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 towards 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 Lee and Swagel, 2000; Maggi and Goldberg, 1999; 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, for more details).[13] To capture the political importance of an industry, we use the percentage share of employment of that industry in all swing states at the beginning of the period. This 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, our IV for NTM_{mt} (like the measure of NTM protection itself) is first defined at the sectoral level (the employment share of each industry j in total employment of swing states) and then projected to each PUMA m according to its employment composition. The IV is thus constructed as follows:

$$indswing_{jt} = \frac{\sum_{i=swing} L_{ijt}}{\sum_{i=swing}\sum_j L_{ijt}} \tag{6}$$

where $indswing_{jt}$ is the employment share of each industry j in total employment of swing states only (states swing in t=2004, 2008, 2012). The projection at the PUMA level is

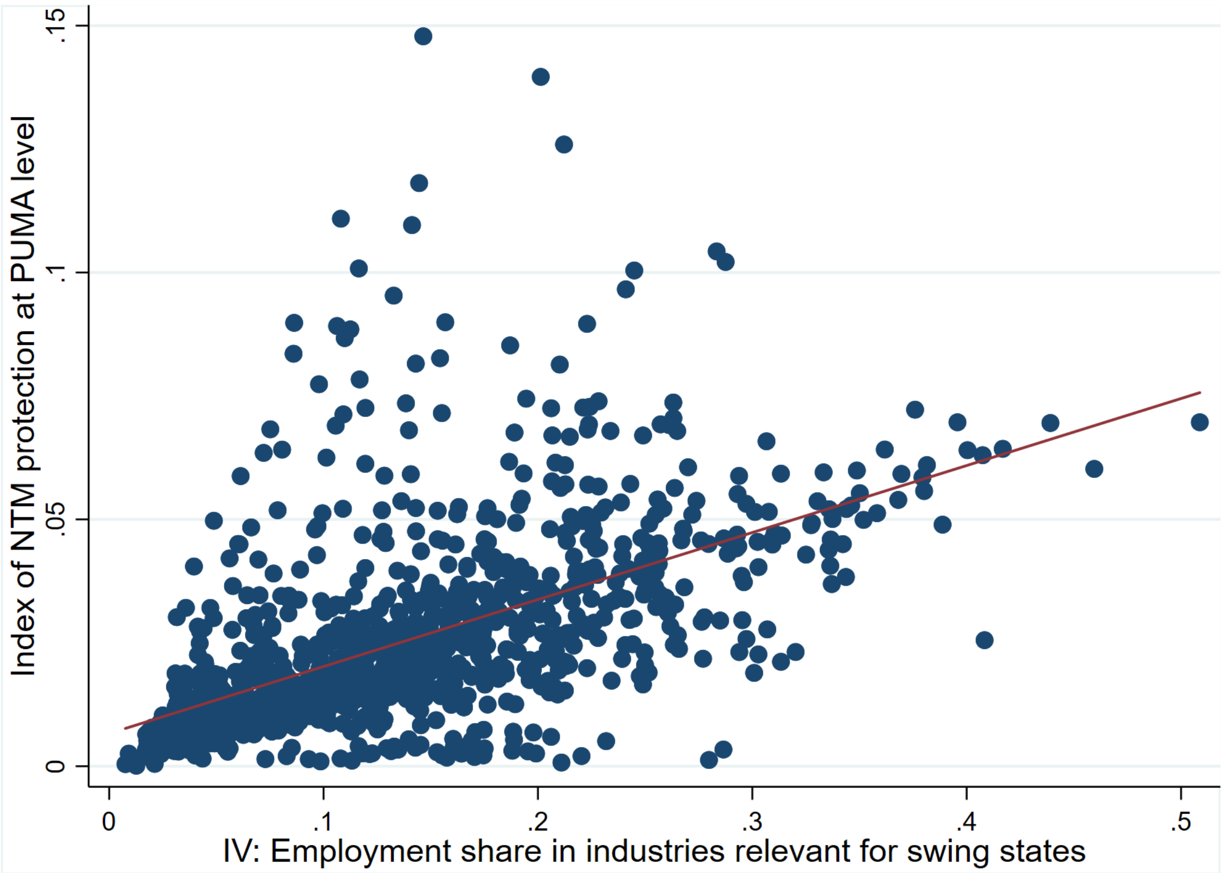
$$indswing_{mt} = \sum_j \frac{L_{mjt}}{L_{mt}} \times indswing_{jt} \tag{7}$$

