Database and analysis linking NTMs in goods and services and global supply chains

How do different types of Non-Tariff Measures affect trade and productivity?

Mahdi Ghodsi, Julia Gruebler, Oliver Reiter, and Robert Stehrer*

Abstract

The global trade slowdown and the public resistance against attempts to stimulate trade through mega-regional trade deals are placing the role of non-tariff measures (NTMs) in the limelight of public discussions. In this work, we examine how different types of NTMs affected global trade, how effects of NTMs can be compared between different types of NTMs and with tariffs, and how important they are in the context of global value chains (GVC). Main contributions of this work are first, the amendment of the WTO Integrated Trade Intelligence Portal (I-TIP) to suit econometric analysis. Second, we estimate the effects of different types of NTMs on trade flows at the HS 6-digit product level for more than 100 countries applying a gravity approach. Results are differentiated by country and product characteristics. Third, we estimate import demand elasticities, which allow computing ad-valorem equivalents of NTMs, rendering NTMs comparable across types and with the level of tariffs. Fourth, a database linking NTMs in goods and global supply chains is prepared, which provides bilateral trade restrictiveness indices that are used to estimate the impact of trade policy measures on labour productivity in goods and services industries.

Our findings suggest: (i) Roughly 60% of all estimates point towards trade-impeding effects of NTMs, with stark differences between NTM types, where measures related to health are more likely to show positive effects than technical regulations. (ii) Highest average import demand elasticities are found for the economically biggest countries in their respective regions and intermediate goods, which appears particularly noteworthy in the context of global value chains. (iii) Simple average AVEs reach up to 8% for SPS measures, 11% for TBTs or even 19% for Antidumping, compared to an average tariff rate of 5%. (iv) While the number of notifications and types of NTMs used increases with income, AVEs of richer countries seem to be lower. (v) Lowest AVEs are found for final consumption goods and highest for goods contributing to gross fixed capital formation. (vi) SPS regulations along GVCs seem to increase labour productivity, particularly in the services sector. Conversely, TBTs appear productivity decreasing, primarily in the non-services sector.

Keywords: non-tariff measures, trade barriers, global value chains, WIOD, gravity model, import demand, elasticity, ad-valorem equivalents, labour productivity, trade restrictiveness index, WTO, I-TIP.

JEL classification: D12, F13, F14

*Mahdi Ghodsi, Julia Grübler and Oliver Reiter are economists at the Vienna Institute for International Economic Studies (wiiw). Robert Stehrer is the Scientific Director of the wiiw.

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1. Introduction

The importance of tariffs as trade policy tools is decreasing as tariff rates have already considerably declined over the last two decades. This is particularly true for intra-industry trade between developed countries such as the European Union (EU) and the US. At the same time, the number of different types of non-tariff measures (NTMs) being applied is increasing. Some literature therefore studies the question, whether these relatively new forms of trade policy tools might serve as substitutes for previously negotiated tariff cuts (e.g. Beverelli et al., 2014; Aisbett and Pearson, 2012; Moore and Zanardi, 2011).

Since the onset of negotiations of the Comprehensive Economic and Trade Agreement (CETA) in 2009 between Canada and the EU, and even more so with the start of negotiations of the Transatlantic Trade and Investment Partnership (TTIP) in 2013 between the US and the EU, the growing importance of NTMs has also been reflected in public debates within the EU on the effects of trade agreements. The Brexit vote – i.e. the decision of the United Kingdom (UK) to leave the EU – finally has put non-tariff measures at centre stage in EU trade talks both on extra-EU as well as intra-EU trade.

By their nature, NTMs cannot be easily compared to tariffs. Typically, they do not only work as ‘pure’ trade policy tools but also serve other purposes, such as the protection of human, animal and plant life. For this reason, fears are articulated in the public that deep trade agreements such as CETA or TTIP might lead to an erosion of standards. Not only the general public but also economists are divided in two camps regarding the question, whether NTMs should or should not be on the negotiation table.

In light of the recently experienced trade slowdown, economists who believe that increased international trade is contributing to higher living standards argue for a reduction or harmonisation of NTMs to stimulate trade which is stagnating since 2011 (e.g. Cadot et al, 2015; Francois et al., 2015; Baldwin and Evenett, 2009). Those who believe that trade has a negative impact on economic prosperity argue not to conclude (in the case of TTIP) or ratify (in the case of CETA) further trade agreements.

Both sides, however, usually presume that NTMs are reducing trade, which – as we shall argue – is not necessarily the case. Only recently, trade economists have started to acknowledge that non-tariff *measures* need not be non-tariff *barriers* (NTBs). For some types of NTMs, such as quotas and prohibitions, the effect on bilateral trade is indisputably negative. Yet, other NTM types, e.g. sanitary and phytosanitary (SPS) measures, bear the potential of quality upgrading which could boost trade. Likewise, some technical barriers to trade (TBTs) such as labelling requirements provide additional information to consumers, potentially shaping consumption patterns and increasing trust, which might be trade-promoting. The World Trade Report of the WTO (2012), which was dedicated to NTMs, concluded that these measures could increase international trade, whenever the positive effect on the demand side is bigger than the negative impact on the supply side.

This work aims at shedding light on questions such as:

- Which types of NTMs are reported to the WTO and how did they evolve over time?
- How did NTMs affect trade between the mid-1990s and today and how did effects differ across NTM types, countries and products?
- How can we compare the effects of NTMs to tariffs?
- What is the impact of NTMs on productivity in industries and services in the context of global value chains?

An analysis in five steps:

The basis of our investigation constitutes a data compilation of NTM notifications to the WTO, accessible via the Integrated Trade Intelligence Portal (I-TIP). Unfortunately, this rich dataset is not available in a form necessary for and compatible to a comprehensive econometric analysis, i.e. following a panel structure, where NTMs are distinctly assigned to products according to a product classification such as the Harmonised System (HS). The first step therefore is to amend and transform the WTO I-TIP database for maximum usability for econometric analysis. We describe various types of NTMs and discuss the distribution of NTM notifications to the WTO along country and product characteristics in Chapter 2.

Based on these data combined with detailed trade statistics we aim at estimating the various components necessary to calculate ad-valorem equivalents which are later on used to assess the impacts on productivity. These components are linked as follows:

$$\underbrace{\frac{\partial\, ln(m_{ih})}{\partial NTM_{ihn}}}_{TE_{ihn}} = \underbrace{\frac{\partial\, ln(m_{ih})}{\partial\, ln(p_{ih})}}_{\varepsilon_{ih}} \underbrace{\frac{\partial\, ln(p_{ih})}{\partial NTM_{ihn}}}_{AVE_{ihn}} \qquad (1)$$

The second step is the estimation of trade effects, denoted as TE_{ihn} for different types of NTMs n, importers i and products h. Results on how imports react to changes of NTMs, i.e. $\partial \ln(\mathrm{m_{ih}})/\partial \mathrm{NTM_{ihn}}$, are shown in Chapter 3.

Estimating import demand elasticities $\varepsilon_{\mathrm{ih}}$ following Kee et al. (2008) constitutes the third step, described in Chapter 4. The analysis shows how imports for specific importer-product-pairs change after alterations of import prices, i.e. $\partial \ln(\mathrm{m_{ih}})/\partial \ln(\mathrm{p_{ih}})$.

Combining insights on the effects of NTMs on trade and import demand elasticities according to equation (1), we can derive ad-valorem equivalents of non-tariff measures in Chapter 5, capturing the price increase that would have had the equivalent effect on imports as the notified NTM.

Finally, translating our work to bilateral effects and applying them to trade in global value chains, we provide estimates of effects of NTMs on countries' labour productivity by industries and services in Chapter 6.

2. Compiling and making use of a new NTM dataset

Despite the growing importance of non-tariff measures in international trade, data on non-tariff measures usable for econometric analysis is still scarce. Many researchers set up their own NTM datasets to answer their research questions for specific products, NTM types and countries (e.g. Li and Beghin, 2014; Peterson et al., 2013).

One of the first types of NTMs, for which a comprehensive database for a wide range of countries and products traceable over time was collected, was antidumping. The databases compiled by Chad Bown (2007) on antidumping measures and later additionally for other temporary trade restrictiveness indicators are provided by the World Bank (Bown, 2016). Recently, joint efforts were made by the World Bank, UNCTAD, ITC, the WTO and regional development banks, to collect data for more types of NTMs and a broader set of countries with special focus on filling the data gaps for developing countries. One of these data collection efforts resulted in the cross sectional CEPII dataset 'NTM-MAP' (Gourdon, 2014) used to evaluate the impact of non-tariff measures (e.g. Cadot and Gourdon, 2016).

A promising data source allowing also for a panel structure of NTM data is the Integrated Trade Intelligence Portal (I-TIP[1]) of the WTO. It is intended to serve as a platform providing all information compiled by the WTO on trade policy measures ranging from regional trade agreements over WTO accession commitments to tariffs and non-tariff measures. We focus on the subsection 'I-TIP Goods', which provides all information on NTMs notified to the WTO that apply to merchandise trade. For simplicity, we will henceforth refer to this subsection as I-TIP database. The following subsections describe our efforts in transforming and complementing this dataset and additional data we used for our econometric investigation.

[1] WTO I-TIP database online: https://www.wto.org/english/res_e/statis_e/itip_e.htm

2.1. NTM types under examination

In our analysis, we consider seven[2] different forms of NTMs[3] and specific trade concerns (STCs) raised against two NTM types. Public debates on NTMs and consumers' concerns are usually addressing sanitary and phytosanitary (SPS) measures, which primarily target the agri-food sector, and technical barriers to trade (TBTs), which aim largely at the manufacturing sector. The literature on the impact of these measures is quickly growing, mainly with a focus on one specific product and/or region (e.g. Dal Bianco et al., 2016; Arita et al., 2015; Gelan and Omore, 2014; Peterson et al., 2013). These two types of NTMs are notified most frequently to the WTO, but – as we shall argue later – they are not necessarily the most trade restrictive ones.

(i) SPS measures aim at protecting human, animal and plant life and can take different forms. If products or characteristics thereof pose a threat to human, animal or plant health, countries can impose temporary prohibitions or restrictions, e.g. in the case of areas affected by avian flu. They can also take the form of standards, e.g. tolerance limits for residues of substances on foodstuff, labelling or hygienic requirements related to food safety. A recent example is a bilateral SPS measure of the EU, blocking the import of dried beans from Nigeria due to pesticide residues at levels exceeding the reference dose as stated by the European Food Safety Authority.[4] However, SPS measures need not address a single product or specific exporting country. The EU, for example, takes measures to prevent the spread of transmissible diseases, such as spongiform encephalopathies[5]. More than 30% of all NTM notifications in our dataset concern SPS measures.

(ii) Technical barriers to trade (TBTs) can take similar forms as SPS measures (prohibition, labelling requirements etc.), but serve a different purpose. An example is an energy labelling requirement for storage cabinets, including those used for refrigeration. The stated aim of the EU is to pull the market towards more environmentally friendly products by providing more information to end-users.[6] While SPS measures mainly target the agri-food sector, TBTs typically affect the manufacturing sector, especially machinery and electrical equipment. TBTs form the biggest group of NTM notifications in our dataset with a share of more than 45%.

We also consider specific trade concerns (STCs) raised at the SPS and TBT committees of the WTO. Member countries of the WTO can raise questions regarding other WTO members' proposed NTMs or their implementation of NTMs. Unfortunately, the reporting of NTMs to the WTO is not complete and sometimes the imposing country becomes reluctant in notifying the imposed NTM, especially when the measure is very trade restrictive or when it is concealing some discriminatory protectionism. Therefore, it is not easy to match all the STC notifications to their imposed NTMs that are directly notified to the WTO.

In the case of TBTs, 306 STCs can be matched to notified TBTs, meaning that there are 306 TBTs subject to STCs of at least one trade partner. However, it is not clear in the TBT database which countries raised concerns on those TBTs. In addition, there are 393 STC(TBT), for which we cannot easily match corresponding notified TBTs. On the side of SPS measures, we find 170 SPS notifications directly notified to the WTO against which STCs were raised by at least one country, while 179 concerns are not directly linked to SPS measures. Adding up STCs regarding SPS measures and TBTs, this group represents 2.5% of all notifications in our data.

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[2] In addition, the WTO I-TIP database includes the NTM types (i) export subsidies (EXS), (ii) tariff-rate quotas (TRQ), (iii) state trading enterprises (STE), (iv) pre-shipment inspection (PSI) and (v) import licensing (LIC), with the former four mainly applicable to the period prior to the establishment of the WTO and the latter lacking information on the date of initiation and entry into force.

[3] A detailed classification of types of NTMs, including examples, is provided by UNCTAD (2013): http://unctad.org/en/PublicationsLibrary/ditctab20122_en.pdf

[4] WTO Document: G/SPS/N/EU/131, 29 June 2015.

[5] WTO Document: G/SPS/N/EU/67, 4 March 2014.

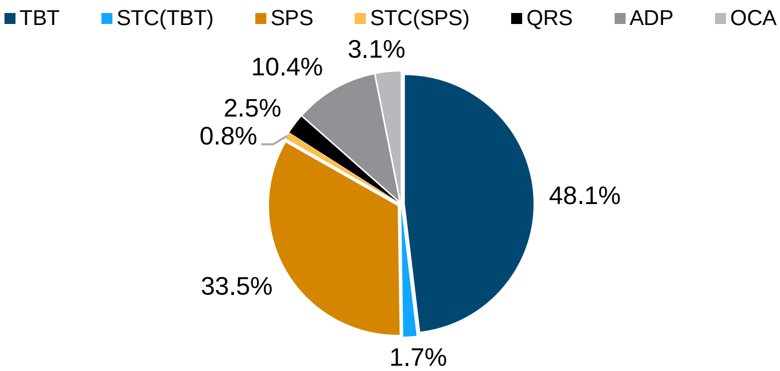
[6] WTO Document: G/TBT/N/EU/178, 28 January 2014.

(iii) A third group comprises so-called counteracting measures, also known as contingent protection measures. Their purpose is to counteract temporarily the negative impact on the importing economy from increased imports. Within this group, antidumping (ADP) is the most prominent trade policy tool, accounting for about 10% of all notifications in our dataset. It is used to combat predatory dumping that causes damage to the domestic industry of the importing country. In case of price dumping and a proof of the damage to the domestic industry, which often gives rise to vivid debates (see e.g. Spearot and Ahn, 2016; or Bown and Meagher, 2010), the importing country can impose antidumping duties, thereby increasing the import price and lowering imports.

Another practice that is considered 'unfair' by WTO norms is to subsidise exports. In this case, the counteracting measures are called countervailing duties (CVD). Safeguard measures (SG) are temporary non-discriminatory policies that apply to a specific product but to all exporters of this product in order to facilitate the importing economy to adjust to a strong increase of imports. Special safeguards (SSG) apply to agricultural products on a bilateral basis in response to a rise in imports or a fall of import prices. Throughout the paper, notifications of these three types of contingent protection are often summarised as 'other counteracting measures' (OCA) due to their small number. Around 1.5% of all notifications are attributable to SSG, while SG and CVD account for a share of 0.9% and 0.8%, respectively.

(iv) In addition to the relatively new NTM types described above, the WTO I-TIP database also covers traditional NTMs such as licencing, quotas or prohibitions, which we refer to collectively as quantitative restrictions (QRS), representing merely 2.5% of the notifications.

Figure 1 / NTM notifications, by Type



Source: WTO I-TIP, wiiw calculations. Note: Total number of notifications to the WTO up to March 2016.

2.2. Exploiting information on notifications to the WTO

The complemented I-TIP database on NTM notifications to the WTO translated to a panel data format is the core dataset of our analysis. Substantial effort has been undertaken to match missing product codes at the HS 6-digit level to each notification. Although we have information on some NTMs that have been initiated since 1979, the data before 1995 is very incomplete. Even in the early years of the WTO, product descriptions and general information on NTMs were imprecise, as members still had to gain experience with the reporting system. The quality of the NTM notification data as well as our interest in transition economies for which data in general, and trade data in particular, is only available since the mid-1990s, gave rise to restricting our analysis to the period after 1995.

The dataset available to us[7] comprised 44,450 measures that have been notified to the WTO secretariat since 1979. The last notification refers to a technical barrier to trade (TBT) initiated by Egypt on 23 March 2016 on vehicles.

For each notification, the I-TIP database offers information on the imposing countries, the targeted partner countries and additional information on the NTM imposed. It covers 140 WTO members as NTM-imposing countries or territories, while the countries affected by these measures include also non-members, amounting to 176 trading partners. In addition, there are measures that apply to all trading partners, for which the partner name 'all members' is assigned. For SPS measures and TBTs an additional variable lists 72 and 58 keywords, respectively, to describe the issues covered by the measure.

'Sub-requirements' further describe the nature of the NTM in question: SPS measures can be reported as regular notifications or as a response to emergency. For special safeguards, this variable informs whether the measure is price or volume based. For safeguards, it describes whether they take the form of specific, ad valorem, or variable tariffs, quotas, or tariff rate quotas. Quantitative restrictions can also apply in different ways. Sub-requirements tell us whether the importer makes use of non-automatic licensing, a ban, a prohibition (with exceptions under defined conditions), a global quota, or a voluntary export restraint.

If available, the I-TIP database also presents information on the date of initiation[8], the date of entry into force and, if applicable, the date of the withdrawal of the measure. Notifications also include a product description, but for less than half of all notifications corresponding HS-codes. For 18,411 notifications, HS-codes of targeted products (ranging from HS 2-digit to HS 12-digit levels) were notified[9]. Considering seven NTM types entering our estimation during the period 1995-2014, product codes were missing for more than 55% of all notified measures. We filled the gaps following a multiple steps automated procedure.

Step 1: *WTO interpreted HS codes.* The WTO has already undertaken a first step in matching HS codes according to the interpretation of measures and product descriptions. These 'WTO interpreted HS codes' were available for 4,725 notifications. They are typically interpreted by WTO members (in particular trading partners facing the NTMs). The accuracy of these codes therefore cannot completely be accredited to the WTO Economic Research and Statistics Division (ERSD).

Step 2: *International Classification Standards (ICS).* The WTO agreements on TBTs and SPS measures require WTO members to notify the ICS classification of the product at the heart of the measure. In addition, some countries use ICS or CAS (a classification for chemical products) in the product descriptions of the NTMs. Extracting these ICS or CAS codes and matching the corresponding HS codes fills the gaps for additional 828 measures, respectively.

Step 3: *Product description*. In this step, we use the information provided in product descriptions of different notifications and fill in the product codes matching the descriptions[10]. This fills the gap for 4,144 measures.[11]

Step 4: *Temporary Trade Barriers Database (TTBD)*. The World Bank publishes data on ADP, CVD, SG and China-specific Safeguards compiled by Bown (2016). For each NTM type we match observations by the country pair and year of initiation (or entry into force) of the NTM and

[7] We are grateful for technical assistance provided by Joaquin Montes at the Economic Research and Statistics Division (ERSD) of the WTO and helpful comments and guidance by Jürgen Richtering, Head Market Access Intelligence Section at ERSD.

[8] For some notifications, either the date of initiation or entry into force is missing. Although measures should be notified before they enter into force, the database contains also measures that were implemented before they were notified to the WTO.

[9] Unfortunately it is not reported, which HS Revision these reported codes refer to. Our baseline product classification is HS revision 2002. Using correspondence tables provided by WITS, we convert all product codes of earlier and later revisions to HS 2002.

[10] Using a cleaned and stemmed version of product descriptions, e.g. using the word 'fish' instead of 'fishes'.

[11] In a similar fashion, we tried to match product descriptions of the World Integrated Trade Solution (WITS) with product descriptions of notifications with missing product codes. However, the structure of WITS product descriptions at the 6-digit level resulted in matchings too error-prone to be considered in this analysis.

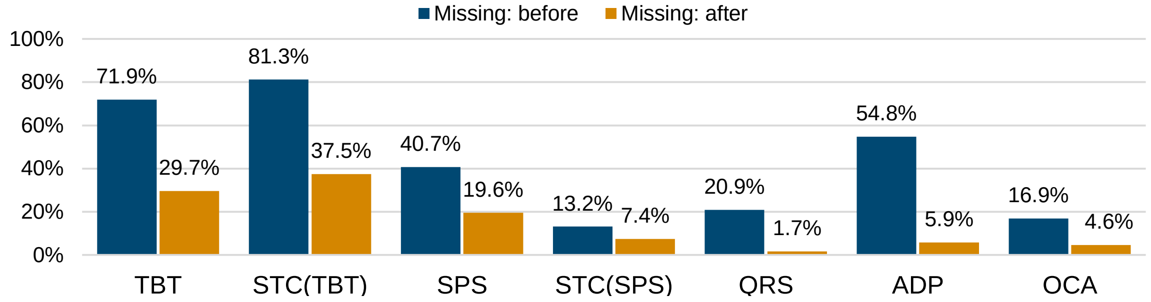
subsequently compare the corresponding product descriptions with a string kernel[12]. Matches with a sufficiently high goodness of fit (70% or higher) add HS codes to 785 measures.

Step 5: *Set comparisons*. Up to this point, all the matching was based on the comparison of the whole string of the product description. In this step, we decompose the product description into sets of words and compare them between notifications containing HS codes and those notifications lacking HS codes. The goodness of fit is measured by the Tversky (1977) index[13]. Considering only matches with a goodness of fit of at least 0.7, this step matches HS codes for another 2,463 notifications.

Three steps proved particularly useful. The comparison of product descriptions led to the imputation of HS codes for 11% of all notifications. A comparison with the *Temporary Trade Barriers Database* (TTBD) compiled by Bown (2016) and published by the World Bank added another 2%. Improvements of this step mainly addressed notifications up to the year 2008. Since then, all information provided by TTBD can be found within the I-TIP database. Another 6.6% of all NTM notifications could be paired with HS codes through a string set comparison of the product description.

Our work effectively reduces the share of notifications with missing HS codes from more than 55% to less than 25%. The NTM type with the highest proportion of missing HS codes were TBTs (72%) followed by ADP (55%) and SPS measures (41%). For QRS and OCA, 21% and 17% of notifications, respectively, did not include product codes. We substantially reduced these shares as depicted in Figure 2.

Figure 2 / Notifications with missing HS codes before and after our matching exercise



Source: WTO I-TIP, wiiw calculations.

2.2.1. The evolution of NTMs over time

Figure 3 shows the growing number of non-tariff measures over time, particularly of TBTs and SPS measures. The last years saw a strong increase of TBT and SPS notifications, culminating a record high of 1,640 new TBT notifications in 2013 and 1,137 new SPS notifications in 2014. Contrasting these figures with the number of specific trade concerns raised at the WTO, we could argue that there were reservations against 2.5% and 3.5% of all SPS and TBT notifications, respectively.

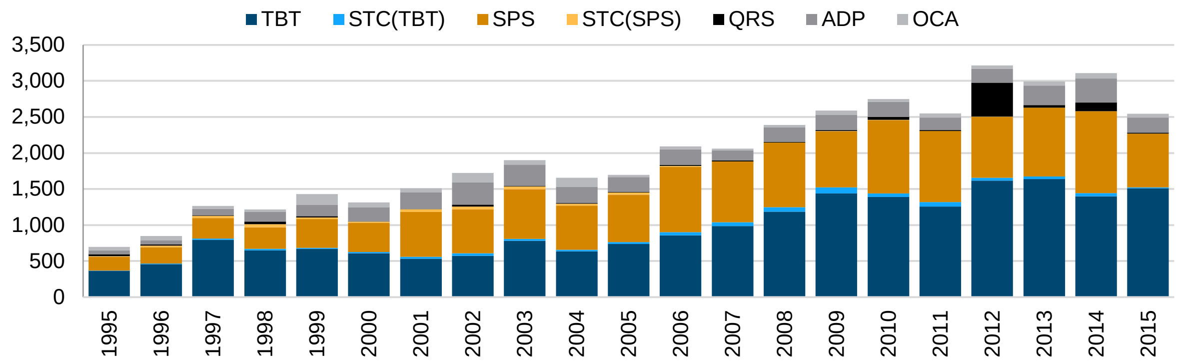
With more than 10% of all notifications, ADP represents the third largest group of NTMs. We note two peaks, in 2002 and again in 2014 with more than 300 notifications each. Other counteracting measures account for around 3% of all notifications. Since 2010 their figures have been driven by countervailing duties, for which an upward trend is observable, with a maximum of 49 notifications in 2014. 30 safeguard measures were notified in 2015. A clear downward trend is, however, visible for specific safeguards, which were heavily used in the late 1990s with 131 notifications in 1999 but have gradually dwindled since then.

[12] We use a string kernel that takes two strings (the two product descriptions) as arguments and computes the number of matching substrings of length 3 or more. See Karatzoglou and Feinerer (2010) for a discussion of string kernels and their implementation for text mining in R.

[13] We calculate the Tversky index, $(X,Y) = |X \cap Y|/|X \cap Y| + \alpha|X - Y| + \beta|Y - X|$, with $\alpha = \beta = 0.5$.

Quantitative restrictions amount to an even smaller share of around 2.5%. They, however, usually target a greater number of exporters than do counteracting measures, which changes relative standing of quantitative restrictions when we translate the initial dataset of notifications into a bilateral format used for estimation. A sharp increase in QRS entering into force is observable for the year 2012. Out of 1,040 notified QRS, more than 300 are attributable to only three importing countries: Australia, Hong Kong and Thailand.

Figure 3 / Number of NTM notifications per year



Source: WTO I-TIP; wiiw calculations. Note: STC summarises specific trade concerns to the SPS and to the TBT committee. Figure for the year 2016 not shown as it comprises the first quarter (Jan. – Mar.) only.

2.2.2. The geographical composition of the use of NTMs

As the I-TIP data is a collection of notifications to the WTO, information on NTM imposing countries is limited to WTO members. With the accession of Afghanistan on 29 July 2016, the WTO counted 164 members. Our investigation covers the period 1995-2014. During that time the WTO grew from 127 (126 countries plus the European Union) to 160 members. However, the I-TIP database covers only 140 members. The Top 5 NTM imposing WTO members are (in descending order) the United States, China, the European Union, Brazil and Canada with more than 1,800 notifications each.

These 140 NTM imposing territories target 176 trading partners (excluding NTMs applicable to all exporting countries). TBTs exclusively target all trading partners. Given that TBTs represent about half of all notifications, the entity '*all partners*' is ranked first. The country most frequently targeted by NTMs is China, followed by the United States, South Korea, the European Union, and Taiwan.

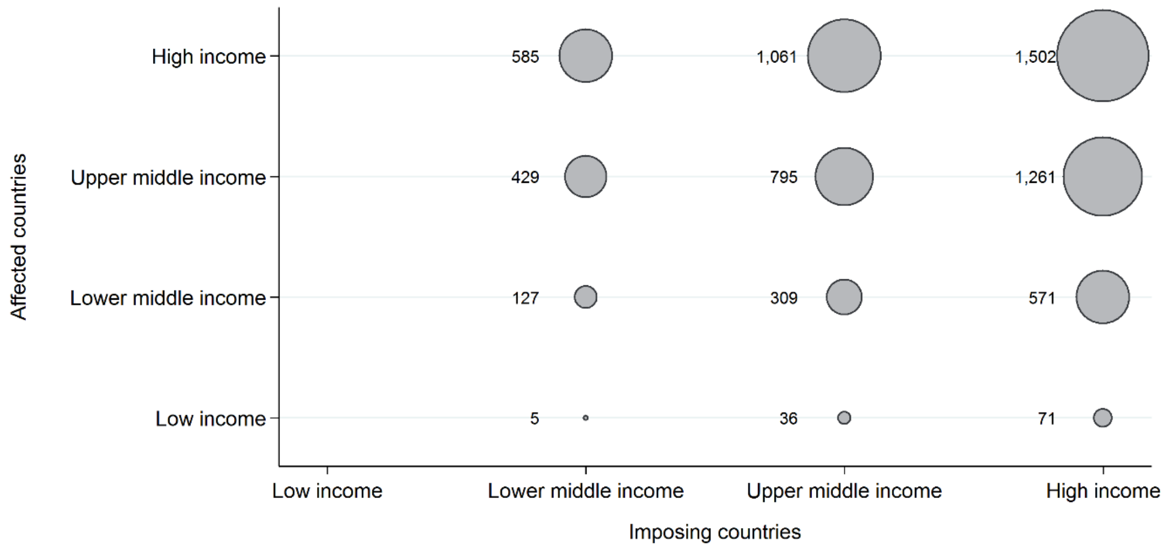
In Figure 4, we visualise this pattern for NTM notifications in force in 2014. Using the income group classification of the World Bank published in July 2015[14], we group countries in our data into low-, lower-middle-, upper-middle- and high-income countries. For NTM notifications issued by or addressing the European Union as a whole, we assigned the high-income group to the EU. We exclude NTMs addressing all trading partners, which drops TBTs and safeguards from the picture and greatly reduces the number of SPS measures. It also erases NTMs imposed by low-income countries from the picture. What is left, are notifications addressing specific countries or regions, predominantly ADP and STCs. We see a strong concentration of NTMs on upper-middle- and high-income countries. While the former are facing the largest number of ADP measures, the greatest number of specific trade concerns is raised against the latter.

Notifications to the WTO indicate that richer countries tend to belong to the heaviest users of NTMs, but simultaneously are most frequently targeted by NTMs. One argument is that developed countries can afford

[14]See http://siteresources.worldbank.org/DATASTATISTICS/Resources/CLASS.XLS, accessed July 2015

and therefore ask for higher standards for products they consume. On the other hand, the dominance of high-income countries in our data is also influenced by differences in reporting, with respect to both accuracy as well as completeness of notifications. Some countries report every NTM applicable, whereas others report only NTMs, which depart from international standards.

Figure 4 / NTMs in force in 2014, by income group of the imposing and affected countries



Source: WTO I-TIP; wiiw calculations. Note: Not including NTMs imposed against all trading partners. Including STCs. When NTMs were issued by or targeting the European Union as a whole, we counted the EU as one single high-income region.

2.2.3. The distribution of NTMs by product characteristics

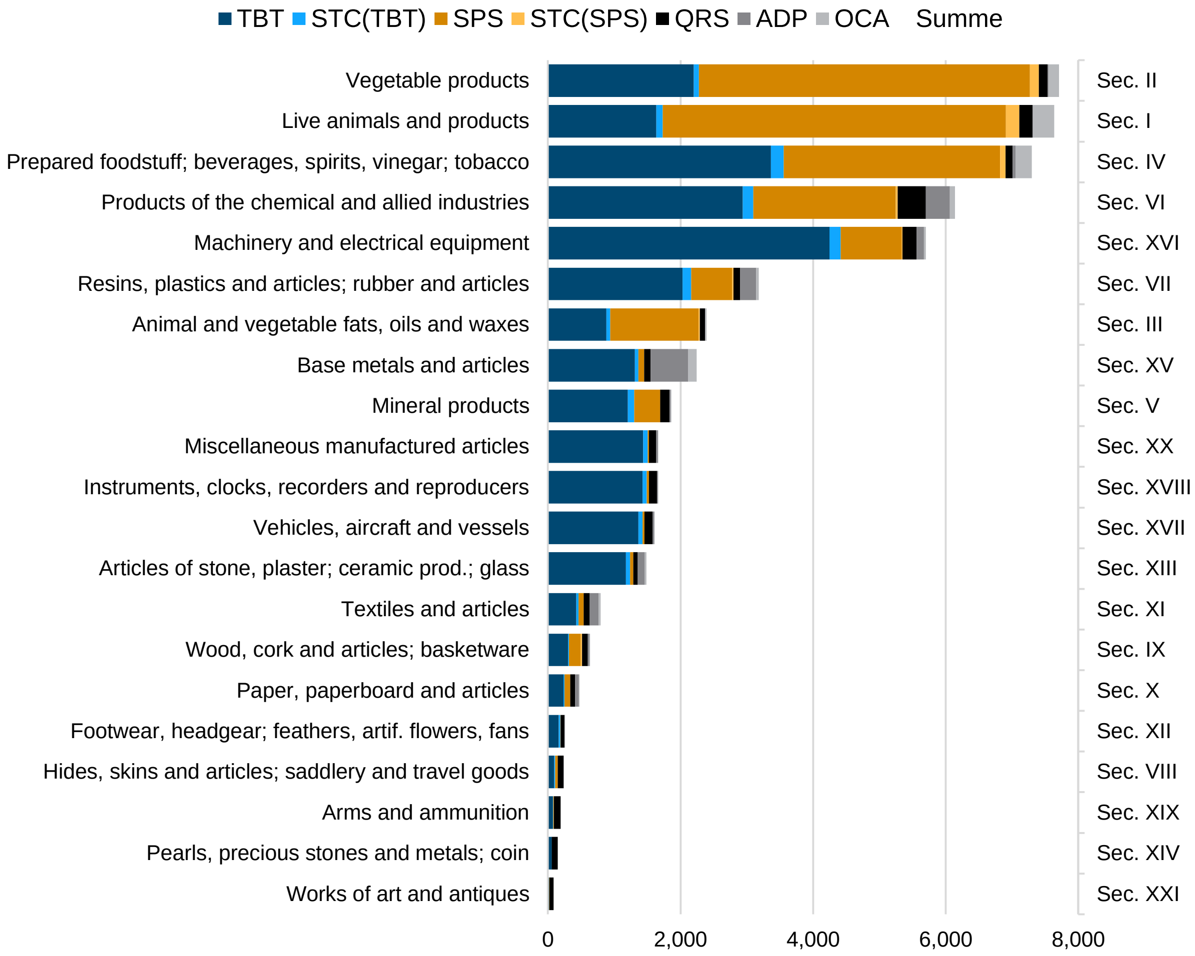
From now on, we focus solely on those notifications for which we could eventually gather information on the products targeted by NTMs. Having this new dataset at hand, an obvious question to be asked is, which products are primarily subject to NTMs and to which types of NTMs?

Splitting NTM notifications according to the 21 product sections of the Harmonised System (Version 2002)[15], it is evident from Figure 5 that the three product groups facing the highest number of NTMs in 2014 belong to the agri-food sector, with live animals ranked first followed by vegetable products, beverages and prepared foodstuff. Remembering that the primary purpose of SPS measures is to protect human, animal and plant life, it is not surprising that this type is dominating NTM notifications addressing agri-food goods.

Products of chemical industries as well as the HS group formed by machinery and electrical equipment still face more than 5,000 notifications each. They are also subject to SPS measures, yet, TBTs form the primary NTM type. Most of the quantitative restrictions (QRS) and a significant number of ADP in our data could be assigned to these two product categories and base metals.

[15] As some notifications apply to products of separate sections simultaneously (e.g. to vegetable products and prepared foodstuff) and therefore feature in multiple sections, the sum of notifications over all sections exceeds the number of notifications reported to the WTO.

Figure 5 / NTMs applying in 2014, by NTM type and HS product section



Source: WTO I-TIP, wiiw calculations.

2.3. External data sources used

Import data were taken from the Commodity Trade Statistics Database (COMTRADE) and complemented by the Trade Analysis Information System (TRAINS) database. We consider ad valorem tariffs at the HS 6-digit level from TRAINS and the WTO Integrated Data Base (IDB) provided by the World Integrated Trade Solutions (WITS) platform. If applicable and available, effectively applied tariff rates entered our dataset. Otherwise, we referred to preferential tariff rates or most-favoured-nation tariff rates.

Data on factor endowments (labour force and capital stock) as well as gross domestic product (GDP) up to the year 2014 were retrieved from the Penn World Tables (PWT 8.0, PWT 9.0); see Feenstra et al. (2013 and 2015). In addition to GDP per capita, we considered the Human Development Index (HDI) of the United Nations and the Economic Complexity Index (ECI) published by Harvard University as measures of economic development. Information on agricultural land was taken from the World Development Indicators (WDI) database of the World Bank and complemented by data provided by the Food and Agriculture Organization of the United Nations (FAO). The Social Economic Activity (SEA) data of the World Input-Output Database (WIOD) provides information on gross output, value added, employment and sectoral deflators.

CEPII provides data on commonly used gravity variables, such as physical distance, colonial ties, or common language. Variables on membership to the WTO and Preferential Trade Agreements (PTAs) were set up according to information provided by the WTO.

3. Estimating the trade effect of NTMs on trade[16]

In this chapter, we evaluate the impact of NTMs on import quantities using the complemented I-TIP database. To do so, we amend a standard-like gravity framework to allow for the estimation of importer-specific effects of NTMs:

$$ln(m_{ijht}) = \beta_{0h} + \beta_{1h}\ln(1 + T_{ijht_{-1}}) + \sum_{n=1}^{N-1}\beta_{2nh}NTM_{nijht-1} + \sum_{i=1}^{I}\beta_{2n\prime ih}\,\omega_i NTM_{n\prime ijht-1}$$
$$+\beta_{3h}c_{ijt_{-1}} + \omega_{\mathrm{ijh}} + \omega_{\mathrm{ht}} + \mu_{\mathrm{ijht}}, \qquad (2)$$
$$\forall h \in H;\ \forall n, n' \in \{ADP, CVD, SG, SSG, SPS, TBT, QRS; STC(SPS), STC(TBT)\}\ where\ n' \neq n$$

Equation (2) is estimated for each product h at the 6-digit level of the Harmonised System (HS). Imported quantities of product h to country i from exporting partner country j at time t are denoted as m_{ijht}. Trade policy instruments included in the regression analysis are tariffs T_{ijht-1} in the form of ad valorem tariff rates (using UNCTAD 1 methodology[17]) and non-tariff measures $NTM_{nijht-1}$.

The NTM variables show the total number of NTM regulations in place[18] and notified to the WTO. Where the information on the date of entry into force is not available, the date of initiation is used. As we are interested in importer-specific effects of NTMs, we further interact the NTM variables with importer dummies ω_i. Two coefficients capture the effect of NTMs on imports: $\beta_{2n\prime ih}$ quantifies the importer-specific impact of one NTM type n' under consideration, while β_{2nh} controls for the effect of all other NTM types in place. The procedure is repeated for all seven NTM types and two sorts of specific trade concerns, such that our results are a collection of all importer-specific coefficients $\beta_{2n\prime ih}$ for all NTM types.

We opted for lagging the trade policy variables by one period for two reasons. The first rationale is that we expect demand, in particular for intermediate products, to react not immediately after policy changes are introduced. The second reason concerns the very nature of contingent protection. Antidumping or counteracting measures as well as (special) safeguards only apply when imports are already strongly increasing and potentially damaging to the domestic industry. If we did not consider a lag, our results for counteracting measures would suffer from an endogeneity bias. Coefficients could pick up the prior import increasing effect, e.g. price dumping by the exporting country, rather than the effect of the NTMs imposed as a reaction to the import influx by the importing country. We expect this endogeneity bias to be markedly reduced by lagging the policy variables by one period.

In addition to trade policy variables, we control for country-pair characteristics that are changing over time. The variable $c_{ijht_{-1}}$ includes a measure for the market potential, i.e. the sum of trading partners' GDPs [Equation (3)]. We also consider an index amended from Baltagi et al (2003) to account for the differences between trading partners of a specific product h with respect to real GDP per capita [Equation (4)]. Furthermore, we take the (dis)similarities of trading partners with respect to three factor endowments k into account, i.e. labour *L*, capital stock *K,* and agricultural land area *A*, relative to GDP [Equation (5)].

$$Y_{ijt} = (GDP_{it} + GDP_{jt}) \qquad (3)$$

$$\left(\frac{GDPpc_{it}^2}{(GDPpc_{it} + GDPpc_{jt})^2} + \frac{GDPpc_{jt}^2}{(GDPpc_{it} + GDPpc_{jt})^2}\right) - \frac{1}{2} \qquad (4)$$

[16] An extended version of this chapter was published as: Ghodsi, M., J. Grübler, O. Reiter, and R. Stehrer (2017). 'The Evolution of Non-Tariff Measures and their Diverse Effects on Trade', wiiw Research Report, No. 419, Vienna, May. – The report and data on estimated trade effects are available online free of charge.

[17] See: http://wits.worldbank.org/wits/wits/witshelp/Content/Data_Retrieval/P/Intro/C2.Ad_valorem_Equivalents.htm

[18] The I-TIP database provides the date of withdrawal for ADP and CVD measures and end dates for some QRS, SG and SSG. For other types of NTMs this information is not available. For our analysis, we assume that they have not been withdrawn since.

$$f_{kijt} = ln\left(\frac{F_{kjt}}{GDP_{jt}}\right) - ln\left(\frac{F_{kit}}{GDP_{it}}\right), F_k \in \{L, K, A\} \quad (5)$$

Other control variables include dummy variables indicating (i) whether the importer and the exporter are members of the WTO, or (ii) whether they are both members of a Preferential Trade Agreement (PTA).

With Equation (2) being estimated for each product h, the constant β_{0h} represents product fixed effects. Time fixed effects ω_{th} aim at taking up economic shocks influencing all trading partners. Country-pair fixed effects ω_{ijh} should account for time-invariant country-pair characteristics such as their geographical distance, whether they are neighbouring countries, share a common language or colonial history. Finally, μ_{ijht} constitutes the error term.

3.1. Empirical results

To start with our analysis we set up a panel dataset of bilateral import flows between WTO members and their trading partners for all products at the HS 6-digit level during the period 1995-2014. We then estimate the effect of NTMs on import quantities, i.e. $\partial ln(m_{ijht})/\partial NTM_{n'ijht-1}$, of Equation (2), using the Poisson maximum likelihood estimator proposed by Santos Silva and Tenreyro (2006).

Throughout we exclude intra-EU trade flows. The main argument to do so stems from the structure of our NTM database: Although we do observe the *quantity* of NTMs imposed by country, we do not observe the *quality* of NTMs, i.e. the degree of heterogeneity – or, in the case of the EU, homogeneity – of the measures. The dataset does not provide information e.g. which packaging requirement or which limit of pesticide residues is more costly to implement. It only tells us that regulations on packaging and pesticides were notified to the WTO. As NTMs for EU Member States are typically set at the EU level, the inclusion of bilateral NTMs for EU members would lead to a downward bias of our results.

Our estimation output covers 5,049 products and 131 importers, resulting in 326,346 importer-product pairs for which at least one NTM type applied. In our dataset, importers on average targeted 3,506 products with at least one type of NTM. 94% of importer-product pairs can be associated with three NTM types or less. For the majority of importer-product pairs (55%) only one kind of NTM applied. Another 28% of observations were targeted by two NTM types, 12% by three types. Yet there are also importer-product pairs for which we find that four (3.8%), five (1.5%), six (0.3%) or even seven (0.03%) NTM categories were used.

Affected products were imported on average by 73 importers. The greatest number of importing countries is recorded for birds' eggs in shell (fresh, preserved or cooked, HS 040700) with 116 importers, followed by seven other agricultural products[19] imported by 115 countries. For 83% of all importer-product pairs we were able to estimate related trade effects, out of which 67% (corresponding to 56% of all importer-product pairs) have shown to be significantly different from zero. We refer to these significant effects as 'binding' trade effects.

3.1.1. Trade effects by type of NTM

A first overview of aggregate estimation results shall give an understanding of the importance of NTMs for trade flows on a global scale. The coefficients of our Poisson estimation procedure $\beta_{2n'ih}$ show how much the *log* of import quantities $ln(m_{ijht})$ is expected to decrease or increase due to an additional NTM. In order to show the effects on import quantities, we transform our coefficients according to Equation (6), such that trade effects $TE_{n'ih}$ can be interpreted as changes in percentages:

$$TE_{n'ih}\ in\ \% = \left(e^{\beta_{2n'ih}} - 1\right) * 100 \quad (6)$$

[19] One meat product (HS 020736), five vegetable products (HS 070190, HS 070310, HS 070610, HS 070690, HS 070990), and fresh apples (HS 080810).

We dealt with extreme values and potential outliers by dropping the tails of the trade effects distribution, which we defined as values three times the interquartile distance (IQ) below the first quartile or above the third quartile of the distribution. No additional maximum or minimum values are imposed. However, by definition, the minimum value for our trade effects is -100%, i.e. the NTM leads to a complete stop of imports. On the positive side, trade-promoting effects of NTMs can exceed 100%.

Table 1 summarises our results when we compute mean and median values of trade effects over all observations, i.e. importer-product combinations, per NTM type. On the left, we consider all computed trade effects, whereas on the right, we consider only trade effects statistically different form zero at the 10% level, which we will henceforth refer to as binding trade effects.