4.1 First stage results

Figure 5 plots the measure of protection based on NTMs against the IV and shows the substantial predictive power of our instrument, which is confirmed by the high and significant level of the F-test in all our first stage regressions. Table 4 reports the results of the first stage regressions for different types of NTMs (all NTMs in column 1, TBT in column 2 and SPS in column 3). The estimates confirm that $indswing_{mt}$ has a large and significant impact on NTM protection. The estimated first stage coefficient is about four times larger for Technical Barriers to Trade (TBT) (col. 2) than for Sanitary and Phytosanitary measures (SPS), which suggests that the determinants of NTMs differ across the two types of 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).

[13] In 2004, the swing states were Florida, Iowa, Michigan, Minnesota, Nevada, New 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. We thank Lorenzo Trimarchi for kindly providing us with his data-set on swing states over time.

FIGURE 5. First stage relationship between NTMs and the incidence of swing states' industries in the employment composition of PUMAs



The F-test of excluded instruments is always highly significant and well above the critical value of 10, which confirms that our instrument is informative and relevant.

Before getting to the main results, it is important to better understand the characteristics of the local labour markets most affected by the instrument, i.e. the 'compliers' PUMAs those that have NTM protection because they have industries that are important in swing states, and they would not have those NTMs if they had zero employment in those industries. In Table 5 we show the first stage separately for the division in quartiles of PUMAs with 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 cell of the table 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 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

Table 4. First stage regression by NTM type

	Dep var: NTM protection		
	NTM	TBT	SPS
	(1)	(2)	(3)
$indswing_{mt}$	10.43***	11.01***	2.588***
	(0.803)	(0.857)	(0.345)
F-excluded instrument	*168.95****	*165.04****	*56.19****
Observations	3,234	3,234	3,234

Notes: Robust standard errors in parentheses *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

workers. PUMAs in the 1st 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 4th 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 1st rather than in the 4th 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 have NTMs due to external factors, and they would not have if their industrial structure had not been similar to swing states').

4.2 Instrument validity

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 is independent of unobservable local factors that affect manufacturing employment and wages (conditional on PUMA fixed effects and other time varying shocks controlled by year fixed effects). 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

$$indswing_{mt} = \beta \Delta Manufempl_{mt-1} + \gamma X_{mt} + \alpha_t + \alpha_m + \varepsilon_{mt} \tag{8}$$

where $\Delta Manufempl_{mt-1}$ is lagged change in manufacturing employment share on working age population, X_{mt} are the same controls of equation 2 and α_t and α_m are time and PUMA fixed

TABLE 5. First stage regression by quartiles of PUMAs characteristics

	1st quartile	2nd quartile	3rd quartile	4th quartile
	Share of manufacturing employment in year 2000			
NTM	23.12***	13.60***	8.823***	7.517***
	(3.254)	(2.797)	(1.448)	(1.000)
TBT	23.50***	13.67***	9.074***	7.788***
	(3.390)	(2.917)	(1.545)	(1.086)
SPS	9.880***	7.253***	3.580***	1.433***
	(1.413)	(1.420)	(0.681)	(0.489)
Observations	813	807	801	813
	Share of blue collars on total employment in year 2000			
NTM	8.019***	10.51***	10.95***	8.363***
	(1.133)	(1.906)	(2.216)	(1.074)
TBT	8.588***	10.77***	11.34***	8.781***
	(1.213)	(2.006)	(2.344)	(1.165)
SPS	0.475*	3.542***	3.189***	1.916***
	(0.258)	(0.801)	(1.102)	(0.504)
Observations	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)
TBT	26.66***	20.57***	13.69***	10.99***
	(4.752)	(2.171)	(1.659)	(1.099)
SPS	13.38***	5.704***	1.371*	2.742***
	(1.983)	(0.948)	(0.757)	(0.429)
Observations	813	819	786	816