Table 1 / Simple average over trade effects of NTMs

	All estimates				*Significant impact of NTMs (p < 0.1)*		
NTM	*Mean*	*Median*	*Obs.*	*NTM*	*Mean*	*Median*	*Obs.*
SPS	-4.95	-2.23	74,744	SPS	-14.22	-19.19	35,814
TBT	-7.17	-4.43	201,229	TBT	-16.82	-19.92	99,382
QRS	-14.03	-12.78	39,230	QRS	-32.41	-64.67	20,767
ADP	2.99	-48.76	23,287	ADP	1.86	-70.90	18,326
CVD	-12.20	-51.89	2,239	CVD	-19.60	-81.82	1,569
SG	64.88	9.83	1,817	SG	103.19	52.17	937
SSG	19.98	-10.47	436	SSG	17.01	-45.20	212
STC(SPS)	51.00	-12.86	8,363	STC(SPS)	68.91	-52.15	5,007
STC(TBT)	18.00	-24.13	46,412	STC(TBT)	19.58	-57.43	29,940
Obs.			397,757	Obs.			211,954

Notes: Considering only importer-product pairs for which at least one NTM type applied. As one importer-product pair can be affected by multiple NTM types, the total number of effects by NTM type (Table 3) exceeds the number of effects by importer-product pairs (Table 2).

Roughly 60% of our estimates show negative effects of NTMs on imports, comparable to findings in recent literature (e.g. Bratt, 2017; Beghin et al., 2015). This share increases to around 67% when only binding trade effects are considered. The share of negative binding trade effects is highest for antidumping measures (72%), countervailing duties (75%) and quantitative restrictions (75%).

3.1.2. Trade effects by importer

The country sample of 124 countries for which trade effects could be computed (out of 131, which entered our analysis) comprises 39 countries of Europe and Central Asia[20]. Canada and the United States form the aggregate for North America. For Latin America and the Caribbean, trade effects were computed for 25 countries. Within Asia, 18 countries belong to East Asia and the Pacific and another four to South Asia. Twelve countries represent the Middle East and North Africa and another 24 countries the region of Sub-Saharan Africa. For the geographical display, we consider two ways of aggregation. The first is to take the simple average over trade effects per importing (i.e. NTM imposing) country, which in turn enters the mean trade effect of a region, as shown in the upper panel of Table 2. In the lower panel we show the results, when we impose import weights using the import values per HS 6-digit product per importing country. The average figures per region correspond to the simple average over all countries of the region, meaning that within a region every country has equal weight.

Both options have their merits. Applying import weights to the trade effects might better reflect the economic importance of a product within an economy than does the simple average figure over all products. On the other hand, if NTMs are trade-impeding, using import weights automatically biases the effect of NTMs towards too small effects. We therefore opt for showing both.

[20] Country groupings according to the World Bank List of Economies (July 2015).

The greatest trade reducing effects are reported for SPS measures and QRS of Sub-Saharan Africa. The most trade supportive effects are found for the region of South Asia for SPS measures and TBTs against which trading partners raised concerns at the WTO. Furthermore, standards and restrictions adopted by Europe and Central Asia seem to be more import-impeding than North American policies.

Although the majority of effects of contingent protection measures are negative – ADP (72%), CVD (75%), SG (47%) and SSG (67%), respectively – there are still numerous positive trade effects, resulting in positive regional aggregates. Three possible explanations, two economic and one econometric in nature, come to our mind. First, our trade effects are importer specific and not bilateral in nature. Therefore, using contingent protection against one exporter might stimulate imports from other origin countries, ultimately resulting in an aggregate positive impact. Second, counteracting measures such as ADP or CVD may lead to price undertakings or to quality adaptions of the exporter in order not to face a duty. In the latter case, a downgrading of the product quality might be a response to circumvent duties and simultaneously boost exports. Finally, it might be that lagging the NTM variable by one year is not sufficient to exclude the possibility that we are measuring the effect '*unfair trading practices*' (such as price dumping or export subsidies) rather than the effect of the NTM imposed to counteract the adverse effects of these policies.

Table 2 / Binding trade effects by region and NTM type

	Region	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Simple average	Europe & Central Asia	-2.55	-13.38	-4.30	0.00	-0.30	0.56	0.00	2.81	2.80
	North America	-0.63	-2.89	-0.19	1.88	-0.29	-0.37	0.17	0.39	2.87
	Latin America & Caribbean	-3.93	-17.57	-1.10	1.24	0.08	2.81	-0.16	0.00	12.65
	East Asia & Pacific	-4.65	-10.57	-0.23	-0.03	-0.03	0.02	0.15	0.68	2.10
	South Asia	33.12	0.36	-0.25	0.77	0.11	2.99	.	11.06	56.57
	Middle East & North Africa	-5.81	-5.81	-5.63	-0.39	-0.64	3.70	-0.06	0.24	0.17
	Sub-Saharan Africa	-22.50	-13.55	-45.28	0.18	0.00	0.04	.	.	-0.55
	Region	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Import-weighted average	Europe & Central Asia	-0.40	-9.17	-5.37	0.48	0.01	0.40	0.03	2.04	1.11
	North America	-0.70	-0.87	0.14	1.16	-0.60	-0.09	0.17	0.50	1.87
	Latin America & Caribbean	1.69	-2.86	-2.57	1.18	0.84	1.49	0.48	0.43	5.25
	East Asia & Pacific	-1.07	-1.57	3.32	3.39	-0.67	0.15	0.07	-0.12	2.09
	South Asia	50.02	1.63	-18.74	2.07	0.21	0.21	.	11.62	25.94
	Middle East & North Africa	-1.47	-4.66	-3.82	-0.07	3.93	3.39	-0.01	0.06	2.99
	Sub-Saharan Africa	-10.77	8.94	-18.26	0.43	0.12	0.08	.	.	-0.22

Notes: Figures refer to binding trade effects (statistically different from zero at 10%).

The problem of possible endogeneity also arises for the estimation of the effect of specific trade concerns raised at the SPS and TBT committees. Some researchers look specifically at STCs, arguing that if countries complain at the WTO against NTMs they are facing, these must be the most trade restrictive ones (e.g. Fontagné and Orefice, 2016; Ghodsi, 2015). Overall, more than 50% of estimated trade effects of STC(SPS) and more than 60% of STC(TBT) show negative signs. Yet, if an importing country makes use of e.g. TBTs, resulting in drops in imports for the affected product, complaints at the WTO against this measure might again increase imports. This problem could be overcome, if a 1:1 match of STCs with respective SPS measures or TBTs of the importing country existed.

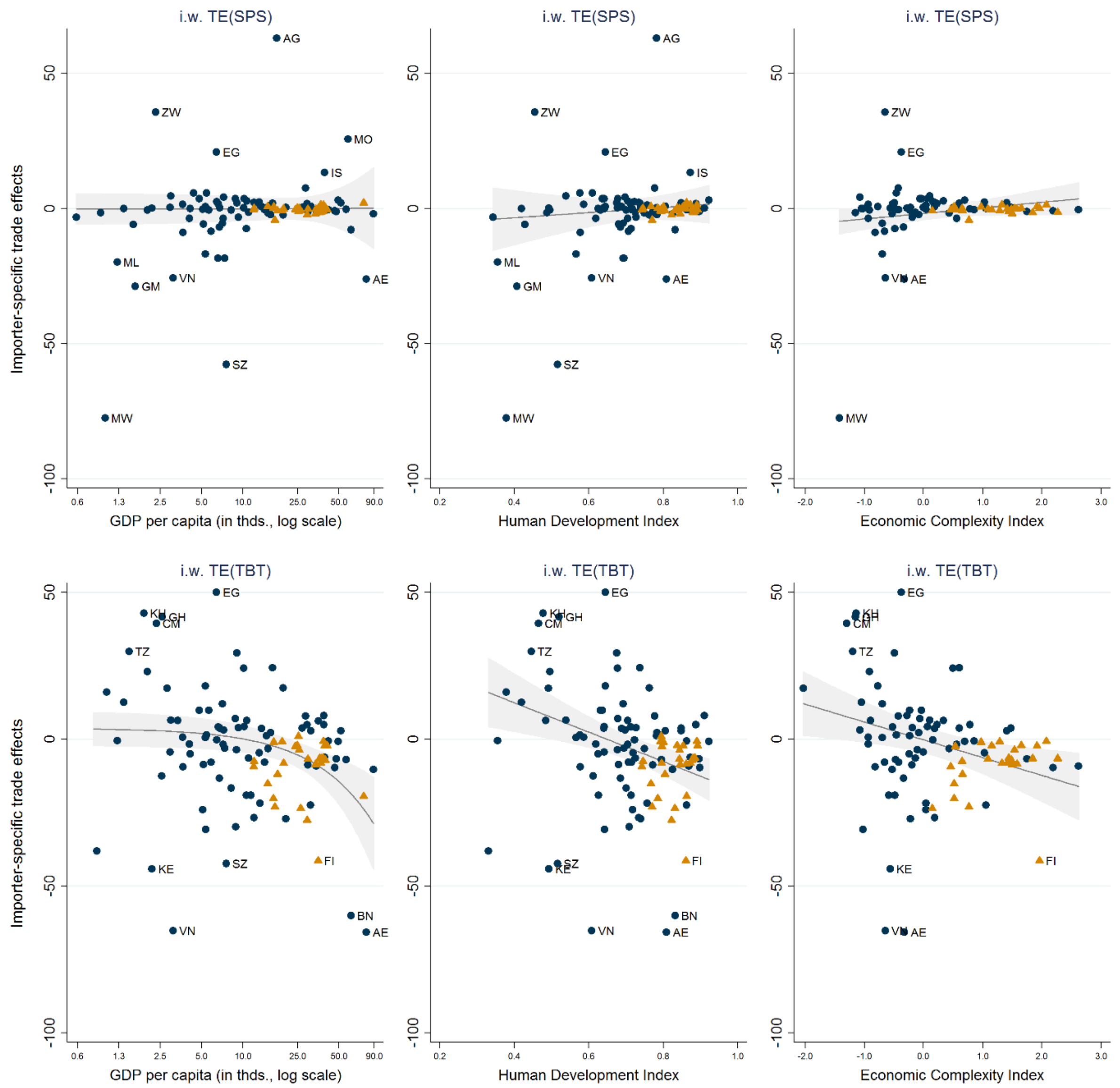
Another way of aggregating our country- and product-specific trade effects is to group them by income groups according to the country classification of the World Bank, as shown in Table 3. Simple average figures suggest that the trade-impeding effects of SPS measures decrease with higher income levels. Conversely, TBTs seem to be more trade restrictive for richer countries. Quantitative restrictions bring imports to low-income countries practically to a halt, while these countries do not (effectively) apply any contingent protective policies. For regions applying these policies, average figures are counterintuitively positive.

Table 3 / Binding trade effects by income group and NTM type

	Income Group	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Simple average	Low income	-10.48	-3.45	-99.99	.	.	.	.	.	.
	Lower middle income	-12.68	-7.16	1.81	0.18	0.11	1.72	0.17	1.46	11.31
	Upper middle income	-5.07	-11.08	-1.87	1.34	-0.01	2.67	-0.09	0.55	10.76
	High income	-1.39	-16.89	-3.43	-0.06	-0.29	0.25	0.01	2.01	2.23
	Income Group	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Import-weighted	Low income	5.83	23.53	-99.66	.	.	.	.	.	.
	Lower middle income	-4.51	-0.86	9.59	1.06	0.21	0.96	0.67	0.67	6.85
	Upper middle income	-1.09	-1.30	-1.26	3.69	0.44	1.49	-0.11	0.73	4.08
	High income	0.98	-9.04	-3.48	0.10	0.07	0.46	0.04	1.52	1.52

Notes: Figures refer to binding trade effects (statistically different from zero at 10%).

Figure 6 / Import-weighted binding trade effects of SPS measures and TBTs by importer



Notes: Figures refer to binding trade effects (statistically different from zero at 10%). i.w. refers to import-weighted by import values. Varying country sample depending on the availability of each index. EU Member States are highlighted as orange triangles.

Given the prominence of SPS measures and TBTs both in terms of their number as well as in public discussions, we additionally plot estimated trade effects per importing country against three measures of economic development in Figure 6.

(i) The first measure from the left is real gross domestic product (GDP) per person in purchasing power parities (PPP) in thousand 2011 US dollars. (ii) In addition to income, the Human Development Index (HDI) published by the United Nations, also covers the health and educational dimension of a country's development. (iii) To capture an economy's development rather than human development, the Centre for International Development at Harvard University looked at the diversification of an economy with respect to the number of products exported and the complexity of domestically produced products, from which they derived the Economic Complexity Index (ECI). For every importing country, we calculated the average value of each indicator over the period 1995-2014, corresponding to the time span of our analysis.

A central statement of the WTO World Trade Report of the year 2012 was that NTMs could be trade enhancing whenever the positive demand shock exceeds the negative supply shock. This seems to hold true for SPS measures to protect human, animal and plant life. TBTs of richer countries, on the contrary, seem to result in higher costs without providing additional benefits, for which consumers or firms are willing to pay.

3.1.3. Trade effects by product types

The effects of non-tariff measures might not only vary by characteristics of the NTM imposing countries but by the type of product targeted by the policy. Every year during the period 1995-2014, imports of intermediates represented more than 52% of global imports and the importance of global value chains as exemplified by intermediate goods trade is increasing over time. Table 4 therefore summarises our estimates according to the use of the product as either (i) intermediate product entering the production of another product, or (ii) good ready for final consumption or (iii) a component contributing to gross fixed capital formation (GFCF). Concordance tables from HS Rev. 1996 to the Broad End-use Category (BEC) classification are used to form these three categories of products.

Simple averages across all calculated trade effects emphasise the trade-impeding effects of SPS regulations and TBTs for intermediates, while quantitative restrictions show similar effects across product types. In import weighted terms, effects of SPS measures, TBTs and QRS on imports of intermediate products and final consumption goods are scaled down considerably, while the negative trade effect for fixed capital becomes even more pronounced.

Table 4 / Binding trade effects by product use and NTM type

	Product use	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Simple average	Intermediates	-3.11	-16.43	-2.99	0.35	-0.19	0.31	0.00	0.90	1.90
	Final Consumption	-2.96	-7.34	-3.16	-0.31	-0.02	0.62	0.04	2.66	3.21
	GFCF	-0.27	-7.75	-3.29	2.01	-0.08	0.06	.	-0.02	6.80
	Product use	SPS	TBT	QRS	ADP	CVD	SG	SSG	STC(SPS)	STC(TBT)
Import-weighted	Intermediates	-0.19	-2.87	-0.04	4.12	-0.02	0.11	-0.01	0.52	1.89
	Final Consumption	-0.41	-1.51	-0.97	0.05	0.40	0.28	0.15	3.62	4.20
	GFCF	-0.65	-6.55	-6.64	1.28	-0.04	0.01	.	0.00	0.62

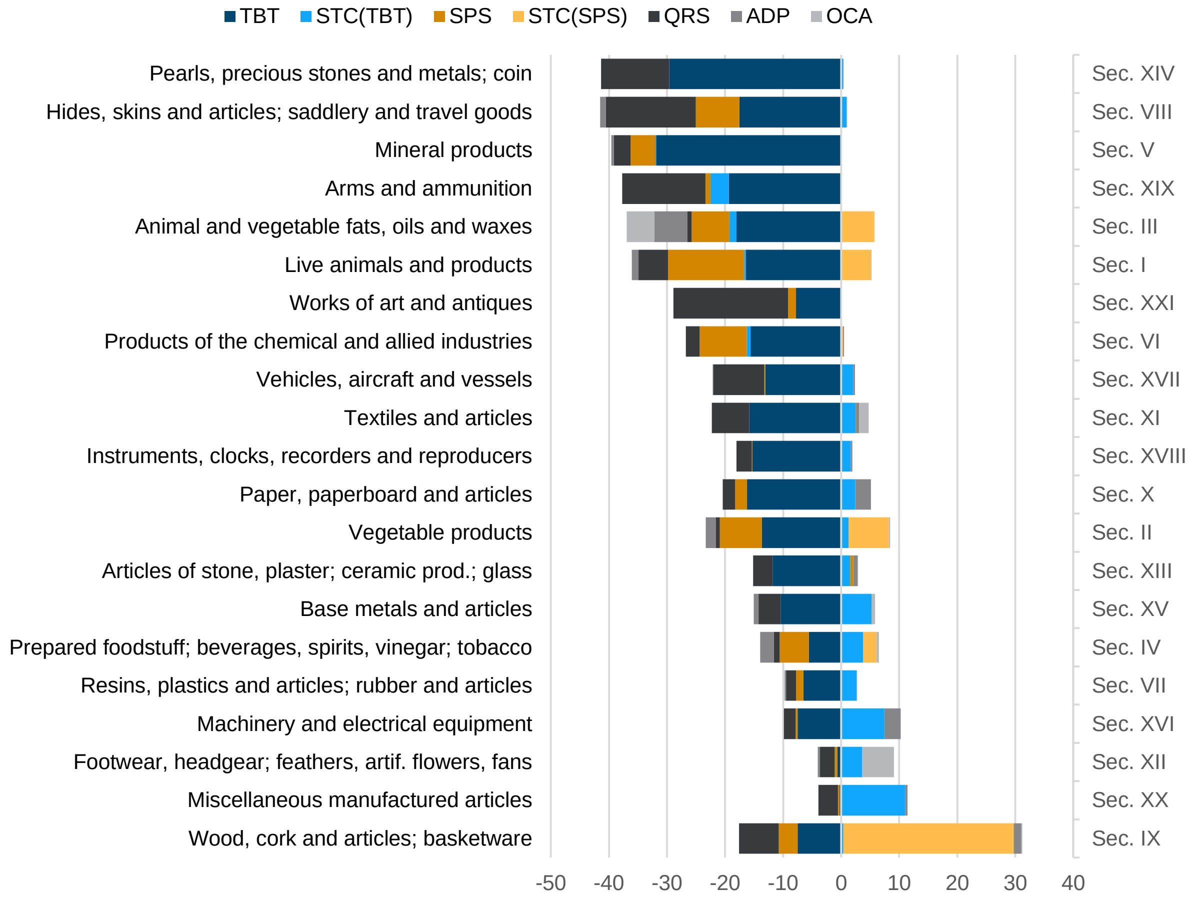
Notes: Figures refer to binding trade effects (statistically different from zero at 10%).

A rationale for the difference in the reduction of the effects when using import weights across product types is the difference in the demand elasticity for those imports. We expect the fastest reaction to price increases for the demand of households, while reactions of firms' demand for intermediates might be slower due to established international production networks. For large investments in assets based on longer-term planning, import demand might be less price elastic, such that the reduction in import quantities might be slower than the policy-induced increase of the import price of these goods (see e.g. Ghodsi et al, 2016b).

The Harmonised System (HS) for international product classifications allows to further aggregate results along main product characteristics. The HS system is organised in 99 chapters, which are grouped into 21 sections. Figure 7 presents simple average trade effects for each HS section.

Luxury products, minerals as well as arms and ammunition represent HS sections showing the greatest import reducing effects of NTMs, greatly attributable to quantitative restrictions and TBTs. These are followed by animal and vegetable fats, as well as live animals, while vegetable products are found half way down the product list.

Figure 7 / Binding trade effects of NTMs by HS section

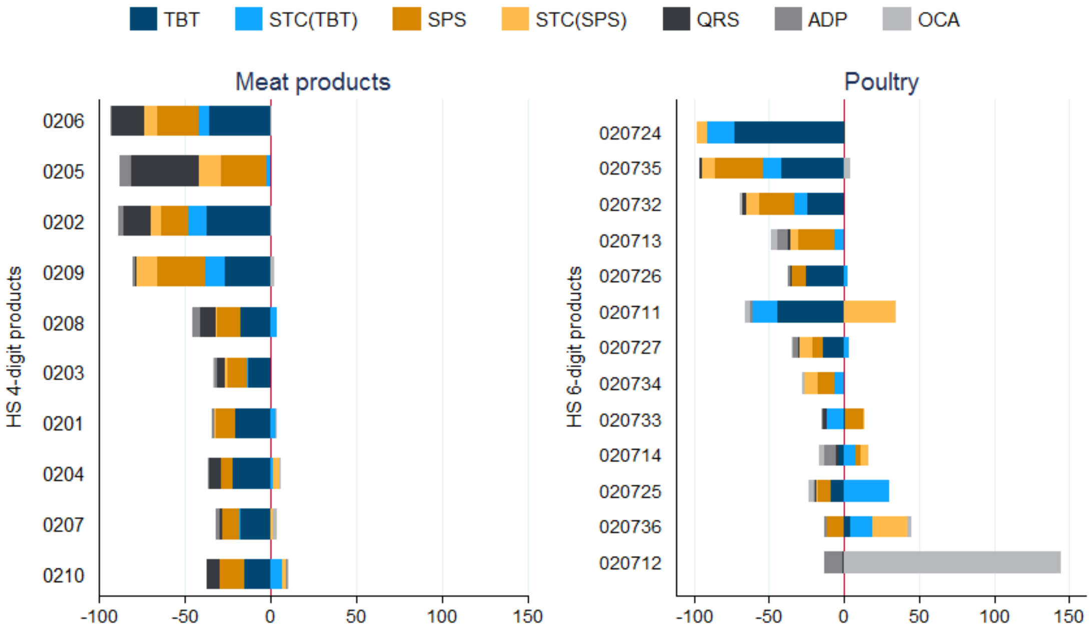


Notes: Considering only importer-product pairs for which at least one NTM type applied. Simple average is computed over all trade effects that are significantly different from zero at the 10% level, grouped by HS section.

Furthermore, our regression output allows taking a closer look at (groups of) products of specific interest. For illustration purposes, we consider meat products (HS 02), which belong to the product groups that are affected by a great variety of different types of NTMs and are imported by a vast number of countries worldwide. Results for meat products, belonging to the HS 2-digit group of meat and edible meat offal, are depicted in the left panel of Figure 8. Meat products in turn represent a group of ten HS 4-digit products. One of them is poultry (HS 0207). The right panel shows the results across 13 HS 6-digit products out of 19 poultry products in total listed in the Harmonised System.

These figures illustrate the diversity of trade effects across products. Overall, TBTs and QRS seem to be of great importance for meat products, particularly for frozen meat of bovine animals (HS 0202), edible offal of certain animals (HS 0206) and meat of horses, asses, mules or hinnies (HS 0205). The aggregate for poultry (HS 0207) suggests that TBTs are more trade restrictive than SPS measures. The right panel then shows which products contribute to this result. Particularly high trade-impeding effects for TBTs were estimated for fresh or chilled turkeys (HS 020724), cuts and edible offal of ducks (HS 020735), and fresh or chilled fowls (HS 020711).

Figure 8 / Trade effects of NTMs for meat products



Notes: Considering only importer-product pairs for which at least one NTM type applied. Simple average is computed over all trade effects that are significantly different from zero at the 10% level. Meat products refers to the HS 2-digit group 02 "meat and edible meat offal" and shows trade effects for underlying HS 4-digit products. Poultry refers to the HS 4-digit group 0207 "meat and edible offal of poultry; of the poultry of heading no. 0105, (i.e. fowls of the species Gallus domesticus), fresh, chilled or frozen" and shows trade effects for underlying HS 6-digit products.

3.2. Conclusion on the trade effects of NTMs

We used the amended data provided by the Integrated Trade Intelligence Portal (I-TIP) of the WTO to estimate the trade elasticity w.r.t. NTMs for more than 100 importers and over 5,000 products over the period 1995-2014. About 60% of all trade effects suggest trade-impeding effects of NTMs, which are particularly pronounced for quantitative restrictions and TBTs.

Geographically, the greatest import restricting effects were found for Sub-Saharan Africa. We also note that standards and restrictions implemented in Europe and Central Asia affect imports more than do North American NTMs. At the product level, we find NTMs to be most trade restrictive for luxury products, minerals as well as arms and ammunition, followed by products of the agri-food sector.

Although we consider it appropriate to aggregate NTM notifications and corresponding estimates of trade effects along country and product characteristics, we want to emphasise the diversity of NTMs and their effects at the disaggregated HS 6-digit product level. The degree of detail for which we provide NTM data and estimate trade effects is exemplified by the case of birds' eggs.

4. Import demand elasticities revisited[21]

In order to compare the impact of different trade policies it is often necessary to make use of import demand elasticities (e.g. Kee et al., 2009; Nizovtsev and Skiba, 2016) answering the question: "*What would be the percentage change in import quantities if the price of the imported good increased by 1%?"*

Trade policy is frequently operational at the tariff line level. However, there are only few studies, which allow the evaluation of demand elasticities for a broad set of products at the disaggregated product level (e.g. Kee et al., 2008; Feenstra and Romalis, 2014). Most available studies have a strong focus on either selected products (e.g. Panagariya et al., 2001; Altinay, 2007) and/or particular importers (e.g. Broda and Weinstein, 2006; Soderbery, 2015).

To the best of our knowledge, the investigation by Kee et al. (2008) is the only work that evaluated price elasticities of import demand for a wide range of products and countries, having the inherent additional advantage of rendering elasticities across countries and products more comparable through the application of a single methodology and dataset for all. Kee et al. (2008) estimated more than 300,000 import demand elasticities across 117 countries for about 4,900 products at the 6-digit level of the Harmonised System (HS revision 1988) for the period 1988-2001. Their estimates are frequently used in various policy analysis (e.g. Kee et al., 2009; Maoz, 2009; Bratt, 2017; Peterson and Thies, 2014; Beghin et al., 2015).

We update their work by computing importer-specific import demand elasticities for the more recent period 1996-2014 (HS revision 1996) and present differences across countries, regions and income levels, as well as by products and sectors. Improved data availability and the inclusion of products not considered in HS revision 1988 allows us to estimate about twice as many import demand elasticities for 167 importing countries and more than 5,000 products.

4.1. Theoretical framework & empirical strategy

The starting point for Kee et al. (2008) is based on Kohli's (1991) GDP function approach. In an economy with N products and M factors of production, the optimal net output vector q_t of an economy (i.e. output including exports and reduced by imports) maximises the value of goods produced in the economy $G_t(\tilde{p}_t \mathrm{A_t}, v_t)$ given exogenous world prices $\tilde{p}_t$, productivity $\mathrm{A_t}$ and factor endowments v_t:

$$G_t(p_t, v_t) \equiv \max_{\mathrm{q_t}}\{\mathrm{p_t q_t}: (p_t, v_t)\} \tag{7}$$

where p_t is the productivity-inclusive and thus country-specific price vector ($p_t \equiv \tilde{p}_t \mathrm{A_t}$). Positive numbers for $\mathrm{q_t}$ refer to output for domestic demand or exports, while negative numbers refer to imported goods. If good n is an imported good then the derivative of the GDP function with respect to its price gives the GDP-maximising import demand function of good n which does neither depend on an income function nor on a specific utility function.

$$\frac{\partial G_t(p_t, v_t)}{\partial \mathrm{p_{ht}}} = \mathrm{q_{ht}}(p_t, v_t), \forall h = 1, \dots, H. \tag{8}$$

In order to evaluate the GDP function empirically, Kee et al. (2008) employ a flexible translog GDP function with indices h and k indicating goods and m and l representing factors of production:

$$\begin{aligned} &\ln G_t(p_t, v_t) \\ &= \mathrm{a_{00t}} + \sum_{h=1}^{H} \mathrm{a_{hht}} \ln \mathrm{p_{ht}} + \frac{1}{2}\sum_{h=1}^{H}\sum_{k=1}^{H} \mathrm{a_{hkt}} \ln \mathrm{p_{ht}} \ln \mathrm{p_{kt}} + \sum_{m=1}^{M} \mathrm{b_{mmt}} \ln v_{mt} + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \mathrm{b_{mlt}} \ln v_{mt} \ln v_{lt} \\ &+ \sum_{h=1}^{H}\sum_{m=1}^{M} \mathrm{c_{hmt}} \ln \mathrm{p_{ht}} \ln v_{mt} \end{aligned} \tag{9}$$

[21] An extended version of this chapter was published as: Ghodsi, M., J. Grübler and R. Stehrer (2016), 'Import Demand Elasticities Revisited', wiiw Working Paper, No. 132, Vienna, November. – The paper and data on estimated elasticities are available online free of charge.

The derivative of $\ln G_t(p_t, v_t)$ with respect to $\ln p_{ht}$ gives the equilibrium share of good h in GDP at period t:

$$\frac{\partial \ln G_t}{\partial \ln p_{ht}} = \frac{1}{\mathrm{G_{ht}}(\mathrm{p_t}, v_t)} \mathrm{q_{ht}}(\mathrm{p_t}, v_t)\mathrm{p_{ht}} \equiv \mathrm{s_{ht}}(\mathrm{p_t}, v_t) \tag{10}$$

which, after imposing restrictions on the functional form of the translog GDP function to ensure that it is homogeneous of degree one with respect to prices and factor endowments and satisfies the symmetry property, results in:

$$\mathrm{s_{ht}}(\mathrm{p_t}, v_t) = \mathrm{a_{0ht}} + \mathrm{a_{hht}} \ln \mathrm{p_{ht}} + \sum_{k \neq h}^{H} \mathrm{a_{hkt}} \ln \mathrm{p_{ht}} + \sum_{m=1}^{M} \mathrm{c_{hmt}} \ln v_{mt}\ , \qquad \forall h = 1, \dots, H. \tag{11}$$

$\mathrm{s_{ht}}$ is the share of good h in GDP (with negative values assigned to imports, and positive values associated with output and exports). Under consideration of the translog parameters of the GDP function, the derivative of $\mathrm{s_{ht}}$ with respect to prices $\mathrm{p_{ht}}$ is given as

$$\frac{\partial \mathrm{s_{ht}}}{\partial \mathrm{p_{ht}}} = \underbrace{\frac{\mathrm{q_{ht}}}{\mathrm{G_t}} + p_{ht}\frac{\frac{\partial q_{ht}}{\partial p_{ht}}}{\mathrm{G_t}} - \frac{q_{ht}p_{ht}}{(\mathrm{G_t})^2}\frac{\partial \mathrm{G_t}}{\partial p_{ht}}}_{see\ eq.(10)} = \underbrace{\mathrm{a_{hht}}\frac{1}{p_{ht}}}_{see\ eq.(11)} \tag{12}$$

where $\mathrm{a_{hht}}$ is a translog parameter stemming from the translog GDP function that captures the change in the share of good h in GDP (which by construction is negative for imported products) when the price of good h increases by 1 %. The multiplication of both sides by p_{ht} and rearranging terms[22] gives the result for the import demand elasticity of imported good h:

$$\varepsilon_{hht} \equiv \frac{\partial q_{ht}(p_t, v_t)}{\partial p_{ht}} \frac{p_{ht}}{q_{ht}} = \frac{a_{hht}}{s_{ht}} + s_{ht} - 1 \leq 0, \forall s_{ht} < 0 \tag{13}$$

If the share of imports in GDP does not change due to changes in import prices ($a_{hht} = 0$), then the implied import demand is unitary elastic, meaning that an increase of the price p_{ht} by 1 % induces a proportional decrease in quantities q_{ht} such that the share in GDP s_{ht} remains constant.

If $a_{hht} > 0$, the share of the imported good h in GDP decreases (i.e. s_{ht} becomes less negative), implying that demand is elastic, such that an increase in the price reduces quantities more than proportional. Finally, if $a_{hht} < 0$, the share of imported good n in GDP increases (i.e. s_{ht} becomes more negative) import demand must be relatively inelastic ($-1 < \varepsilon_{hht} < 0$), as quantities respond less than proportionately to a change in prices. Thus, for small shares and goods in accordance with the law of demand it holds:

$$\varepsilon_{hht} \begin{cases} [-100; -1)\ if\ a_{hht} > 0 \\ -1\ if\ a_{hht} = 0 \\ (-1; 0]\ if\ a_{hht} < 0 \end{cases} \tag{14}$$

Empirically, Kee et al. (2008) implemented this strategy by using a parameterisation from a fully flexible to a semi-flexible translog function following Diewert and Wales (1988) and by restricting all translog parameters to be time invariant in order to handle the large number of goods at the HS 6-digit level.[23] The resulting share equation is

$$s_{ht}(p_t, v_t) = a_{0h} + a_{hh} \ln \frac{p_{ht}}{\overline{p_{kt}}} + \sum_{m=1, m \neq l}^{M} c_{hm} \ln \frac{v_{mt}}{v_{lt}}, \forall\ h = 1, \dots, H. \tag{15}$$

where p_{ht} is measured using unit values of imports, $\overline{p_{kt}}$ is a weighted average of the log prices of all non-h goods. Therefore, the share of good h in GDP is a linear function of factor endowments and the price of good h relative to an average price of all non-h goods. Factors of production used in this analysis comprise

[22] The multiplication of both sides with $\mathrm{p_{ht}}$ and remembering that, (i) $\frac{\partial G_t}{\partial p_{ht}} = \mathrm{q_{ht}}$, (ii) $\partial s_{ht} \equiv q_{ht}\mathrm{p_{ht}}/\mathrm{G_t}$ and (iii) $\varepsilon_{hht} \equiv \frac{\partial q_{ht}(\mathrm{p_t}, v_t)}{\partial q_{ht}} \frac{\mathrm{p_{ht}}}{\mathrm{q_{ht}}}$ results in $s_{ht} + s_{ht}\varepsilon_{hht} - (\mathrm{s_{ht}})^2 = \mathrm{a_{hht}}$.

[23] The parameterisation from a fully flexible to a semi-flexible translog function reduces the number of parameters to be estimated from H(H-1)/2+H to H diagonal elements of the substitution matrix.

labour, capital and agricultural land. Following Caves et al. (1982), Kee et al. approximate $\overline{\ln p_{kt}}$ with the observed Tornqvist price index $\ln p_{-ht}$ of all non- h goods using the GDP deflator p_t.

$$\ln p_{-nt} = \frac{(\ln p_t - \overline{s_{ht}} \ln p_{ht})}{(1 - \overline{s_{ht}})}, with\ \overline{s_{ht}} = \frac{(\overline{s_{ht}} + \overline{s_{ht-1}})}{2} \tag{16}$$

Pooling data across countries and years for each good h, while employing country and year fixed effects, the final share equation estimated by Kee et al. (2008) for each good n takes the following form:

$$s_{hit}(p_{hit}, p_{-hit}, v_{it}) = a_{0h} + a_{hi} + a_{ht} + a_{hh} \ln \frac{p_{hit}}{p_{-hit}} + \sum_{m=1, m \neq l}^{M} c_{hm} \ln \frac{v_{mit}}{v_{lit}} + u_{hit}, \qquad \forall h = 1, \dots, H. \tag{17}$$

where a_{hi} and a_{ht} denote country and time fixed effects, respectively, when running regressions by product h. It is assumed that the structural parameters of the semiflexible translog GDP function are common across countries up to a constant. Equation (11) can be estimated with data on importer-specific product shares in GDP, the GDP deflator, unit values, and information on factor endowments.

Final modifications allow (i) for the correction of a possible endogeneity bias by using instruments for unit values, and (ii) for the correction of a selection bias by following a two-step procedure.

The basic intuition of the import demand elasticity is that if prices increase, demand for these goods decreases. However, if an economy experiences a positive demand shock, prices might react to demand and increase, resulting in reversed causality and simultaneity bias. We therefore instrument the unit values of good h by two measures:

First, we use the simple average of the Tornqvist price index for product h computed over all countries except importing country i, i.e. over the rest of the world. Remembering from equation (16) that the price of non- h goods can be expressed as the GDP deflator adjusted for the share and price of good h, the price index for good h over all non- i importing countries (indexed j) can be computed in a similar fashion:

$$IV_1\left(ln \frac{p_{hit}}{p_{-hit}}\right) = ln \frac{\bar{p}_{hjt}}{\bar{p}_{-hjt}} = \underbrace{\ln\left(\sum_j \frac{p_{hjt}}{J}\right)}_{\ln(\bar{p}_{hjt})} - \underbrace{\left(\frac{\ln \sum_j \frac{p_{jt}}{J} - \sum_j \frac{\bar{s}_{hjt}}{J} \ln \sum_j \frac{p_{hjt}}{J}}{\left(1 - \sum_j \frac{\bar{s}_{hjt}}{J}\right)}\right)}_{\ln(\bar{p}_{-hjt})}, j \neq i \tag{18}$$

The reasoning is that we expect world price indices of good h to be positively correlated with the importing country's price index for the same product thereby affecting import demand. However, while a domestic demand shock might affect an economy's domestic and import prices, we assume countries not to shape price indices of the rest of the world – an assumption which can be violated for large economies such as the US or China.

A second instrument is the trade-weighted average distance of the importing country to its trading partners. The intuition being that the price of imported products is expected to be higher for products that have to be transported over greater distances, while distance might not be correlated with domestic demand for good h.

$$IV_2\left(ln \frac{p_{hit}}{p_{-hit}}\right) = \sum_r x_{rt}\ distance_{ri} \tag{19}$$

where $distance_{ri}$ is the physical distance between importer i and exporter r and x_{rt} is the share of an exporter r in total exports of good h in period t.

However, results using these instruments might still suffer from a selection bias, as unit values entering our analysis are calculated based on positive import flows. Country and year fixed effects can reduce the bias resulting from unobserved variables. Yet, due to the possibility that zero trade flows in our data are the result of countries' selection not to import, we follow an amended form of the Heckman two-stage estimation procedure. In the first step of the two-stage estimation procedure, the selection equation (20) evaluates the probability of non-zero trade flows. The dependent variable is equal to 1 if the share of good n in country i's

GDP is smaller than zero (i.e. imports are greater than zero). It is regressed on a product-specific term γ_{0h}, time fixed effects γ_{ht}, country fixed effects γ_{hi}, as well as the previously introduced instruments and factor endowments, captured in z_{hit}. ϵ_{iht} is an error term. From this first step, the inverse Mills ratio (ϕ_{hit}) is obtained, which enters the outcome equation (22) in the second step as an explanatory variable, which should solve the omitted variable bias in the presence of sample selection.

A drawback of this procedure is, that probit model estimations with country fixed effects suffer from the incidental parameters problem. It means that as we are using a big panel data set incorporating many fixed effects, probit models are more likely to render biased and inconsistent estimates, as they do not converge to their true value as the number of parameters (i.e. fixed effects) increases with sample size. In line with Kee et al. (2008) we therefore substitute country fixed effects with time averages of the exogenous variables and instruments $\bar{z}_{ni}$ in the first stage [Equation (21)].

$$Prob[s_{hit} < 0] = \gamma_{0h} + \gamma_{ht} + \gamma_{hi} + \delta_{1h} z_{hit} + \epsilon_{iht}, \qquad \forall h = 1, \dots, H. \tag{20}$$

$$Prob[s_{hit} < 0] = \gamma_{0h} + \gamma_{ht} + \delta_{1h} z_{hit} + \delta_{2h} \bar{z}_{\text{hi}} + \epsilon_{iht}, \qquad \forall h = 1, \dots, H. \tag{21}$$

$$(s_{hit} | s_{hit} < 0) = a_{0h} + a_{ht} + a_{hh} \ln \frac{p_{hit}}{p_{-hit}} + \sum_{m=1, m \neq l}^{M} c_{hm} \ln \frac{v_{mit}}{v_{lit}} + d_h \bar{z}_{\text{hi}} + \tau_h \hat{\phi}_{\text{hit}} + u_{hit}, \quad \forall h = 1, \dots, H. \tag{22}$$

Finally, using the average import shares of each importing country i and estimates of a_{hh} the resulting import demand elasticity of country i for good h is computed as

$$\hat{\varepsilon}_{hhi} \equiv \frac{\partial q_{ht}(p_t, v_t)}{\partial p_{ht}} \frac{p_{ht}}{q_{ht}} = \frac{\widehat{a_{hh}}}{\overline{s_{hi}}} + \overline{s_{hi}} - 1. \tag{23}$$

4.2. Empirical results

On average, each HS 6-digit product in our sample was imported by 155 countries. Countries in the sample imported on average 4,790 products, ranging from a minimum of 1,593 products for Djibouti to 5,121 products for France. We dropped observations for which bilateral import values were reported but bilateral quantities were missing in order to avoid a bias of unit values entering our estimation procedure.

We performed three estimations: first, employing simple fixed effects (FE), second, introducing instrument variables to the fixed effects estimation procedure (FEIV) and finally, substituting the fixed effects approach by a two-step procedure to account for a possible sample selection bias (SSB). From these results, we constructed our final set of elasticity estimates.

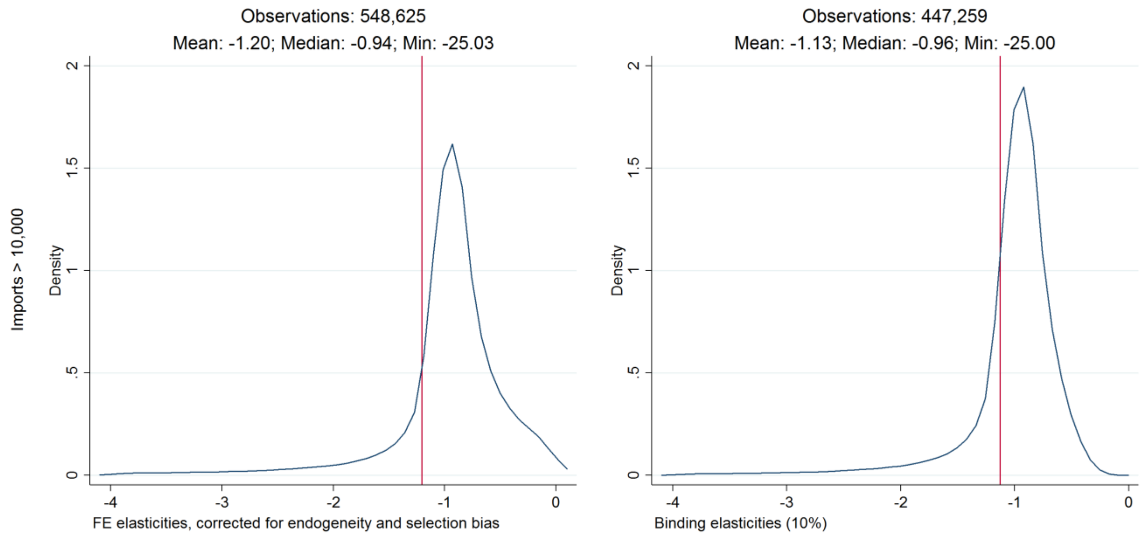
We based our decision when to replace FE results by FEIV results upon two criteria: (i) The Hansen J-statistic reports the validity of instruments, with the null hypothesis that instruments are exogenous. (ii) The Anderson-Rubin F-statistic shows whether instruments have an impact on the endogenous variable, with the null hypothesis that the endogenous regressors in the structural equation are jointly equal to zero. We therefore replaced FE estimates by FEIV results only if the Hansen J-statistic was greater than 0.1 and the Anderson-Rubin F-statistic was smaller than 0.1.

In addition to these two instrument variable criteria, when the coefficient of the inverse mills ratio (τ_h) in equation (22), indicating whether our results might suffer from sample selection bias, was found to be statistically different form zero at the 10% level FEIV results were replaced by SSB results. The distribution of elasticity estimates looks quite similar for all modifications, with mean elasticities smaller, i.e. more negative, than -1.6 but median elasticities larger than -1. Corrections for endogeneity and a selection bias leave median values unchanged but shift mean values towards -2. For our preferred specification we additionally dropped observations where import values of one importer for one specific product never exceeded 10,000 USD per year during the period 1995-2014, which does not alter results on the median elasticity, but drastically reduces the highest elasticities from close to -100 to -25.

Extreme values and potential outliers were dealt with in two steps: First, we dropped the tails (0.5% from either side) of the distribution. Second, we dropped positive elasticities, as we are not concerned with products that violate the law of demand, such as Giffen goods. These steps reduce the number observations from 687,927 to 548,625 import demand elasticity estimates, of which roughly 80% show to be significantly different from zero at the 10% level. We will henceforth refer to the latter as binding elasticities.

While the distribution of our results on first sight very much resembles the findings of Kee et al. (2008) with a big spike around unitary elasticities and a quick flattening out of the distribution, our average elasticity of -1.20 is much less elastic than the mean elasticity reported by Kee et al. (2008) of -3.12. Our results suggest that the most elastic HS 6-digit product is facing an elasticity of -25.03. However, the data provided by Kee et al. (2008) spans from zero to far beyond -100.[24].