Notes: Each cell shows the coefficient on $indswing_{mt}$ from a different regression of NTM, TBT and SPS 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 year 2000, at the beginning of our sample period. Robust standard errors in parentheses *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

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 6 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 we have in mind is that politicians decide to put NTMs on products/industries that are important in swing states for political reasons and NTMs then 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 states" 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 we show in column 2 of Table 6 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 8 but the dependent variable is $Pr_t(m = swing)$ i.e. PUMA m belongs to a swing state in year t). As expected, the coefficients are always insignificant.

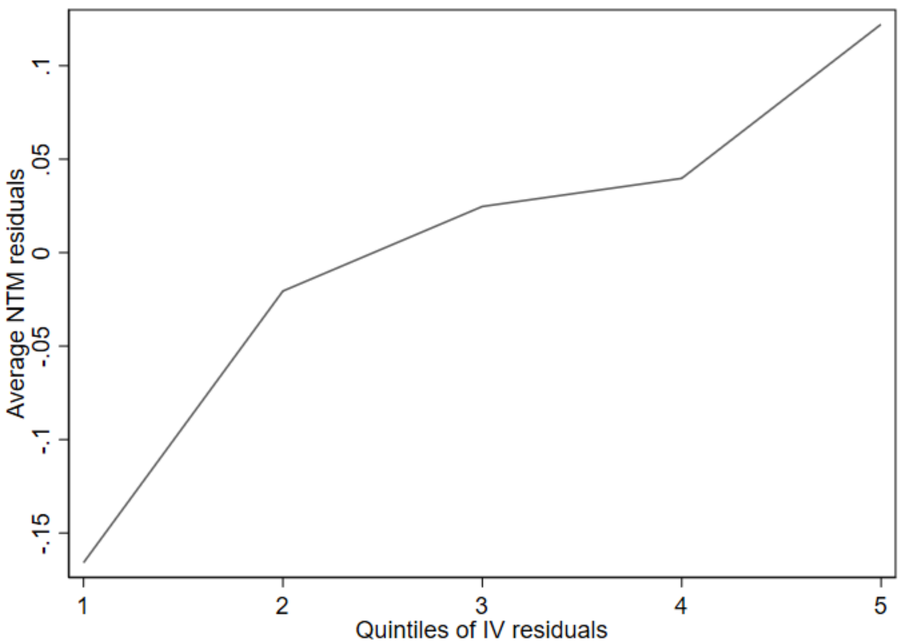
We conduct an additional test to assess the validity of our IV. We separately regress the instrument and the instrumented variable on the controls and we plot the residuals in Figure 6. In particular, Figure 6 reports on the X axis the quantiles of the residuals of a regression of the instrument $indswing_{mt}$ 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 relationship between the instrument variable and the instrument is monotonic.

Table 6. Instrument validity checks

Dep. Var:	$indswing_{mt}$	PUMA belongs to a swing state
	(1)	(2)
$\Delta Manufempl_{mt-1}$	-0.000	0.006
	(0.001)	(0.006)
Observations	2,156	2,156
Number of PUMA	1,078	1,078

Notes: 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 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 start of period PUMA share of the national population. Robust standard errors in parentheses are clustered by state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level

Figure 6. First stage: Monotonicity of the instrument



Notes: 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.

5 Results

Table 7 presents the estimates of the relationship between local exposure to Chinese import competition, NTM protection and US manufacturing employment and wages. The dependent variables are the 5-year change in the share of manufacturing employment in the working-age population in PUMA m (columns 1 to 3) and the 5-year change in log hourly wages in manufacturing (columns 4 to 6).