Figure 9 / Distribution of elasticity estimates at the HS 6-digit level



Note: Binding elasticities refer to estimates significantly different from zero at the 10% level.

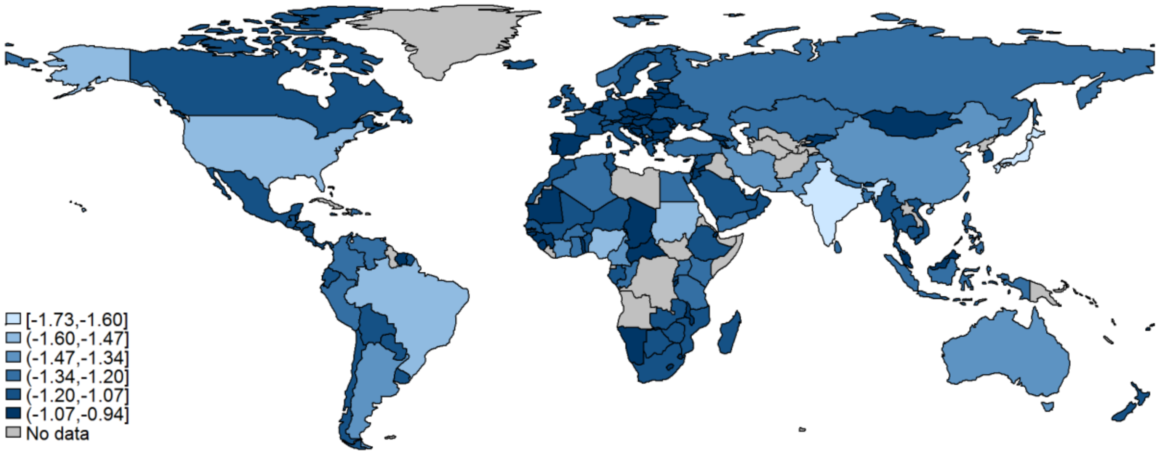
4.2.1. Elasticities by importer

This section aims to discuss geographical patterns of the distribution of import demand elasticities. We start by discussing elasticity aggregates by country, and proceed by computing regional average elasticities and finally illustrate average elasticities by income group.

Figure 10 illustrates simple average binding elasticities with a world map. It makes use of six equally sized intervals, with lighter colour shadings indicating more elastic import demand and darker shading pointing towards less elastic or inelastic demand. On the American continent, the United States and Brazil stand out showing the most elastic import demand in North and South America, respectively. In Europe, particularly inelastic demand was found for Eastern European countries and the Iberian Peninsula. Looking at Asia and Oceania, India and Japan clearly stand out as the countries with the most elastic demand for imports. To the south of the equator, African countries' imports seem to respond only little to price changes. To the north of the equator, however, the picture is very diverse. Countries for which we were not able to compute import demand elasticities due to missing data are mainly found in Africa and Central Asia.

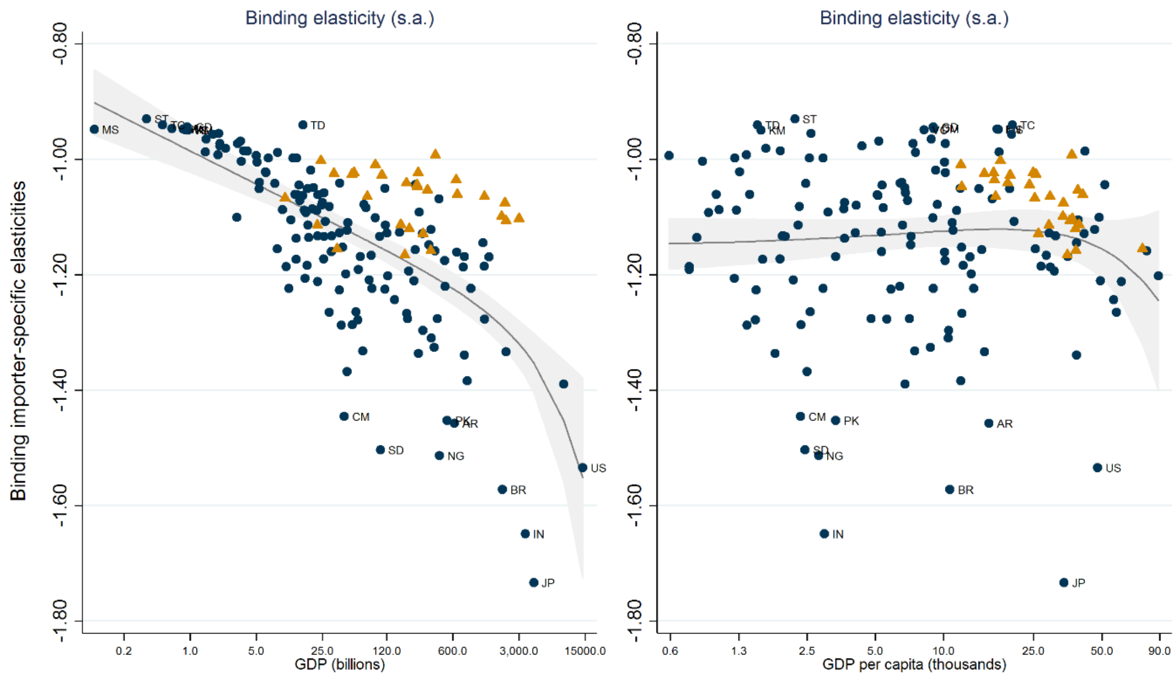
[24] 91 products attributable to 45 importing countries show elasticities equal or greater than -300.

Figure 10 / Simple average binding elasticities per country



Note: Binding elasticities refer to estimates significantly different from zero at the 10% level.

Figure 11 / Binding elasticities over income



Note: s.a. refers to the simple average per country computed over all HS 6-digit products: $\sum_n \hat{\varepsilon}_{nni}/N$. Binding elasticities refer to estimates significantly different from zero at the 10% level. GDP p.c. refers to the average expenditure-side real GDP per capita per country measured at chained PPPs in thousand 2011 USD for the period 1995-2014. EU Member States highlighted as orange triangles. The fitted line stems from a second order fractional polynomial estimation of binding elasticities on GDP per capita.

Figure 11 elaborates on country differences by plotting country-specific import demand elasticities against GDP and GDP per capita at purchasing power parities (PPP), respectively. Note that we opted for showing GDP per capita in log scales, i.e. the difference between two ticks on the x-axis indicates a doubling of income at PPP.

As we have already observed looking at the world map, the countries with the highest simple average elasticities in absolute terms – Japan, India, Brazil, the United States, Nigeria – belong with the exception of Japan to the most populous countries in their respective regions. They are associated with the economically most important countries in the region, but the difference in GDP per capita between these countries is huge. On the other end of the spectrum, the ten countries associated with the lowest import demand elasticities are small island states, with the exception of landlocked, poverty- and violence-ridden Chad.

The most intuitive interpretation would be, that both physically larger and economically more developed countries can substitute imported products by domestically produced goods more easily, whereas small island states and poor countries lack the capacities of developing and maintaining a diverse set of domestic industries and are more dependent on imports. This assumption is in line with the finding that the picture reverses when focusing on the most important traded commodities in terms of trade volumes by attaching import weights to every HS 6-digit product within a country. We find that bigger economies are associated with a lower import-weighted average elasticity. For imported products, which can be substituted by domestically produced goods, we would expect that import demand is more elastic and that trade volumes are lower compared to products, which are not produced domestically. Employing import-weights therefore would scale down elasticities of products facing domestic competition and puts more emphasis on products for which countries are more dependent on imports.

By contrast, looking at the overall picture of the right panel of Figure 11 does not allow assuming that richer countries are associated with more or less elastic demand. However, focusing on the sub-sample of Members States of the European Union a trend towards more elastic demand for richer countries is visible, which is not only a matter of the absolute size of the economy.

Table 5 summarises our previously discussed possible determinants of differences of import demand elasticities across countries by regressing binding importer- and product-specific elasticities on country characteristics. We find a higher share of the imported good n in GDP to be associated with a less elastic demand. Economically and physically bigger economies, captured by GDP and its surface area, show significantly higher (i.e. more negative) import demand elasticities.

We approximate a country's status of development by three different measures. These three measures are GDP per capita, the Human Development Index (HDI) and the Economic Complexity Index (ECI). In addition to GDP per capita, the HDI published by the United Nations considers the dimensions health and education to describe a country's level of development. The ECI provided by the Center for International Development at Harvard University captures how diversified an economy is with respect to the level of complexity of products and the number of products it exports and can be considered as an alternative measure for development (Hausmann et al., 2011). These three measures grasp different dimensions of development but are closely related and do show that demand become less elastic with a higher level of development but that this effect is diminishing. Positive coefficients on the dummy variables for landlocked countries and Small Island Developing States (SIDS) in in line with our expectation that countries that are more dependent on imports exhibit a less elastic import demand. Finally, the table shows that membership to the EU or the WTO is associated with lower price responsiveness, whereas a higher share of fuel exports in GDP points towards more elastic demand.

Table 5 / Regression of binding import demand elasticities on country characteristics

	(1)		(2)		(3)		(4)	
Product's share in GDP	9.048	***	5.685	***	5.878	***	4.615	**
	[1.237]		[1.335]		[1.363]		[1.855]	
GDP	-0.078	***	-0.045	***	-0.043	***	-0.044	***
	[0.004]		[0.003]		[0.003]		[0.003]	
$(GDP)^2$	0.004	***	0.002	***	0.002	***	0.002	***
	[0.000]		[0.000]		[0.000]		[0.000]	
Economic Development	0.001	***	0.002	***	0.418	***	0.038	***
	[0.000]		[0.000]		[0.084]		[0.003]	
$(Economic\ Development)^2$	-0.000	***	-0.000	***	-0.259	***	-0.023	***
	[0.000]		[0.000]		[0.066]		[0.002]	
Area	-0.009	***	-0.007	***	-0.006	***	-0.006	***
	[0.001]		[0.001]		[0.001]		[0.001]	
Landlocked	0.033	***	0.017	***	0.022	***	0.025	***
	[0.005]		[0.004]		[0.004]		[0.005]	
Small Island Developing State	0.120	***	0.041	***	0.038	***	0.018	**
	[0.006]		[0.005]		[0.005]		[0.009]	
EU membership	0.101	***	0.082	***	0.082	***	0.079	***
	[0.005]		[0.005]		[0.005]		[0.006]	
WTO membership	0.014	**	0.019	***	0.026	***	0.029	***
	[0.006]		[0.005]		[0.005]		[0.006]	
Exports of fuels in % of GDP	-0.031	***	-0.028	***	-0.035	***	-0.017	***
	[0.006]		[0.005]		[0.005]		[0.006]	
Constant	-1.155	***	-1.164	***	-1.316	***	-1.159	***
	[0.006]		[0.005]		[0.027]		[0.006]	
Observations	442,281		442,281		431,369		343,471	
R^2	0.006		0.306		0.308		0.317	
Economic Development	*GDP p.c.*		*GDP p.c.*		*HDI*		*ECI*	
Product fixed effects	No		Yes		Yes		Yes	

Standard errors in brackets; * p < .10, ** p < .05, *** p < .01

Note: GDP measured as expenditure-side real GDP in PPPs (trillion 2011 USD) for the period 1995-2014; GDP p.c. refers to the average expenditure-side real GDP per capita per country measured at chained PPPs (ten thousand 2011 USD) for the period 1995-2014; Land area measured in million square kilometres.

4.2.2. Elasticities by product categories

In this section, we seek to elaborate further on differences and commonalities along various product groups. We start by illustrating how elasticities vary between the agri-food and the manufacturing sectors. Considering first simple averages, we find that for a great majority of countries in our sample, 158 out of 167, the agri-food sector appears to face a more elastic demand than the manufacturing sector. However, when imposing product-specific import weights – separately for each sector – the import demand for products of the manufacturing sector shows to be more elastic for 91 countries, as opposed to nine countries without import-weights.

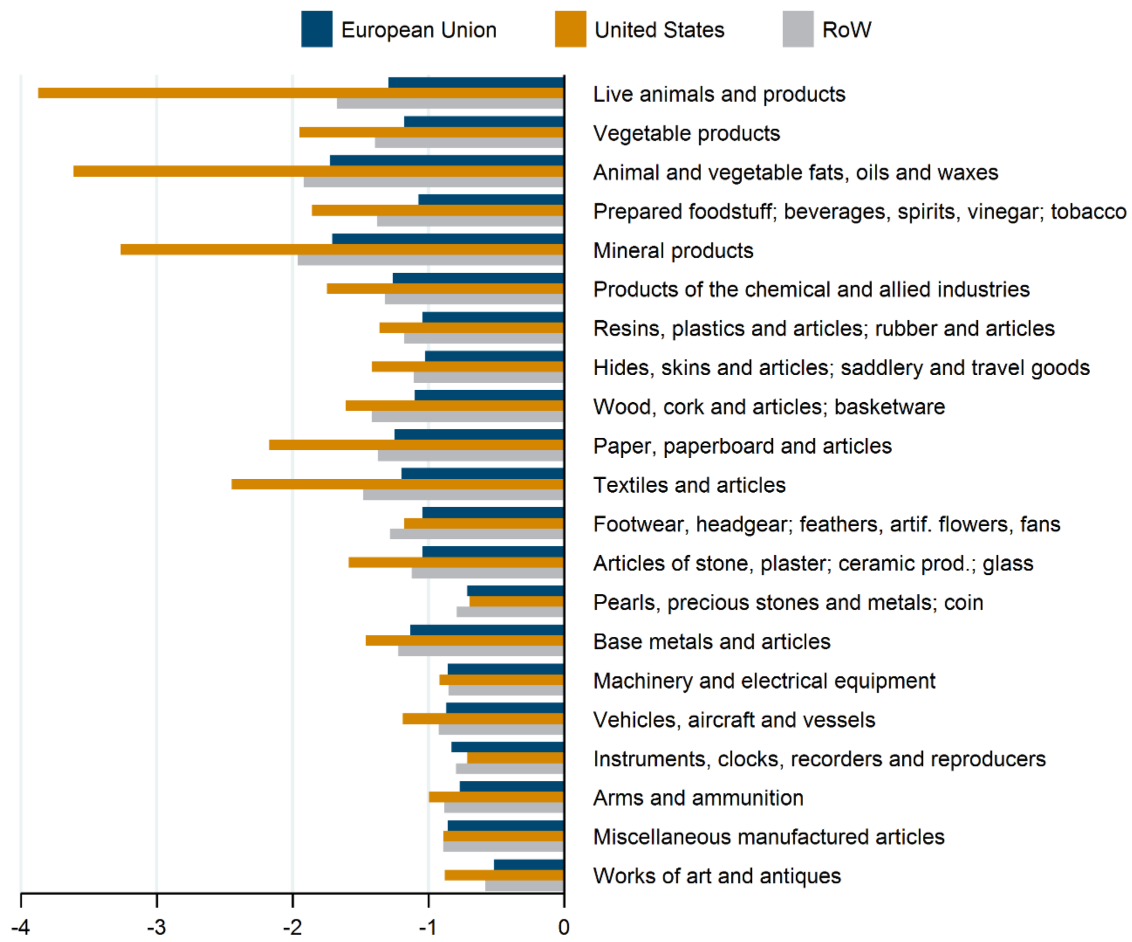
Focusing on import- weighted results, there is a tendency observable that for countries exhibiting an *overall price-elastic* demand, the manufacturing sector is more elastic than the agri-food sector. The top 5 countries with the most elastic total import demand form a very diverse group of countries consisting of the Seychelles, Singapore, Sierra Leone, Congo and Switzerland.

By contrast, for countries for which we estimated an *overall price-inelastic* demand, imports of the agri-food sector seem to be more price-responsive. The bottom 5 countries, for which the least elastic total import demand was estimated, represent countries rich in natural resources – particularly fossil fuels – led by Russia and followed by Venezuela, Australia, Kuwait and Saudi Arabia.

The ranking of elasticities for agri-food products from most elastic to inelastic is led by China, the United States and Argentina with import-weighted elasticities of around -1.04. The lowest import demand elasticities for the agri-food sector were evaluated for Kazakhstan and New Zealand, followed by Kuwait, Saudi Arabia and Australia.

As regressions were run separately for every product at the HS 6-digit level, a natural second step is to look at aggregates for the 21 HS sections, with the first four sections representing the agricultural sector. Binding simple average elasticities per section for the European Union, the United States and the rest of the countries in our sample (RoW) are illustrated in Figure 12.

Figure 12 / Binding simple average elasticities per HS Section



Note: Binding elasticities refer to estimates significantly different from zero at the 10% level.

The graph shows, first, that highest import demand elasticities for all three territories can be attributed to animals, meat and fats, as well as mineral products. Vegetable products and prepared foodstuff show more modest elasticity estimates, comparable with products of the chemical industry. Second, with very few exceptions, import demand of the United States is more elastic than import demand of the European Union. It has to be noted, however, that figures for the EU represent average elasticities over Member States without differentiating between extra- and intra-EU trade. Third, product categories for which import demand is relatively inelastic, i.e. smaller than -1 for every country group, belong to the luxury segment (such as works of arts, peals and precious metals), or concern machinery and electrical equipment and finally arms and ammunition.

Technology seems to be a promising candidate for at least partly explaining this pattern. Using a correspondence table from HS 6-digit products to ISIC 4-digit industries (International Standard Industrial

Classification) we can differentiate our import demand elasticity results for the manufacturing industries with respect to the OECD technology intensity definition as proposed by Hatzichronoglou (1997). Indeed, simple t-tests reveal that distributions of elasticities are significantly different between various technology intensity groups, with more R&D content being associated with lower mean and median elasticities in absolute terms. Some manufactured products, as well as products belonging to the agricultural sector, were not assigned to any technology intensity class (low, medium-low, medium-high or high technology intensity). Median elasticities of these products were found to be not significantly different from median import demand elasticities for low-tech manufacturing products.

A different product classification is adopted for input-output tables, as used by the World Input-Output Database (WIOD[25]) (Timmer et al., 2015). Out of 35 sectors currently included in the WIOD database, our data covers seventeen sectors, as our analysis is restricted to trade in goods and does not include trade in services. Table 6 presents our results split up by these sectors.

Table 6 / Elasticities by WIOD sector

Sector		All Elasticities			Binding Elasticities		
		Simple avg.	Country w.a.	Sector w.a.	Simple avg.	Country w.a.	Sector w.a.
c1	Agriculture, Hunting, Forestry and Fishing	-1.376	-0.946	-0.934	-1.246	-0.959	-0.959
c2	Mining and Quarrying	-1.695	-1.008	-1.011	-1.413	-1.008	-1.012
c3	Food, Beverages and Tobacco	-1.529	-0.953	-0.959	-1.335	-0.970	-0.989
c4	Textiles and Textile Products	-1.411	-0.986	-1.004	-1.310	-0.997	-1.017
c5	Leather, Leather and Footwear	-1.324	-1.000	-0.972	-1.318	-1.042	-0.991
c6	Wood and Products of Wood and Cork	-1.333	-1.005	-0.981	-1.306	-1.025	-0.992
c7	Pulp, Paper, Printing and Publishing	-1.319	-0.942	-0.956	-1.297	-0.956	-0.976
c8	Coke, Refined Petroleum and Nuclear Fuel	-2.347	-1.178	-1.306	-1.876	-1.167	-1.305
c9	Chemicals and Chemical Products	-1.316	-0.929	-0.924	-1.231	-0.947	-0.952
c10	Rubber and Plastics	-0.991	-0.944	-0.944	-1.034	-0.963	-0.967
c11	Other Non-Metallic Mineral	-1.138	-0.967	-0.952	-1.160	-0.980	-0.983
c12	Basic Metals and Fabricated Metal	-1.189	-0.938	-0.953	-1.148	-0.958	-0.987
c13	Machinery, Nec	-0.864	-0.882	-0.862	-0.917	-0.906	-0.895
c14	Electrical and Optical Equipment	-0.817	-0.840	-0.884	-0.851	-0.874	-0.911
c15	Transport Equipment	-0.932	-0.924	-0.928	-0.972	-0.940	-0.945
c16	Manufacturing, Nec; Recycling	-1.054	-0.906	-0.887	-1.032	-0.919	-0.902
c17	Electricity, Gas and Water Supply	-2.649	-2.636	-1.868	-2.035	-2.051	-1.868

Note: Simple avg. refers to the simple average computed over all country-averages per WIOD sector . Country w.a. refers to the simple average over country specific import-weighted elasticities per WIOD sector. Sector w.a. refers to the import-weighted average over country specific import-weighted elasticities. Binding elasticities refer to estimates significantly different from zero at the 10% level.

Independently of the weights employed and whether we consider all estimates or only binding elasticities, the energy sectors, i.e. 'Electricity, Gas and Water Supply' and 'Coke, Refined Petroleum and Nuclear Fuel', surprisingly always appear as the most demand-elastic. Restricting our analysis to HS27 (Mineral fuels, mineral oils and products of their distillation) and considering the pre- and the post-crisis period separately, we do find that demand for goods destined for final consumption was particularly elastic prior to the onset of the global economic crisis. However, it appeared very price-inelastic between 2009 and 2014, even in comparison to mineral products used as intermediate products. Note, however, that the energy sectors are largely covered by statistics on trade in services, which are not covered by our analysis. The results for 'Electricity, Gas and Water Supply' are based on only 118 estimates for two HS 6-digit products for which commodity trade data is available[26]. The sector 'Coke, Refined Petroleum and Nuclear Fuel' is covered by 39 HS 6-digit products and 3,884 estimates. Other WIOD sectors represent on average 378 HS 6-digit products and 47,389 elasticity estimates.

[25] See www.wiod.org

[26] 270500 – Coal Gas, Water Gas, Producer Gas, Similar Gases (Other than Petroleum Gas); 271600 – Electrical Energy.

Simple average elasticities are also high for food, beverages and tobacco, but making use of import weights the sector shifts halfway down the ranking. The sectors for electrical and optical equipment, other machinery and transport equipment feature as the most price-inelastic sectors.

In addition to sectoral classifications, one might expect differences in import demand elasticities with respect to the way they are used in the economy. Imports might be used as (i) final consumption goods, (ii) intermediate goods in the production process of final goods, or (iii) by firms in the form of stocks or gross fixed capital formation (GFCF). This analysis is particularly interesting in today's context of a global trade slowdown, or even '*trade plateau'* (Evenett and Fritz, 2016), and negotiations of mega-regional trade deals in which non-tariff measures play a prominent role. Every year during the period 1995-2014 imports of intermediates represented more than 52% of global imports. The importance of global value chains as exemplified by intermediate goods trade is increasing over time, with only three major setbacks in 1998, in 2009 following the global economic and financial crisis and in 2014. We borrow a correspondence table that links HS 6-digit products to these three broad categories, with about 15% of products being reclassified for the WIOD project to account for the fact that some products qualify for more than one category (e.g. HS 940540 electric lamps and lighting fittings). Table 7 summarises our results for these three categories. It is evident at first sight that intermediate goods face the most elastic demand, followed by final consumption goods, while demand for GFCF goods appears throughout quite price-inelastic. This result remains unchanged when excluding the energy sector[27].

Table 7 / Elasticities by product use

	All elasticities			Binding Elasticities		
Weights	Inter-mediates	Final consumption	GFCF	Inter-mediates	Final consumption	GFCF
Simple avg.	-1.265	-1.175	-0.819	-1.181	-1.135	-0.885
Country w.a.	-0.959	-0.928	-0.858	-0.942	-0.909	-0.844
Product use w.a.	-0.942	-0.904	-0.828	-0.922	-0.878	-0.813

Note: Simple avg. refers to the simple average computed over all country-averages per product category of its use . Country w.a. refers to the simple average over country specific import-weighted elasticities per product category. Product use w.a. refers to the import-weighted average over country specific import-weighted elasticities. Binding elasticities refer to estimates significantly different from zero at the 10% level. GFCF refers to Gross Fixed Capital Formation.

Table 8 summarises our discussion on cross-product differences in import demand elasticities. We find a positive coefficient on a product's share in GDP. Other factors that potentially decrease the price elasticity of demand are (i) the technological intensity of a product, (ii) the number of countries exporting a specific product and (iii) the number of importers of a specific product. One argument would be that technology-intensive products cannot be substituted easily by domestic production. The number of exporting countries per product is a proxy for the possibility to substitute between different exporters. The greater the number of suppliers of a specific product, the easier it is for the importing country to substitute imports between different source countries, leaving the share of a product in per cent of GDP unchanged. The number of importers per product might be an indication of the market power of the exporting country. The greater the number of importers of one specific product per exporter, the smaller an importer's bargaining power and its import demand elasticity.

Negative coefficients are found for the sector dummy, indicating that agri-food products on average face a more elastic import demand. The regression table once more highlights that on average goods contributing to gross fixed capital formation (base line) face the most inelastic demand, followed by final consumption goods and intermediate goods. These findings persist even when fuels (column 3) and products without an assigned technology intensity measure (column 4) are excluded from the regression. Differences in import

[27] WIOD sector c18: Coke, Refined Petroleum and Nuclear Fuel.

demand elasticities across all these variables are statistically significant, but the predictive power of these product characteristics is very limited.

Table 8 / Regression of binding import demand elasticities on product characteristics

	(1)	(2)	(3)	(4)
Product's share in GDP	2.722 **	0.957	1.360	-0.265
	[1.211]	[1.206]	[1.839]	[1.815]
Sector dummy (1 = agri-food)	-0.063 ***	-0.068 ***	-0.084 ***	-0.087 ***
	[0.006]	[0.006]	[0.006]	[0.007]
Number of exporters per product	0.003 ***	0.003 ***	0.003 ***	0.002 ***
	[0.000]	[0.000]	[0.000]	[0.000]
Number of importers per product	0.005 ***	0.005 ***	0.005 ***	0.005 ***
	[0.000]	[0.000]	[0.000]	[0.000]
Low tech	-0.056 ***	-0.058 ***	-0.090 ***	0
	[0.008]	[0.008]	[0.008]	[.]
Medium low tech	0.001	0.006	-0.027 ***	0.047 ***
	[0.009]	[0.009]	[0.009]	[0.005]
Medium high tech	0.035 ***	0.046 ***	0.011	0.085 ***
	[0.008]	[0.008]	[0.008]	[0.005]
High tech	0.221 ***	0.225 ***	0.190 ***	0.270 ***
	[0.010]	[0.010]	[0.010]	[0.007]
Final consumption good	-0.093 ***	-0.095 ***	-0.095 ***	-0.119 ***
	[0.007]	[0.007]	[0.007]	[0.007]
Intermediate good	-0.154 ***	-0.149 ***	-0.150 ***	-0.144 ***
	[0.006]	[0.006]	[0.006]	[0.005]
Constant	-1.884 ***	-1.872 ***	-1.822 ***	-1.974 ***
	[0.015]	[0.015]	[0.015]	[0.016]
Observations	*447,259*	*447,259*	*443,596*	*412,607*
R^2	0.033	0.044	0.043	0.046
Importer fixed effects	No	Yes	Yes	Yes
Fuels excluded	No	No	Yes	Yes
Baseline technology	non-classified	non-classified	non-classified	low

Standard errors in brackets; * p < .10, ** p < .05, *** p < .01; *Fuels referring to HS 2-digit product 27: Mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes.

4.3. Conclusion on re-estimated import demand elasticities

We update the work of Kee et al. (2008) for the more recent period 1996-2014. Improved data availability and the inclusion of products not considered in HS revision 1988 allow us to estimate about twice as many import demand elasticities. The presented results are differentiated by country and product characteristics.

Countries exhibiting the highest average elasticities belong to the economically most important countries in their respective regions, while most countries with the lowest import demand elasticities are small island states. Import-weighted results suggest that especially countries rich in natural resources – particularly fossil fuels – are facing an inelastic import demand, with the agri-food sector for these states being more price-responsive than the manufacturing sector. Europe, too, is characterised by a rather inelastic import demand, particularly for Eastern European countries and the Iberian Peninsula.

Both the European Union and the United States show the highest elasticities for live animals, animal and vegetable fats and mineral products. Inelastic demand is found for luxury goods such as pearls or works of art, machinery and electrical equipment, arms and ammunition and in the case of the EU but not the US for vehicles and aircrafts. Distinguishing between the use of products, it is evident that intermediate goods face the highest elasticities, which appears particularly noteworthy in the context of an increasing importance of global value chains and production fragmentation, the global trade slowdown since 2011 and ongoing negotiations of mega-regional trade deals.

Splitting the period 1995-2014 into a pre- and post-crisis period indicates that after 2008 import demand became more elastic, particularly for intermediate goods. A final specification suggests that allowing the effect of prices on the product composition of GDP to vary by the economic development of countries along the income group classification of the World Bank, suggests that import demand elasticity is U-shaped. The poorest countries seem to be the least price-responsive with respect to imports, while the majority of middle-income countries is centred around unitary elasticity, with richer countries again being less sensitive to price changes.

5. Making NTM types comparable[28]

A way to contrast the effects of NTMs on trade with the impact of tariffs on trade but also to render the effects of different types of NTMs more comparable is to compute the ad valorem equivalents (AVEs) of NTMs, capturing the impact of non-tariff measures on prices. Dean et al. (2009), Kee et al. (2009), Beghin et al. (2015), Cadot and Gourdon (2016) or Bratt (2017) contributed to this branch of literature. Ferrantino (2006) offers a detailed description of methods frequently used to quantify the effects of NTMs on trade flows and prices by NTM type.

One method to calculate AVEs is to analyse the price wedge resulting from the implementation of NTMs, applied e.g. by Dean et al. (2009), Rickard and Lei (2011), Nimenya et al. (2012) or Cadot and Gourdon (2016). The amount of information necessary for this analysis restricts most of the papers to the analysis of very few – mainly agricultural – products for a small set of countries. The papers by Dean et al. (2009) and Cadot and Gourdon (2016) are rather rare exceptions. Another drawback of this method is that domestic prices in the absence of NTMs are not observable. Therefore, domestic prices affected by NTMs are often directly compared to international prices, neglecting the possible impact of differences in product quality. Furthermore, NTMs occur at different stages along the supply chain, which makes a comparison of different prices along the production and distribution chain (e.g. Cost, Insurance and Freight (CIF), Delivered Duty Paid (DDP)) for a single product necessary. In the case of prohibitive NTMs, no prices are observable at all.

The other branch of literature has been triggered by a contribution of Kee et al. (2009), who infer the AVEs of NTMs indirectly in a two-step approach. They assess the impact of NTMs on the imports with a gravity model. The results are then converted to AVEs using import demand elasticities, which are estimated beforehand. The main advantage of the gravity approach in comparison to the price wedge approach is that the former relies on trade data, which are more abundant at the disaggregated product level than price data. In addition, it can be used for broad panel analysis, i.e. for a big set of countries and products, with different NTMs evolving over time. Yet, the indirect approach has drawbacks too. Like the price gap method, this approach does not distinguish the quality of domestic from foreign goods, influencing the impact of NTMs. In addition, AVE calculations are based on import demand elasticities, which are themselves estimates. Acknowledging the advantages and drawbacks of either approach, we aim at contributing to the latter branch of literature.

Kee et al. (2009) find that the average AVE of all products affected by NTMs is 45%, and 32% when weighted by import values. Furthermore, they report a great variation of AVEs across products and countries, with highest AVEs found for agricultural products and for low-income countries in Africa. Importantly, Kee et al. (2009) restricted their AVEs to be positive, i.e. by employing parameter restrictions they forced all NTMs to have only import-restricting effects comparable to tariffs. However, given market imperfections, NTMs can also serve to facilitate trade. Beghin et al. (2015) therefore, re-estimate the gravity approach proposed by Kee et al. (2009) for standard-like NTMs for the years 2001 to 2003, allowing for positive and negative values of AVEs of NTMs. In their analysis, 12% of all products at the HS 6-digit level

[28] An extended version of this chapter was published as: Ghodsi, M., J. Grübler, and R. Stehrer (2016). 'Estimating Importer-Specific Ad Valorem Equivalents of Non-Tariff Measures', wiiw Working Paper wiiw, No. 129, Vienna, September. – The paper and data on estimated AVEs are available online free of charge.

were affected by technical regulations. Out of these, 39% exhibited negative AVEs – i.e. an import-facilitating effect. Bratt (2017) concludes, that overall, NTMs impede rather than facilitate trade, with a median AVE of more than 10%. However, almost half of all AVEs computed show a positive effect on trade. Furthermore, he finds that the effects of NTMs are primarily driven by the NTM imposing importing countries, where AVEs of NTMs are highest for low-income countries for both sectors. In addition, Bratt (2017) highlights that NTMs targeting the food sector are more import-restricting than NTMs in the manufacturing sector.

Previous calculations of AVEs of NTMs (Kee et al., 2009; Beghin et al., 2015 and Bratt, 2017) were conducted on cross sectional data due to lack of information on and variation of NTMs. Having a rich database on NTMs obtained from WTO I-TIP we are extending their approach to a panel analysis. Moreover, and maybe most importantly, previous calculations were not distinguishing NTM types whose diverse attributes by motives would bring various trade consequences. In this chapter, we differentiate major categories of NTMs, which can provide better insights on the implications of the use of different NTMs. In addition, the amount of applied NTMs was not considered in previous studies. Rather, the existence of NTMs was captured by employing dummy variables. Our analysis is based on the intensity of use of NTM types by counting the number of reported NTMs. Finally, we allow the effects of NTMs to differ by the NTM imposing, i.e. importing, country.

Following Kee et al (2009) we make use of the estimates on the impact of NTMs on trade (TE_{ihn}) presented in chapter 3 and estimates of import demand elasticities ($\varepsilon_{\mathrm{ih}}$) discussed in chapter 4 to derive ad-valorem equivalents of different types of non-tariff measures ($\mathrm{AVE}_{\mathrm{ihn}}$).

5.1. Empirical results

We considered two different samples for our analysis. The first sample includes all bilateral import flows of all countries covered by the WTO I-TIP database. The second sample excludes intra-EU trade flows. The reason is that we do observe the number of imposed NTMs per country, but not the degree of heterogeneity in terms of quality of NTMs. As we expect a higher degree of homogeneity of NTMs addressing imports across the EU, including intra-EU trade and therefore a higher number of similar NTMs would lead to a downward bias in our AVE estimation results.

Considering the full sample – 5,221 products at the HS 6-digit level and 118 importers – our investigation results in 616,078 importer-product combinations, for which in 259,721 cases, i.e. roughly 42%, at least one NTM applied between 2002 and 2011.[29] Depending on the specification and after excluding potential outliers, we are able to provide AVE estimates for at least 30% and up to 47% of all importer-product pairs for which at least one NTM was in force and notified to the WTO. Extreme values and potential outliers were dealt with in two steps: First, we dropped the tails of the distribution, by defining the maximum (minimum) values as those values three times the interquartile distance (IQ) above (below) the third (first) quartile of the distribution, i.e. we specify the possible set of AVEs by the interval [Q1-3×IQ;Q3+3×IQ]. Second, we defined the lower bound for negative AVEs at -100%. The rationale behind it is that the domestic price of a product can only be reduced by a maximum of 100%.

5.1.1. AVEs by type of NTM

Table 9 gives a first overview of our AVE results, reporting the mean and median computed over all importer-product combinations for each NTM type. It is grouped into four parts. The left panel shows the results for the full sample, while the right panel reports the results when intra-EU trade flows are excluded

[29] Results on AVEs are currently updated to the period 1995-2014, as has already been done for estimating elasticities. Therefore there is no perfect match between elasticity estimates presented in the previous chapter and elasticity estimates used in this chapter to compute AVEs.

prior to the estimation. The upper part shows summary statistics for all computed AVEs, while the lower part reports only *binding* AVE estimates, meaning that the impact of NTMs on import quantities was statistically different form zero at the 10% level.

Table 9 / Simple average AVEs and tariffs over all importer-product pairs

	Full sample				Excluding intra-EU trade			
	NTM	*Mean*	*Median*	*Obs.*	*NTM*	*Mean*	*Median*	*Obs.*
All	ADP	14.0	23.5	6,031	ADP	13.3	23.4	5,947
	CVD	2.9	10.3	697	CVD	5.5	15.0	692
	QRS	-2.0	0.0	3,922	QRS	-0.8	0.3	3,782
	SG	4.5	3.4	91	SG	2.7	7.1	90
	SSG	0.5	5.3	154	SSG	9.1	16.3	76
	SPS	0.9	0.0	24,481	SPS	2.9	0.3	21,021
	STC(SPS)	-5.2	1.1	3,658	STC(SPS)	-6.2	-0.1	3,645
	TBT	2.7	0.8	54,298	TBT	4.1	2.1	49,356
	STC(TBT)	8.9	16.6	12,112	STC(TBT)	9.1	17.3	11,937
	Tariffs	3.4	1.4	74,617	Tariffs	5.0	3.1	68,532
	AVEs Total			105,444	AVEs Total			96,546
significant impact of NTMs on import quantities (p < 0.1)	ADP	20.8	44.0	4,198	ADP	19.4	43.7	4,133
	CVD	7.0	32.5	479	CVD	9.9	34.6	467
	QRS	0.8	8.6	1,407	QRS	2.5	11.9	1,380
	SG	21.5	46.7	38	SG	14.9	46.8	41
	SSG	14.2	28.4	58	SSG	18.9	34.6	44
	SPS	4.1	1.1	8,374	SPS	8.2	6.4	8,888
	STC(SPS)	-4.7	19.1	2,267	STC(SPS)	-5.9	15.8	2,242
	TBT	8.6	6.8	19,768	TBT	10.8	11.2	21,620
	STC(TBT)	18.9	48.2	7,334	STC(TBT)	19.0	48.5	7,179
	Tariffs	3.4	1.4	43,923	Tariffs	5.0	3.2	37,180
	AVEs Total			43,923	AVEs Total			45,994

Note: Results based on Poisson estimation and elasticity estimates significantly different from zero at the 10% level. Average tariffs computed over all observations with at least one non-zero AVE.

We can observe, first, that the total number of importer-product specific AVEs is reduced by about 8% when we exclude intra-EU trade. However, the number of AVEs, for which a significant effect of NTMs on import quantities was computed, increases by 5%, driven by TBTs (+9%) and SPS measures (+6%). This is the effect we would expect, given that a great share of trade of each EU Member State concerns intra-EU trade for which the same NTMs apply (or are mutually recognised) and therefore should not affect intra-EU trade. Henceforth, we therefore focus on the analysis of AVEs excluding intra-EU trade.

Second, our AVE results are dominated by TBTs, for which we could compute about as many importer-product specific AVEs as for all other NTMs taken together. Average AVEs for TBTs are found to be about one percentage point lower than average tariff rates, while binding AVEs for TBTs are found to be more than twice as large as average tariffs.

Third, AVEs differ greatly between NTM types, with the highest average AVEs found for antidumping measures, followed – with some distance – by TBTs for which specific trade concerns were raised (STC(TBT)) and safeguard measures. Fourth, overall AVEs show positive mean and median values, pointing towards an overall import-impeding effect of NTMs. It has to be kept in mind, though, that counteracting measures are designed to reduce imports. By contrast, SPS measures and TBTs might be (mis-)used as (discriminatory) trade policy tools but primarily aim at improving the quality of products, packaging or the information provided to consumers. Positive AVEs for SPS measures and TBTs therefore not only indicate import-restricting effects but in addition point towards possible quality-increasing effects of NTMs. A split up in positive and negative AVEs reveals that we find 27% more positive AVEs than negative ones, i.e. the share of negative AVEs is roughly 45%. Restricting our view to only binding AVEs, the share of negative AVEs reduces to below 40%. This finding is in line with recent literature, e.g. Beghin et al. (2015) and Bratt (2017), allowing for positive and negative AVEs.

In order to derive policy relevant implications we continue our analysis by exploring AVEs by importer, location and income as well as by product according to the Harmonised System (HS) and broad economic categories (BEC).

5.1.2. AVEs by importer

Different countries apply different types of NTMs. Even the same NTM type can have an import-promoting effect for one country and an import-impeding effect for another. On the one hand, the average AVE per NTM for one specific importer can be influenced by the purpose and quality of the NTM measure imposed. On the other hand, it is influenced by the structure of imports, i.e. the product mix, their price elasticity and the trading partners: First, depending on the structure of the domestic industry, imports of a specific product can be substitutes or complements to domestic production, which influences the impact of NTMs. Second, not every country imports every product. For example, as we shall show later on, our analysis reveals high AVEs for arms and ammunition. If some countries do not import arms and ammunition, their average AVEs are, ceteris paribus, lower than those of countries that do import arms and ammunition.

In the following, we often summarise AVEs for countervailing duties and (special) safeguards under the heading ‘other counteracting measures’ (OCA) as they are all measures reacting to a high import influx and – as reported Table 9 – are small in numbers. In addition, we aggregate AVEs for specific trade concerns on SPS measures and TBTs under the terms STC for reasons of readability.

As SPS measures and TBTs are the predominant NTMs in our data and form the heart of ongoing political discussions, specifically with respect to the formation of deep mega-regional trade agreements such as the Transatlantic Trade and Investment Partnership (TTIP) and the Trans-Pacific Partnership (TPP), we first restrict our attention to the analysis of AVEs computed for these measures.

Trade-weighted AVEs result in 41 countries showing overall import-promoting and 55 countries with import-impeding effects of SPS measures and TBTs. However, if NTMs are indeed trade barriers they would naturally reduce imports. Consequently, using import values as weights for AVEs, we likely underestimate the import-impeding effects of the use of NTMs. When we calculate importer-specific AVEs by using the simple average over all products, 69 countries show import-impeding effects and only 28 countries are left showing overall trade-enhancing effects of SPS measures and TBTs.[30] Yet, imposing no weight on evaluated AVEs does not account for existing import structures of economies and overemphasises the importance of AVEs for certain products. The truth will lie somewhere in between.

Generating country rankings with and without import weights often yield similar results, but it need not necessarily be the case. Considering the sum of import-weighted binding AVEs for SPS measures, TBTs and corresponding STCs we find the highest import restrictions for the Central African Republic, Ecuador and Indonesia. Romania, Bulgaria and Finland are the EU Member States that can be found within the top 20. Yet, the majority of EU members is found halfway down the list. We find the lowest average AVE for SPS measures, TBTs and their corresponding STCs for Bolivia, Barbados and Venezuela. Germany is ranked 5th after Turkey. Also Croatia[31], the Czech Republic and Estonia can be found among the top 20.

[30] Please see the Appendix for a full list of all importers and their simple average country-specific AVEs by NTM type.

[31] Croatia does not feature as an EU member country within our analysis (as it acceded to the EU in 2013 while our analysis is restricted to 2011). Therefore, trade between Croatia and the EU is not excluded from our econometric analysis. In the run up to accession and specifically after signing the Stabilisation and Association Agreement in late 2001, Croatia’s NTMs might have adapted to standards of the EU, which in 2012 was Croatia’s main trading partner absorbing more than 60% of its exports.

In light of ongoing trade negotiations at the European level, it is worth exploring how heterogeneous EU members are with respect to NTMs. If we rank EU members from 1 to 27, with 1 indicating the highest AVEs and 27 representing the lowest AVEs, we find that the rankings are very similar when using simple averages over all products, or when computing simple averages only over products significantly affected by AVEs. In these two cases, the 'new' EU-12 Member States that acceded to the EU in 2004 and 2007 appear more trade restrictive than the 'old' EU-15 Member States, with Malta, Romania and Cyprus representing the Top 3, while the Bottom 3 is formed by EU-15 Member States, namely Germany, Portugal and France. If we impose import weights, we still find Malta and Romania among the Top 5, but also Finland with relatively high AVEs for TBTs. At the end of the list, we again find Germany, this time followed by the Czech Republic and Estonia. When employing import weights, quite some EU-15 members drift towards the centre, e.g. Ireland and the UK, with Slovenia and Slovakia instead taking their place.

Why can AVEs among EU member countries differ? The reasons can be manifold. First, EU Member States indeed differ by the NTMs they employ. Looking at the number of notifications to the WTO in force by 31 May 2015, we find that the share of the sum of notifications of individual EU Member States in per cent of NTMs notified by the EU is close to 5% for SPS measures and 62% for TBTs. EU-12 countries account for 17% and 40%, respectively. There are no national NTMs notified for quantitative restrictions, antidumping and countervailing duties. However, there are more than eight times as many national safeguard measures in place, compared to safeguards notified by the EU. All these notifications by individual EU Member States are attributable to EU-12 members.