We start to comment the results on NTM in panel A focusing on IV estimates which arguably capture exogenous variation in NTMs. Our estimates reveal that, as expected, increasing exposure to Chinese import competition reduces manufacturing employment: we find that an increase by 1000 dollars in per-worker exposure to import competition leads to a reduction in manufacturing employment by about 0.74 (0.86 in the OLS results) percentage points (see columns 1 and 2 of panel A in Table 7). Reassuringly, the magnitude of the effect is similar to that found in Acemoglu et al. (2016) and in Autor et al. (2013a) for a different period (2000–2007) and using a different definition of local labour market.

Turning to our main variable of interest, our estimates indicate that, conditional on exposure to Chinese imports (the 'China shock'), NTMs significantly increase manufacturing employment. In particular, as for the OLS results, conditional on the degree of the PUMA's import exposure, a one standard deviation increase in the NTM-protection index (i.e. the weighted share of employed workers protected by NTMs) increases by 0.36% the share of workers employed in manufacturing. The IV estimates are four times larger than the OLS estimates: a one standard deviation increase in the NTM index increases by 1.3% the share of employed workers in manufacturing. Therefore, it is reasonable to argue that unobservable shocks have affected the changes in NTMs and employment shares of manufacturing workers in the opposite way: for example, unobservable import shocks, not absorbed by the measure of imports, increase NTMs and decrease the share of manufacturing employment, resulting in a downward bias in the OLS specifications; alternatively, politicians tend to put NTMs on industries where manufacturing is already declining and the identification through swing states isolates some variation that is orthogonal to the actual decline in manufacturing (i.e. politicians put NTMs in swing states irrespective of the decline in manufacturing).

To appreciate the size of the effect, consider that manufacturing employment declines by 1% every five years in the average PUMA (last row of Table 7) and thus an increase by 1.3% more than offsets the declining trend in an average PUMA, indicating that a (large) increase in NTM protection has potentially a large effect on employment in manufacturing. Since the standard

Table 7. Effect of NTMs on manufacturing employment and wages

	Δ employment in manufacturing			**Δ log hourly wage manufacturing**		
	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: All NTMs			
$\Delta Impexposure_{mt}$	-0.859***	-0.739***	0.546	-0.005	-0.001	-0.028
	(0.112)	(0.111)	(0.925)	(0.006)	(0.006)	(0.027)
NTM_{mt}	0.358***	1.317***	9.491*	0.028***	0.056**	-0.116
	(0.075)	(0.383)	(5.629)	(0.006)	(0.022)	(0.163)
interaction			4.396			-0.092
			(3.253)			(0.094)
			Panel B: TBT			
$\Delta Impexposure_{mt}$	-0.855***	-0.732***	0.179	-0.005	-0.001	-0.021
	(0.112)	(0.111)	(0.516)	(0.006)	(0.007)	(0.018)
TBT_{mt}	0.355***	1.248***	6.701**	0.025***	0.053**	-0.069
	(0.070)	(0.362)	(2.869)	(0.006)	(0.021)	(0.100)
interaction			3.006*			-0.067
			(1.742)			(0.061)
			Panel C: SPS			
$\Delta Impexposure_{mt}$	-0.904***	-0.929***	-1.407***	-0.008	-0.009	-0.006
	(0.115)	(0.113)	(0.170)	(0.006)	(0.006)	(0.008)
SPS_{mt}	0.028	5.310***	-3.363	0.057***	0.224**	0.281*
	(0.175)	(1.889)	(3.400)	(0.016)	(0.094)	(0.161)
interaction			-4.048***			0.027
			(1.051)			(0.050)
Average outcome	-0.993	-0.993	-0.993	0.121	0.121	0.121

Notes: $N = 3234$ (1078 PUMAs, three 5-year changes). Dependent variables are 5-year change in the percentage of working age population employed in manufacturing (columns 1 to 3) and 5-year difference in log hourly wages in manufacturing sector (columns 4 to 6). All regressions include the controls X_{mt} described in equation (2), as well as PUMA and year dummies. Models are weighted by start of period PUMA share of the national population. Robust standard errors in parentheses are clustered by state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

deviation and the mean value of the NTM index are respectively 0.025 and 0.026, a one standard deviation increase in the NTM index is like 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=0.018) of the NTM protection distribution, such as, for example, Baldwin County (Alabama), to a PUMA at the 80th percentile (NTM index=0.043), such as San Joaquin County (California), both measured in 2005. However big, an increase by one standard deviation of the NTM index also corresponds to the growth in NTM protection experienced by some PUMAs over the 2000–2010 period. For example, in Montgomery, Alabama, NTM protection grew from around 0.01 in 2000 to around 0.035 in 2010. Similarly, in Tazewell County, Illinois, the protection index moved from almost 0 in 2000 to 0.025 in 2010, thus increasing by exactly one standard deviation.

Regarding wages (columns 4 to 6 of Table 7), we find a non-significant effect of import exposure on manufacturing wages. These results are consistent with Autor et al. (2013a): they find that an additional 1,000 dollars per worker imports from China over a decade reduced a commuting zone's mean weekly earnings by 0.759 log points (see their table 6). However, when estimating separately the impacts on manufacturing and non-manufacturing sectors, they found no effect on the wages of manufacturing workers. When we look at the effect of NTMs we see that a one standard deviation increase in the NTM index is associated with a significant 0.56 percent increase in the hourly wages of manufacturing workers (0.3 in the OLS estimates). A possible interpretation of these results is that wages adjust to import penetration shocks in various ways but still manufacturing workers are paid more than average in PUMAs where manufacturing is more NTM-protected. The positive and statistically significant estimates on wages further confirm that NTMs protect the demand for manufacturing jobs.

When we compare the results in panel A with those in panel B for TBT and panel C for SPS, we notice that the most important difference lies in the effect of the interaction term (NTM*import exposure) on employment in manufacturing. The main effect of NTM protection on employment and wages in manufacturing is always positive and significant in all cases (when we look at IV results), but when we introduce an interaction term between NTM and exposure to Chinese import competition (columns 3 and 6) TBT and SPS results differ radically. The positive interaction coefficient in Panel B (TBTs) reinforces the interpretation of the main result that NTMs have mitigated the effect of a (potential) China shock: the more an exposed PUMA is NTM-protected, the higher is the impact on manufacturing employment. On the contrary the interaction term in panel C (SPS) is strongly negative and significant. We interpret this difference with the different nature of TBT and SPS measures. SPS mainly regard agricultural goods and the high correlation of SPS measures across the EU and the US (see Section 3.2) may mean that neither our measure of exposure to the China shock nor the NTM index are correct measures when we consider SPS. In fact, Chinese exports to the EU may not provide a good (potential) exposure measure for the US if the EU and US use similar NTMs: in this case the low level of Chinese exports in food categories in the US may result from Europe also protecting its market rather than from the effect of NTMs. Secondly, our NTM index is based on STC against the US but it 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, so one might think that for agricultural goods one could construct import shocks that are not restricted to China. For this reason in the rest of the paper we focus on TBT only.

5.1 Employment composition and other outcomes

In the following tables, we investigate further the effects of NTMs looking into their impact on the composition of employment (skilled and unskilled workers; manufacturing and non-manufacturing sector) and into their effects on participation in the labour force and/or outmigration (it could be that workers hit by the China shock fall into unemployment or out of the labour force). We will rely only on IV results.

So far, we have focused on the impact of NTMs on average manufacturing employment; however the total effect may mask differences between skilled (i.e. with a college education) and unskilled workers. We present the results by education in Table 8. Our estimates suggest that the exposure to import competition reduces the relative manufacturing employment of both skilled and unskilled labour, albeit more for the latter. We therefore find a skill-biased impact of the China shock that is counterbalanced by the effect of NTMs [14].