Second, countries differ by their economic structure and trade relations, i.e. by the product mix that they import, their price elasticity for imports and their trading partners, which can be driven among other reasons by historical ties, the integration in global value chains or heterogeneous preferences of consumers across the EU. In this paper, we are not going to unravel the Pandora box of intra-EU differences in AVEs. However, we will shed light on how AVEs differ by products, product groups and the use of products as intermediates, consumption goods or gross fixed capital goods.

In order to evaluate the global impact of NTMs, we aggregate our country-based AVE results according to their regional affiliation as laid out in the list of economies provided by the World Bank[32], which comprises 215 countries. The share of each region, in terms of number of countries according to the World Bank's list, resembles the shares of our country sample composition – with the exception that we include a greater proportion of countries in Europe and Central Asia and fewer countries from Sub-Saharan Africa due to data limitations in our NTM data as previously mentioned. Keeping the over-representation of European and Central Asian economies and under-representation of Sub-Saharan African countries in mind, we continue to elaborate patterns of the effects of NTMs by region.

Let us refer to the upper panel of Table 10 as the *'product panel'*. It shows results if we calculate the simple average over all country-specific AVEs, which by themselves constitute simple averages over all traded HS 6-digit products per country. That is, within each country, every product has equal weight, independent from its actual economic importance. It might therefore be regarded as the upper bound of the import effects of NTMs per region. For SPS measures and TBTs, we find the highest AVEs for Sub-Saharan Africa, comparable with tariffs of 10.5% and 6.3%, respectively. It is followed by the regions Europe and Central Asia and East Asia and Pacific. The only region that experiences SPS measures and TBTs on average as trade-promoting is North America. The Middle East and North Africa as well as Europe and Central Asia show high import-hampering AVEs for quantitative restrictions. Considering the sum of binding AVEs for SPS measures, TBTs and QRS, 7 EU member countries feature among the Top 10 and 16 EU member countries in the Top 20, respectively.

One might wonder, why we also report negative AVEs, i.e. trade-promoting effects, for antidumping and other counteracting measures. We can think of three plausible explanations, which we also referred to in

[32] Please refer to Appendix 7 and Appendix 8 for the categorisation of our country sample according to the World Bank List of Economies (July 2015).

chapter 3. The first reason is an econometric issue. It might be that using a one year lag is not sufficient to rule out that we are capturing the effect of predatory export policies (such as dumping or export subsidies) instead of the effect of the measures that aim to counteract these policies (such as antidumping and countervailing duties). The second reason is economic in nature. Counteracting measures target very specific products of very specific exporters. These measures might therefore substantially reduce imports from one destination but simultaneously enable other new exporters to enter the market. A third reason could be the quality adaption of the exporter as a response to the NTM.

Overall, regional AVE results on measures other than SPS and TBT need to be interpreted with greater caution: On the country level, we report binding AVEs of SPS measures and TBTs for 82 and 90 countries, respectively. Other measures are very much limited to North America, Europe and East Asia. We find binding AVEs for antidumping and other counteracting measures for 56 and 51 countries, respectively and in addition binding AVEs for QRS for 36 countries.

Table 10 / Binding AVEs by region

	Region	SPS	TBT	QRS	ADP	OCA	STC
PRODUCT (s.a. over country-specific s.a. AVEs)	Europe & Central Asia	4.4	5.2	20.5	16.7	12.9	14.6
	North America	-0.3	-2.6	.	-2.8	7.0	-5.5
	Latin America & Caribbean	2.8	5.4	4.1	29.3	0.1	5.7
	East Asia & Pacific	3.7	5.6	7.3	3.3	18.4	-10.2
	South Asia	2.4	0.7	.	10.2	100.6	-39.2
	Middle East & North Africa	0.7	6.1	27.2	7.6	27.8	11.0
	Sub-Saharan Africa	10.5	6.3	.	4.5	64.6	44.0
COUNTRY (s.a. over country-specific w.a. AVEs)	Europe & Central Asia	1.1	-0.8	0.0	6.2	1.3	-0.1
	North America	-0.4	-1.5	.	1.8	-0.2	-8.1
	Latin America & Caribbean	-4.1	4.0	-0.3	3.2	-0.8	-0.3
	East Asia & Pacific	4.3	9.6	1.2	3.5	0.1	-5.0
	South Asia	-2.8	-4.3	.	-4.4	0.3	-12.0
	Middle East & North Africa	-2.7	11.2	3.7	2.3	-9.4	2.5
	Sub-Saharan Africa	27.3	34.8	.	-1.3	0.2	34.7
WORLD (iw.a. over country-specific w.a. AVEs)	Europe & Central Asia	0.3	-3.3	-0.6	3.5	-1.2	-3.6
	North America	-0.5	-3.3	.	1.8	0.2	-6.5
	Latin America & Caribbean	0.9	2.4	0.0	2.4	-0.5	18.7
	East Asia & Pacific	-2.0	5.1	-0.1	1.2	0.1	-3.5
	South Asia	-5.1	-8.0	.	-16.3	0.0	-11.7
	Middle East & North Africa	-0.4	11.4	0.1	1.3	-0.3	0.1
	Sub-Saharan Africa	-0.3	2.5	.	-1.1	0.2	1.1

Note: Results are based on Poisson estimation excluding intra-EU trade. s.a. and w.a. refer to simple and import-weighted averages, respectively.

The second panel of Table 10 puts import weights on every product within each country, accounting for economic structures of each importer. Yet, the regional figure is the simple average over all importing countries, i.e. puts equal weight to each importing country. We therefore label this panel the *'country panel'*. In comparison to the *product panel*, we observe a shift towards import-promoting effects. Yet, the import-impeding effects of SPS measures and TBTs prevail for Sub-Saharan Africa as well as for the East Asia and Pacific region. Average AVEs for quantitative restrictions and counteracting measures are drastically scaled down, which is what we expect, given the very nature of these NTM types.

As countries within regions are of different sizes and economic powers, we calculated a third panel, which we refer to as the '*world panel*', in which we apply import weights for each country within a region. That is, more emphasis is given to global players within each region, such as Brazil in Latin America, South Africa in Sub-Saharan Africa, India in South Asia or China and Japan in East Asia, in order to better grasp the current impact of NTMs on a global scale. Even in this case, TBTs appear to be lowering imports in four out of seven world regions on average.

Although more than 50% of the total number of imposed NTMs are attributable to high-income countries, as we have previously seen from the descriptive statistics on the WTO I-TIP data, our estimates of AVEs do not reveal that they are also the most trade-restrictive ones. According to the income group classification of the World Bank, our analysis includes 10 low-income countries, 25 lower-middle-income countries, 30 upper-middle-income countries and 53 high-income countries.Applying the income group classification of the World Bank, Table 11 shows that low-income countries appear to have by far the most restrictive SPS measures and TBTs in place, while AVEs for other NTM types did not apply (or were not reported). By contrast, lower-middle-income countries show the lowest AVEs for SPS measures, and depending on the import weights also for TBTs, but the highest AVEs for other counteracting measures. Upper middle and high-income countries indeed show lower AVEs for SPS measures and TBTs, but also apply a wider range of different trade policy instruments. Although many 'hard' NTMs such as quotas are phasing out due to the regulations of the WTO, quantitative restrictions still seem to be trade restrictive, particularly for upper middle income countries, while antidumping deserves special attention in high income countries.

Table 11 / Binding AVEs by income level

	Income	SPS	TBT	QRS	ADP	OCA	STC
PRODUCT (s.a. over country-specific s.a. AVEs)	Low income	13.6	8.6	.	.	.	.
	Lower middle income	0.5	4.2	.	6.3	52.8	7.2
	Upper middle income	3.3	6.4	12.2	23.1	21.0	8.0
	High income	4.1	4.6	19.1	14.1	5.9	10.1
COUNTRY (s.a. over country-specific w.a. AVEs)	Low income	27.4	58.5	.	.	.	.
	Lower middle income	-5.9	7.2	.	-1.4	4.0	6.8
	Upper middle income	2.0	4.8	0.2	2.5	0.3	2.7
	High income	0.4	1.8	0.2	6.1	-1.0	-2.0
WORLD (w.a. over country-specific w.a. AVEs)	Low income	0.9	18.0	.	.	.	.
	Lower middle income	-3.8	-4.6	.	-13.1	0.3	-9.4
	Upper middle income	-3.0	0.1	0.1	1.2	0.1	2.3
	High income	0.1	-0.4	-0.3	2.5	-0.5	-4.2

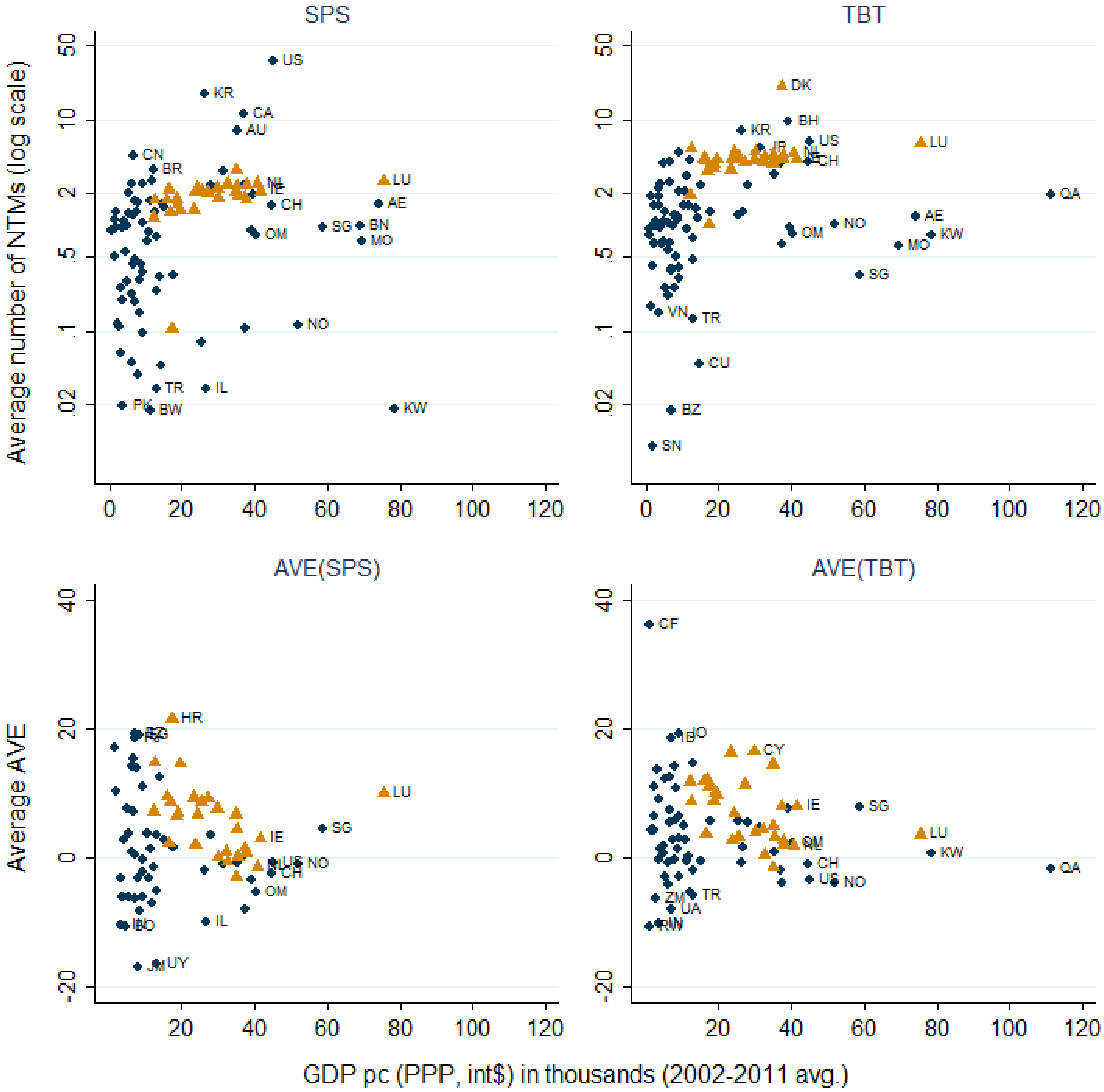
Note: Results are based on Poisson estimation excluding intra-EU trade. s.a. and w.a. refer to simple and import-weighted averages, respectively.

Given its political importance, specifically with respect to multilateral negotiations, we illustrate the linkages between income and (the effect of) NTMs by plotting the number of SPS measures and TBTs imposed as well as their corresponding average AVEs against GDP per capita in purchasing power parities (PPP) in Figure 13. The upper panel summarises the number of NTMs per importer, calculated as the simple average over all imported HS 6-digit products, while the lower panel plots the simple average AVEs.

Looking at the average number of NTMs imposed on imported products, the impression is that it first increases with income and at some threshold starts to fall again. Note that we make use of log scaling in order to better see the dynamics among countries making little use of NTMs so far. This means that jumps from one horizontal line to the next, e.g. from Pakistan to Norway, or from Australia to the United States, indicate a quintupling of NTMs applying to imported products. For EU member countries (highlighted as triangles), a clear tendency towards a higher number of NTMs for richer countries is observable. Extracting the number of notifications to the WTO of NTMs in force by 31 December 2015 (not broken down to country-product lines), we find for eight 'old' EU-15 Member States and one 'new' EU-12 country that no national NTM is notified in addition to those reported by the European Union. The share of NTMs issued by EU-12 states in total national SPS and TBT notifications is 17% and 40%, respectively. The lower number of NTMs for EU-12 countries can therefore be explained by (i) a higher number of national NTMs imposed by EU-15 members in addition to NTMs notified by the EU, (ii) the fact that a wide range of EU SPS measures and TBTs applied to EU-12 countries only from 2004 or 2007 onwards, respectively, and (iii) by the composition of products that are actually imported.

Turning to the lower panel of the graph, showing simple average AVEs by country, one might argue for a trend towards zero AVEs of NTMs. Poorer countries show a wide range of AVEs from strongly negative to strongly positive. Yet, with increasing income, the range of AVEs decreases. For EU members, we do observe a clear downward trend, yet, with most countries showing on average positive AVEs.

Figure 13 / NTMs and binding AVEs of imported products for SPS and TBT over income



Note: Simple averages over HS 6-digit products. Excluding intra-EU trade. Labels are shown for countries forming the Top and Bottom 5% of the distribution and countries whose income over the period 2002-2011 on average exceeds 40,000 international Dollars at PPP p.c. EU members are shown as triangles. Trinidad and Tobago with an average AVE(SPS) of 64.6 and Belize with an average AVE(TBT) of 49.9 were omitted from the graph.

Summing up, we find that using simple averages over all products and excluding intra-EU trade, 62 countries show import-hampering effects of SPS measures, TBTs and corresponding STCs compared to 37 countries for which an import-promoting effect was computed. Focusing on binding AVEs increases the import-restricting effect, which is, however, scaled down to a great extent when employing import weights. The latter can either be the result of import-impeding NTMs imposed on products that are relatively unimportant for international trade or of the effectiveness of NTMs in reducing trade. We therefore argue for looking at simple as well as import-weighted averages of AVEs for broad cross-country comparisons and elaborating policy-relevant differences on a case-by-case basis.

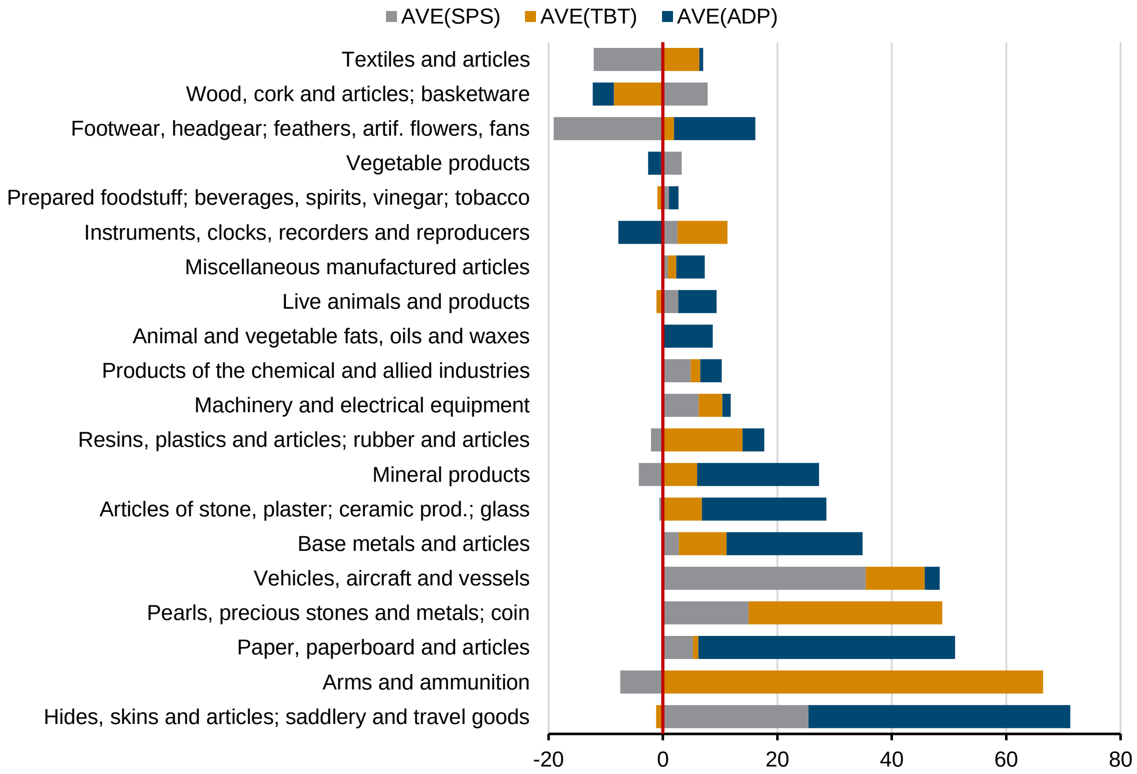
In addition, we observe that richer countries employ a greater variety of NTM types and make more frequently use of these tools, while simultaneously we see diminishing AVEs along increasing incomes. The highest AVEs for SPS measures and TBTs are found among low income countries and are associated with Sub-Saharan Africa. However, the highest AVEs for quantitative restrictions and counteracting measures are found for high income and upper middle income countries, where quantitative restrictions feature prominently in the region Middle East and North Africa, while we should be alarmed about the use of antidumping in Europe and Central Asia.

5.1.3. AVEs by product

In this section, present results of AVEs along the same lines as we discussed trade effects of NTMs in chapter 3. First, we aggregated results to 97 HS 2-digit groups and further to 21 HS sections. In addition, we make use of a correspondence table from HS to BEC constructed for the World Input-Output Database (WIOD[33]) to explore patterns along the types of products with respect to their use as final consumption goods, intermediate goods or goods contributing to gross fixed capital formation.

The highest import-weighted binding AVEs for SPS measures are computed for aircraft and spacecraft (115, HS 88), works of art (71, HS 97) and musical instruments (49, HS 92), and the lowest for railway or tramway locomotives (-100, HS 86), cork and articles thereof (-57, HS 45), and wool (-27, HS 51). On the side of TBTs, arms and ammunition (67, HS 93) face the highest AVEs, followed by aircraft and spacecraft (63, HS 88) as well as printed books and newspapers (58, HS 49), while the lowest AVEs are found for prepared feathers (-80, HS 67), tin and articles thereof (-40.1, HS 80) and headgear (-30, HS 65).

Figure 14 / Simple average by section over country-specific import-weighted binding AVEs



Note: Results based on Poisson estimation excluding intra-EU trade.

[33] See www.wiod.org

Agricultural products appear neither among the products with the highest nor among those with the lowest AVEs. It can be noted however, that with the exception of tobacco, sugar, animal fats and edible vegetables, all agricultural products show on average positive AVEs for SPS measures. For TBTs we find positive effects for half of all agricultural product groups. Live animals face the highest AVEs computed for TBTs and quantitative restrictions. Sugar and dairy products are particularly affected by antidumping. The highest AVEs of specific trade concerns in the agri-food sector are found for tobacco and cereals.

Figure 13 shows our results for binding AVEs by HS section. We first apply import weights by section for each importer and then take the simple average over all importers. We opted for plotting the three most often applied NTM types. The graph strongly points towards import-restricting effects of NTMs, especially for antidumping measures, showing that although notifications of SPS measures and TBTs dominated in our database, less frequently used and more traditional policy instruments still appear to be of great concern.

In order to observe the impact of AVEs along the production and supply chains, we further break down our product level results into the broad economic categories (BEC). We make use of a correspondence table from HS 6-digit products to three broad categories: (i) intermediate goods, (ii) final consumption goods, and (iii) goods contributing to gross fixed capital formation (GFCF). Simple averages, as shown in the first part of the Table 12, refer to the mean of AVEs over all products that (partly) belonged to one BEC category. Import-weighted means – on the importer level and the global level – were derived by multiplying imports by BEC weights and summing up over each BEC category. We thereby account for the average importance of specific HS 6-digit products within each product group over all countries in our sample and for their importance in global trade.

What we learn from this calculation is that the highest AVEs for all types of NTMs are found for products contributing to gross fixed capital formation. Final consumption goods are facing high trade barriers in the form of quantitative restrictions and counteracting measures, but AVEs calculated for SPS measures and TBTs for final consumption goods are very low. Given the importance of global value chains, an in depth analysis of the restrictiveness of antidumping measures and TBTs for trade in intermediates is advisable.

Table 12 / Binding AVEs by BEC/WIOD classification

Total	BEC	SPS	TBT	QRS	ADP	OCA	STC
PRODUCT	Intermediates	11.7	14.8	36.1	27.2	20.9	8.8
(s.a. over country-	Final Consumption	2.1	1.3	31.4	15.4	2.7	4.9
specific s.a. AVEs)	GFCF	31.9	20.8	64.2	34.2	53.6	25.5
COUNTRY	Intermediates	1.4	5.9	-0.2	5.3	0.2	-0.7
(s.a. over country-	Final Consumption	1.0	-1.9	-0.4	1.9	-0.2	-1.3
specific w.a. AVEs)	GFCF	10.8	12.6	1.7	1.5	1.9	2.0
WORLD	Intermediates	-3.6	2.1	-0.1	2.8	-0.5	-1.5
(w.a. over country-	Final Consumption	0.2	-4.9	-1.0	0.3	-0.4	-5.6
specific w.a. AVEs)	GFCF	2.8	1.0	0.8	0.9	0.6	0.6

Note: BEC = Broad Economic Categories; GFCF = Gross Fixed Capital Formation. Results based on Poisson estimation excluding intra-EU trade. s.a. and w.a. refer to simple and import-weighted averages, respectively.