In fact, NTMs increase employment for both skilled and unskilled workers, albeit more for

[14] Autor et al. (2013a) strangely find a skill-biased effect only in the non-manufacturing sector: in their paper, a CZ's additional 1,000 dollars of total 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)

the unskilled (a one standard deviation increase in NTM increases employment of the unskilled by 0.76%). Employment of unskilled workers in manufacturing declines by 0.9% over five years in an average PUMA (see Table 2), therefore an increase by 0.76% almost totally offsets the decline. The effect on skilled workers is also substantial: an increase of one standard deviation in NTMs increases by 0.56% the employment of the skilled (manufacturing employment declines only by 0.08% every five years for workers with a college degree). Furthermore NTMs (a one standard deviation increase in the index) also increase wages of the unskilled by 9% in 5 years (above an average 5-year increase of 9%) while they have an insignificant effect on average wages of college educate workers. The results in panel A (NTM) and in panel B (TBT) do not show any discernible difference.

Our results of NTMs protecting employment and wages of the unskilled is partially in contrast with Barba Navaretti et al. (2019) who find that exporting firms in France respond to the increased complexity associated with a restrictive NTM by raising the share of skilled workers, such as managers, at the expense of blue collars and white collars. That paper however looks at substitution of workers within (exporting) firms rather than at the overall effect at the local labour market level. At the local level a positive effect of NTMs on employment and wages of the unskilled is coherent with a skill-biased impact of the China shock to the detriment of the unskilled.

Lastly, Table 9 presents the results of the estimates investigating the effects of NTM on non-manufacturing employment, on the share of the population not in the labour force (NILF) and on unemployment. Consistently with Autor et al. (2003a), we confirm that the exposure to Chinese import competition tends to increase unemployment and reduce labour force participation at the PUMA level. On the contrary, NTM helps reducing unemployment, while they do not have any significant impact on labour force participation. In addition, as shown in column 1 of Table 9, we do not find any effect of NTM-protection on employment in the non-manufacturing sector.

6 Conclusions

Rising import competition from low-income countries has been an important cause of the decline in manufacturing employment in many advanced economies, as documented by a growing

Table 8. Effect of NTMs on manufacturing employment and wages, by education. IV estimates

	Δ employed in manufacturing		**Δ hourly wages in manuf.**	
	high skilled (1)	**low skilled** (2)	**high skilled** (3)	**low skilled** (4)
		Panel A: All NTM		
$\Delta Impexposure_{mt}$	-0.195***	-0.544***	-0.002	0.003
	(0.035)	(0.096)	(0.007)	(0.007)
NTM_{mt}	0.563***	0.763**	0.037	0.097***
	(0.197)	(0.320)	(0.022)	(0.024)
		Panel B: TBT		
$\Delta Impexposure_{mt}$	-0.192***	-0.540***	-0.001	0.004
	(0.036)	(0.096)	(0.007)	(0.007)
NTM_{mt}	0.533***	0.723**	0.035	0.092***
	(0.187)	(0.302)	(0.021)	(0.023)
Average outcome	-0.0831	-0.912	0.152	0.0909

Notes: $N = 3234$ (1078 PUMA, three 5-year changes). Dependent variables are: 5-year change in the percentage of working age population employed in manufacturing and 5-year difference in log hourly wages in manufacturing sector. High 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 include the controls X_{mt} described in equation (2), as well as PUMA and year dummies. Models are weighted by start of period PUMA share of the national population. Robust standard errors in parentheses are clustered by state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

number of papers. Most of the current literature investigates the impact of import competition, ignoring the role of trade policy. In this paper, we studied the impact on US manufacturing employment and wages of non-tariff measures (NTMs), which became increasingly important as tariffs reduced over time. We contribute to the literature by constructing a novel index of NTM protection at the local labour market level, based on the recently released WTO database on Specific Trade Concerns. Among the different types of NTM, we focus on Technical Barriers to Trade (TBT) rather than on Sanitary and Phyto-Sanitary Standards (SPS), because the latter are substantially correlated across the US and the EU and may therefore be already captured in our measure of US exposure to Chinese import competition based on Chinese exports to Europe. We identify the causal effect of NTMs using the (arguably exogenous to local demand shocks) political incentive to protect industries in swing states during presidential elections. We find that, conditional on a measure of exposure to Chinese import competition, PUMAs where manufacturing industries were more protected through NTMs experienced lower unemployment and in particular significantly higher employment in manufacturing (both skilled and

Table 9. Effect of NTMs on non-manufacturing employment, unemployment rate and labour force participation

	Dep.Var: Δ Fraction of working age population		
	Employed in non-manuf	**Unemployed**	**Out of labour force**
	(1)	(2)	(3)
		Panel A: All NTM	
$\Delta Impexposure_{mt}$	0.035	0.003***	0.336***
	(0.148)	(0.001)	(0.098)
NTM_{mt}	0.013	-0.012***	-0.392
	(0.568)	(0.003)	(0.455)
		Panel B: TBT	
$\Delta Impexposure_{mt}$	0.035	0.003***	0.334***
	(0.150)	(0.001)	(0.100)
NTM_{mt}	0.012	-0.011***	-0.371
	(0.538)	(0.003)	(0.431)
Average outcome	0.414	0.000571	0.615

Notes: N = 3234 (1078 PUMA, three 5-year changes). Dependent variables: 5-year change in the percentage of working age population that is employed in non manufacturing sectors; unemployed; not in the labour force (NILF). Employment, population, and income data are based on US Census and American Community Survey data. All regressions include the controls X_{mt} described in equation (2), as well as PUMA and year dummies. Models are weighted by start of period PUMA share of the national population. Robust standard errors in parentheses are clustered by state. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

unskilled) and higher wages for the unskilled (we find therefore a skill-biased impact of NTMs in favour of the unskilled). A PUMA which moves from the 50th to the 80th percentile of the NTM-protection measure basically offsets the decline in manufacturing employment that hit the average PUMA in the period 2000–2015. Overall, we find that trade policy, and in particular the use of NTMs to protect domestic products, plays a role in mitigating the effects of import exposure on manufacturing employment. This finding may help shed some light on the effect of trade policy on inequality, at a time when the use of tariffs versus NTMs is still debated in US trade policy.

References

[1] Anderson, J. and P. Neary. (1994), 'Measuring the Restrictiveness of Trade Policy' *World Bank Economic Review* 8: 151–169.

[2] Acemoglu, D., Autor, D.H., Dorn, D., Hanson, G.H., and Price, B. (2016) 'Import Competition and the Great U.S. Employment Sag of the 2000s'. *Journal of Labor Economics*, 34(S1): S141–S198

[3] Autor, D.H., Dorn, D., and Hanson, G.H. (2013a). 'The China Syndrome: Local Labor Market Effects of Import Competition in the United States,' *American Economic Review*, 103(6): 2121–68

[4] Autor, D.H., Dorn, D, and Hanson G.H. (2013b). 'The geography of trade and technology shocks in the United States'. *American Economic Review*, 103(3): 220–25

[5] Autor, D.H, Dorn, D. and Hanson, G.H., Song, J. (2014) 'Trade Adjustment: Worker Level Evidence', *Quarterly Journal of Economics*, 129(4), 1799–1860

[6] Autor, D.H, Dorn, D. and Hanson, G.H. (2016) 'The China Shock: Learning from Labor Market Adjustment to Large Changes in Trade'. *Annual Review of Economics*, 8: 205–240

[7] Barba Navaretti, G., Fontagne, L., Orefice, G., Pica, G., and Rosso, A. (2019). TBTs, Firm Organization and Labour Structure – The Effect of Technical Barriers to Trade on Skills, CESifo Working Paper No. 7893.

[8] Beghin, J.C., Disdier, A.C., and Marette, S. (2015). Trade restrictiveness indices in the presence of externalities: An application to non-tariff measures. *Canadian Journal of Economics*, 48(4):1513–1536.

[9] Beverelli, C., Boffa, M. and A. Keck (2014) 'Trade Policy Substitution: Theory and Evidence from Specific Trade Concerns', WTO Staff working paper ERSD-2014-18.

[10] Cadot, O. and Gourdon, J. (2016). Non-tariff measures, preferential trade agreements, and prices: New evidence.*Review of World Economics*, 152(2):227–249.

[11] Conconi, P., DeRemer, D., Kirchsteiger, G., Trimarchi, L. and Zanardi, M. (2017), Suspiciously timed trade disputes, *Journal of International Economics*, 105 (C): 57–76.

[12] Fontagne L., Orefice G., Piermartini R., Rocha N. (2015), Product Standards and Margins of Trade: Firm-Level Evidence, *Journal of International Economics*, 97(1): 29–44.

[13] Gawande, K. and Bandyopadhyay, U. (2000), Is Protection for Sale? Evidence on the Grossman–Helpman Theory of Endogenous Protection, *The Review of Economics and Statistics*, 82 (1):139–152.

[14] Ghodsi, M. (2016): 'Determinants of specific trade concerns raised on technical barriers to trade EU versus non-EU', *Empirica*, 45(1): 83–128

[15] Gourdon, J. (2014): CEPII NTM-MAP: A Tool for Assessing the Economic Impact of Non-Tariff Measures, Working Papers 2014-24, CEPII research center.

[16] Hakobyan, S. and McLaren, J. (2016) 'Looking for Local Labor Market Effects of NAFTA', *The Review of Economics and Statistics*, 98(4): 728–741.

[17] Herghelegiu, C. (2018) The political economy of non-tariff measures, *The World Economy*, 41(1): 262–286

[18] Lee, Jong-Wha, and P. Swagel (2000). Trade Barriers And Trade Flows Across Countries and Industries. *The Review of Economics and Statistics*, 79(3), 372–382.

[19] Kee, H.L., A. Nicita, and M. Olarreaga (2009), 'Estimating Trade Restrictiveness Indices', *Economic Journal* 119: 172–199.

[20] Lake, J. and Millimet, D. (2016). Good jobs, bad jobs: What's trade got to do with it?, IZA Discussion Papers 9814, Institute of Labor Economics (IZA).

[21] Leamer, Edward E. (1990). The Structure and Effects of Tariff and Non tariff Barriers in 1983, in R. W. Jones and A. Krueger (Eds.), *The Political Economy of International Trade: Essays in Honor of Robert E. Baldwin* (Cambridge, MA: Basil Blackwell).

[22] Ma, X. and McLaren, J. (2018). A Swing-State Theorem, with Evidence. NBER Working Paper No. 24425.

[23] Maggi, G. and Goldberg, P.K. (1999). Protection for Sale: An Empirical Investigation. *American Economic Review*, 89(5), 1135–1155.

[24] Marette, S. and Beghin, J. (2010). Are Standards Always Protectionist? *Review of International Economics*, 18(1):179–192

[25] Muuls, M. and Petropoulou, D. (2013). A Swing State Theory of Trade Protection in the Electoral College. *Canadian Journal of Economics*, 46(2):705–724

[26] 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

[27] Orefice, G. (2017). Non-tariff Measures, Specific Trade Concerns and Tariff Reduction, *The World Economy*, 40(9): 1707–2030

[28] 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.

[29] Trimarchi (2020). Trade Policy and the China Syndrome, Working Papers ECARES 2020-15, ULB – Universite Libre de Bruxelles.

[30] WTO (2012). World Trade Report 2012: Trade and public policies: A closer look at non-tariff measures in the 21st century, World Trade Organization, Geneva