5.2. Conclusion on AVEs of NTMs

Recent literature has started to acknowledge that non-tariff measures need not necessarily be non-tariff barriers. Especially SPS measures and TBTs bear the potential to increase trade. Our analysis confirms that SPS measures and TBTs are found to both impede as well as promote trade, depending on the NTM imposing country and product under consideration.

While we find richer countries to apply more NTMs than poorer countries, we also observe smaller effects of NTMs for richer countries compared to poorer countries. At the product level, we cannot confirm findings of previous studies, which indicated that especially trade in agri-food products is negatively affected by NTMs. Splitting up products according to their purpose of use we find the highest AVEs of NTMs for products contributing to gross fixed capital formation. Given the slowdown of global trade growth and the increasing importance of global value chains, a further in-depth analysis of the restrictiveness of antidumping measures and TBTs for trade in intermediates is advisable.

Finally, positive AVEs for SPS measures and TBTs might point towards the quality-increasing effects of these measures, as they aim at the protection of human, animal and plant life and at guaranteeing quality of packaging and information provided and therefore have implications, which are reaching far beyond the impact on international trade.

6. Effects of NTMs trickling through value chains

Considering global value chains (GVCs), we can track NTMs' traces using measures of backward and forward linkages. Backward linkages thereby refer to a firm's relation with its suppliers, while forward linkages are a firm's relation to its customers, which can be other firms or the final consumer. Diverse impacts of various types of NTMs need to be carefully taken into consideration when studying their role in GVCs. Usually, tariffs and NTMs levied on the first-stage inputs of production exhibit a direct impact on the cost of production. However, heterogeneous effects of NTMs at previous stages of production crossing different borders might affect costs and trade patterns of downstream sectors, i.e. sectors using targeted products as intermediate inputs. Against this backdrop, we study the way sectoral effects of non-tariff measures trickle through GVCs across forty economies in the world and evaluate the role of NTMs in the growth of labour productivity of services and non-services sectors based on WIOD data.

6.1. Non-tariff measures in the context of global value chains (GVCs)

The concept of global value chains (GVCs) stems from the first concepts of classical economics' theory of value by Piero Sraffa (1975) in his book titled 'Production of commodities by means of commodities'. In the 1980s, Hopkins and Wallerstein (1977) elaborated the concept of commodity chains in a research proposal on the modern world system. They described commodity chains as the process in which raw materials, services including transportation, or even food consumed by workers, at any stage of production are transformed to an ultimate consumable item. Later on, Gereffi (1994) established a study framework on global commodity chains (GCC) in a meso or micro perspective. In the research fields of industrial organisation and structural governance the concept changed from global commodity chains to global value chains (see e.g. Porter, 1985). Studies such as Gereffi et al. (2005), and Gereffi and Sturgeon (2013) then used the idea of GVCs for explaining the industrial characteristics and sectoral performances through inter-firm and inter-industry relations.[34]

Decreasing tariffs and the reduction of other trade barriers resulting from international and multilateral trade agreements led to a dominant role of GVCs in the world economy. Offshoring strategies, outsourcing of activities and the global fragmentation of production of goods and services are emerging due to reduced transaction costs resulting from technological developments in recent decades, particularly in the transport sector and the information and communication technology (ICT) industry, with the latter playing an increasingly important role in GVCs (Backer and Miroudot, 2013).

The relevance of GVCs was emphasised more recently in efforts compiling inter-country input-output data, such as the World Input-Output Database (WIOD) by Timmer et al. (2012, 2015), which was recently updated (Timmer et al., 2016). Many scholars have proposed and used frameworks to track the evolution of

[34] For further study on the conceptual evolution of GVC, see Bair (2005).

GVCs based on WIOD data. Antràs et al. (2012) established a framework to calculate upstreamness of sectors as their relative position along GVCs. Using the same methodology and considering the whole world as a single economy, Miller and Temurshoev (2015) find that upstreamness across countries has increased due to trade liberalisation. Moreover, Backer and Miroudot (2013) show that the number of stages within GVCs has increased during the period 1995-2008. In addition, services and manufacturing sectors are becoming more intertwined, and their shares of value-added in each other's value-added are becoming increasingly important in the globalisation process (OECD, 2013).

The interlinked sectors within GVCs can be referred to as network of industries, in which a simple shock, e.g. a change in tariffs or NTMs, in one industry is inducing effects along the GVC. Rouzet and Miroudot (2013) proposed a framework to calculate the cumulative tariffs levied on inputs of a sector. Miroudot et al. (2013) use the same methodology to estimate cumulative tariffs on the inputs of services sectors and thereby track the effects of tariffs on non-services industries on the production and exports of services. They find a downward trend of cumulative tariffs on services sectors for the majority of countries during the years 2000 to 2009 due to trade liberalising WTO commitments. Muradov (2017) also uses this concept to calculate the accumulated tariffs crossing borders.

The relationship between productivity growth and trade openness is also widely studied (e.g. Harrison, 1996; Edwards, 1998; Frankel and Romer, 1999; Rodriguez and Rodrik, 2001). Grossman and Helpman (1993) argued that diffusion of knowledge through imported inputs of production increases the innovative capacities of the importing country and consequently its productivity. Coe et al. (1997) identified channels through which R&D spillovers affect productivity. Among those channels, imports of intermediate inputs and capital goods transfer the inner technology of products produced in a country to another affecting the productivity of the producers in the destination country. In addition to this direct link, scholars found technology spillovers from a third country in the middle of the supply chain, e.g. Lumenga-Neso et al. (2005). Thus, similar to tariff shocks discussed above, it is possible that technology shocks disperse along GVCs. Nishioka and Ripoll (2012) tested the direct and indirect effects of technology spillovers through intermediate inputs based on input-output tables. Using WIOD, Foster-McGregor et al. (2014) found a positive relationship between the growth of the R&D contents of intermediate inputs and labour productivity growth.

Based on the findings, concepts, and methodologies of these branches of literature, we evaluate the effects of NTMs along GVCs, providing bilateral trade restrictiveness indices (BRI) and estimates of the impact of seven types of NTMs on labour productivity growth using WIOD data.

6.2. Methodology

The methodological approach is divided into four stages. At the first stage, bilateral import demand elasticities are estimated, building on the methodology described in chapter 4. Based on insights gained in chapters 3 and 5, we derive bilateral ad-valorem equivalents (AVEs) of NTMs. The third stage provides the calculation of bilateral trade restrictiveness indices (BRIs) that are levied on inputs of production for each sector. The fourth stage then analyses the impact on labour productivity growth.

6.2.1. Bilateral import demand elasticities

This analysis is an extension of our work presented in chapter 4 based on Kee et al. (2008), allowing for bilateral elasticity estimates based on bilateral trade flows at the 6-digit product level of the Harmonized System (HS) as provided in the World Input-Output Database (WIOD) over the period 1995-2009.[35]

[35] Data on socio-economic accounts compatible with WIOD end in 2009.

We remember from Equation (17) in chapter 4 that starting from a flexible GDP function we can derive the share of an imported good h in GDP, which in turn allows estimating import demand elasticities. We modify our strategy for estimating unilateral import demand elasticities by allowing the share of a good to vary by the trading partner, as shown in Equation (24).

$$s_{ijht}(p_{ijht}, p_{ij-ht}, v_{it}) = \alpha_0 + \alpha_{ijh} + \alpha_t + \alpha_h \ln\frac{p_{ijht}}{p_{ij-ht}} + \sum_{m\neq l, m=1}^{M} c_{mht} \ln\frac{v_{mit}}{v_{ilt}} + u_{ijht}, \qquad (24)$$

$$\forall h \in H, \qquad \forall i = 1, \dots, I, \qquad \forall j = 1, \dots, J$$

where s_{ijht} is the share of product h (in WIOD sector W) shipped from country j to country i in terms of the GDP of importing country i at time t. p_{ijht} is the price (unit value) of the imported product. v_{mit} and v_{ilt} refer to factor endowments of labour, capital and agricultural land for production in country i. α_{ijh}, α_t, and u_{ijh}^{t} are country-pair-product fixed effects, time-specific effects, and the error term, respectively. p_{ij-ht} is the Tornqvist price index (Caves et al., 1982) of all other non-h goods $-h$ as described in chapter 4. Adapted to bilateral product shares in GDP it is constructed using the GDP deflator p_{it} of country i at time t as follows:

$$\ln p_{ij-ht} = \frac{(\ln p_{it} - \bar{s}_{ijht} \ln p_{ijht})}{(1 - \bar{s}_{ijht})}, with \ \bar{s}_{ijht} = \frac{(\bar{s}_{ijht} + \bar{s}_{ijht-1})}{2} \qquad (25)$$

In order to increase efficiency, we can estimate Equation (25) by each product h instead of by importer-product ih. This procedure additionally allows for testing the joint significance of price parameters of importers within one single regression. As we are interested in elasticities by importers, we further interact the price indicator $\frac{p_{ijht}}{p_{ij-ht}}$ with importer dummies α_i. Thus, Equation (24) is transformed into the following equation that can be estimated by product h:

$$s_{ijht}(p_{ijht}, p_{ij-ht}, v_{it}) = \alpha_0 + \alpha_{ijh} + \alpha_t + \sum_{i=1}^{I} \alpha_{ih} \ln\frac{p_{ijht}}{p_{ij-ht}} + \sum_{m\neq l, m=1}^{M} c_{mht} \ln\frac{v_{mit}}{v_{ilt}} + u_{ijht}, \qquad \forall h \in H, \qquad (26)$$

For the purpose of calculating accumulated AVEs at a level that allows assessing the effects of backward and forward linkages, we are bound to use the WIOD industry classification in our analysis. Assuming homogeneous functional forms of price parameters for the HS 6-digit products within each WIOD category W, and controlling for their heterogeneity using country-pair-product fixed effects (FE) α_{ijh}, we estimate equation (26) by each WIOD industry encompassing all 6-digit products via the relevant concordance tables. In this sectoral specification, parameters α_{ih} – as many as the number of importers I – are therefore estimated for each sector[36].

As argued in the recent gravity literature (see Head and Mayer, 2014) we need to control for multilateral resistances. This means that the sector-bilateral relationships between two countries can be affected by trade relationships of third countries. Since we do not have data on factor variables at the sector and product level, we additionally include importer-sector-time α_{iH_2t} and exporter-sector-time α_{jH_2t} FE, where sector H_2 is a 2-digit HS code sector comprising its 6-digit traded products. The use of country-specific sector-time fixed effects leads to the exclusion of country-level production factor variables. Therefore, the final equation we estimate becomes:

$$s_{ijht}(p_{ijht}, p_{ij-ht}, v_{it}) = \alpha_0 + \alpha_{iH_2t} + \alpha_{jH_2t} + \alpha_{ijh} + \sum_{i=1}^{I} \alpha_{ih} \ln\frac{p_{ijht}}{p_{ij-ht}} + u_{ijht}, \qquad (27)$$

$$\forall h \in \mathrm{H}$$

[36] Kee et al. (2008) suggested another method to calculate elasticities of sectorial levels using the elasticities from disaggregated product levels. Such sectorial aggregates of elasticities can be provided upon request.

As we do not want our results to be driven by economically small trade flows often linked to infrequent shipments, we exclude trade flows at the 6-digit product level whose value did not exceed 10,000 USD during the period of the analysis. As shown in chapter 4, this restriction indeed leads to a lower number of observations but more consistent elasticity estimates. In order to derive estimates robust to heteroscedasticity – which after controlling for fixed effects arises from bilateral-product shocks over time – we cluster the variance-covariance vectors of the error terms u_{ijh}^{t} by country-pair-products.

By construction, the share of imports in GDP is negative, which gives the import demand elasticity of country i for good h imported from country j derived from its GDP maximizing demand function as follows:

$$\hat{\varepsilon}_{ijh} \equiv \frac{\partial q_{ijht}(p_t, v_t)}{\partial p_{ijht}} \frac{p_{ijht}}{q_{ijht}} = \frac{\widehat{\alpha_{ih}}}{\overline{s_{ijh}}} + \overline{s_{ijh}} - 1, \qquad \forall\, s_{ijh}^{t} < 0; , \qquad \widehat{\varepsilon_{ijh}} \begin{cases} < -1\ if\ \widehat{\alpha_{ih}} > 0 \\ = -1\ if\ \widehat{\alpha_{ih}} = 0 \\ > -1\ if\ \widehat{\alpha_{ih}} < 0 \end{cases} \tag{28}$$

where $\overline{s_{ijh}}$ is the average share of all imports of products within sector W from country j to the importer i in country i's GDP during the period.

6.2.2. Sectoral AVEs of NTMs

Building on our work presented in chapter 5, we use a gravity framework to estimate the impact of seven types of NTMs on bilateral import quantities by WIOD sector. Although trade-weighted averages of the number of NTMs, the effective coverage, or the frequency index of NTMs are regularly used in the literature to derive sectoral numbers for NTMs (Bora et al., 2002; Disdier et al., 2008; Bao and Qiu, 2010) the endogeneity bias induced by trade-weights is a major concern. We therefore opt for regressions by WIOD sector comprising all corresponding 6-digit products traded bilaterally.

The economic literature on NTMs points to the induced effects for users of intermediate products and consumers imported final goods (e.g. Disdier and Marette, 2010; Beghin et al., 2015), which can vary across societies with diverse preferences. Despite a possible increase in prices, NTM-induced quality improvements might increase demand for a targeted product in an importing country where buyers have preferences for higher quality and can afford it. Consequently, countries with similar production technologies and standard-like regulations might still be affected unequally by new NTMs due to different preferences of their users. Therefore, we differentiate the impact of NTMs by importing countries using the importer-interaction terms, similar to our estimation procedure for deriving bilateral import demand elasticities[37] in the previous section. The gravity specification is as follows:

$$\begin{aligned} &\ln(m_{ijht}) \\ &= \beta_{0h} + \beta_{Th} \ln(1 + T_{ijht-1}) + \sum_{i=1}^{I}\sum_{n=1}^{N} \beta_{nih} NTM_{nijht-1} + \beta_C C_{ijkt} + \beta_{iH_2t} + \beta_{jH_2t} + \beta_{ijh} + \mu_{ijht}\ , \\ &\forall h \in \mathrm{H}, \qquad \forall n \in \{ADP, CVD, SG, SSG, QRS, SPS, TBT, STC(TBT), STC(SPS)\} \end{aligned} \tag{29}$$

where $\ln(m_{ijht})$ is the natural logarithm of the import quantity of product h to country i from country j at time t. C_{ijkt} comprises dummy variables indicating whether both trade partners are EU or WTO members in a specific point of time t. β_{ijh}, β_{iH_2t}, and β_{jH_2t} are country-pair-product, importer-sector-time, and exporter-sector-time fixed effects (FE), respectively, introduced to capture multilateral resistances. Using fixed effects results in the exclusion of traditional gravity variables such as GDP, contiguity, or distance from the regression. Estimations are run by each WIOD sector encompassing all corresponded 6-digit traded products, with error terms μ_{ijht} being clustered by the country-pair-products.

[37] Some WIOD sectors comprise a very large number of HS 6-digit products. Therefore, using country-pair interaction terms to differentiate the impact by exporters and importers is not plausible due to computational shortages. Separate estimations could be run by product using interaction terms, resulting in estimates of the bilateral impact of NTMs at the HS 6-digit product level, which can be provided upon request.

Equation (29) incorporates the coefficients capturing the impact of tariffs β_{Th} and the importer-specific impact of non-tariff measures β_{nih} on imports. NTM_{nijht} are stocks[38] (count variables) of the same seven types of NTMs and two sorts of specific trade concerns, which we discussed in previous chapters. For instance, TBT_{ijht} shows the stock of TBTs in force at time t (since 1995)[39] maintained by importing country i on product h against trade partner j. In order to reduce the simultaneity bias of the trade policy measures and the trade flows causing endogeneity, we use a one year lag for tariffs and NTMs in the regression. Due to the mutual recognition principle discussed in chapter 3 we set NTMs for intra-EU trade flows to zero. We estimate Equation (29) nine times (for each NTM type) for each sector. Each time one of the NTMs n is interacted with the importer dummy, whereas the rest of the NTMs are kept as control variables.

Finally, we collect all coefficients of NTMs (β_{nih}) to derive their corresponding AVEs. For this purpose, bilateral import demand elasticities ε_{ijh} from the previous stage are used.:

$$AVE_{nijht} = \frac{1}{\varepsilon_{ijh}} \frac{\partial\, ln(m_{ijh})}{\partial NTM_{nijht-1}} = \frac{e^{\beta_{nih}} - 1}{\varepsilon_{ijh}} \qquad (30)$$

After AVEs for each type of NTM are evaluated, we calculate the bilateral restrictiveness index (BRI_{ijh}) as the summation of AVEs for all trade policy measures τ (i.e. all NTMs and weighted average tariffs during the period 1995-2009) imposed by country i against product h imported from country j.

$$\overline{BRI_{ijh}} = \sum_{\tau} \overline{AVE_{\tau ijh}} \ , \qquad \tau \in \{T, ADP, CVD, SG, SSG, QRS, SPS, TBT, STC(TBT), STC(SPS)\} \qquad (31)$$

where $\overline{AVE_{\tau ijh}}$ stands for the period averaged AVE of trade policy measure τ. The estimation of equation (29) results in the average impact of NTMs during the period. Therefore, we also take the average of annual tariffs over the same period and use it in equation (31).

6.2.3. Cumulative AVEs in GVCs

Following Miroudot et al. (2013) the cumulative AVEs of NTMs and tariffs along GVCs can then be tracked. For notational convenience, denote the various types of AVEs calculated in the previous stage for the period 1995-2009 by τ_{ijh}. Each product h in a given country i is influenced by NTMs through three channels.

The first channel concerns direct trade policies (τ_{1ijh}) that the government of country i imposes on imports of product h from country j. Traditional tariffs and trade-restricting NTMs (i.e. showing positive AVEs) are often implemented to support the domestic industry for product h, by shielding it from foreign competition. However, some quality-enhancing NTMs stimulate imports of products (and thus show negative AVEs) and thereby increase competition in the domestic market. The second channel refers to trade policy measures that a product h in country i is facing at export destination j (τ_{2ijh}).

Finally, the third channel affects intermediate inputs of a given industry h crossing different borders, which is captured by indirect trade policy measures τ_{3ijh}. Trade policies in country i against imports of product h (from country j) affect industries h' using product h in their production process as intermediate input. NTMs might result in higher costs for the industries using targeted products intensively. However, depending on the type of trade policy instrument used, effects can differ across industries due to changes in price and quality of imported inputs along GVC.

In order to calculate τ_{3ijh} we follow Miroudot et al. (2013). The costs for the production of one unit of good h resulting from trade policy τ amount to $\sum_{ks} a_{ksjh}\tau_{1jks}$. $a_{ks,jh}$ denotes the technical coefficient of sector s in

[38] We have also tested a specification only using hits or flows of NTMs going in force rather than stocks of existing NTMs; in another specification using only a dummy variable instead of the number of flows of NTMs. The results of these two specifications stay very close and consistent for many of the products. These results are available upon request.

[39] In the I-TIP NTM database of the WTO, around 92% of notifications entered into force in the year of initiation; around 2% of NTMs entered into force around 18 months after being initiated. Where available we use the information of entry into force; otherwise we refer to the year of initiation.

country k that is used as input in the production of product h in country j. τ_{1jks} is the first channel trade policy τ imposed by country j on the import of industry s from country k.[40] Going one stage back along the GVC, we need to consider trade policies τ imposed on the inputs of the above calculated stage (i.e. the effects on 'inputs of inputs') as $\sum_{xz}\sum_{ks} a_{ksjh}\tau_{1jks}\, a_{xzks}\tau_{1kxz}$, with a_{xzks} representing the amount of sector z in country x used in the production of sector s in country k. Adding up all effects of trade policies τ at previous stages of production, we obtain the required measure of τ_3. Using matrix algebra, this measure can be summarised as follows:

$$\tau_3 = \left[e \times B \times \sum_{n=0} A^n\right]' = [e \times B \times [I - A]^{-1}]' \qquad (32)$$

where A is a $J \times J$ matrix of technical coefficients, e is a row vector of ones, B is a $J \times J$ matrix of element-by-element multiplications of technical coefficients with τ; $B = A{:}\times \tau$ (where $:\times$ denotes element-by-element multiplication). At the end, τ_3 is a column vector indicating the trade cumulative restrictiveness of trade policies levied on inputs of production of each country-sector pair. Technical coefficients are calculated using the Leontief inverse based on the World Input-Output Database (WIOD). The AVEs discussed earlier are estimated for the period 1995-2009. Therefore, the average of technical coefficients over the period, i.e. $A = \frac{1}{15} \times \sum_{t=1995}^{2009} A_t$ is used. As mentioned above, for cumulative bilateral tariffs, we use the import-weighted average bilateral tariffs during the period.

6.3. Results on the cumulative restrictiveness of NTMs along GVCs

Our analysis results in several datasets for the period 1995-2009. First, we provide a dataset on bilateral import demand elasticities estimated at each WIOD industry including all corresponding HS 6-digit products. Second, by estimating the AVEs of NTMs, we have a dataset of direct bilateral AVEs for seven types of NTMs and two sorts of specific trade concerns (STC) notified against 6-digit products within each WIOD industry level imported to a country (τ_{1ijh}). Moreover, the summation of all AVEs and average tariffs within each WIOD industry gives a dataset on bilateral restrictiveness indices BRI_{1ijh} and/or BRI_{2ijh}. Third, using matrix algebra, we construct a dataset of τ_{3ijh} indicating the cumulative restrictiveness of trade policy measures towards inputs for a specific country-sector. Summing up all τ_{3ijh} for a given industry h in country i similar to equation (31) returns the aggregate bilateral restrictiveness index on the inputs of production in the local country-industry (BRI_{3ijh}). The elasticity and direct AVE datasets are only available for manufacturing industries. The dataset on indirect restrictiveness indices is compiled for both services and non-services WIOD sectors using input-output linkages.

6.3.1. Direct trade policy measures

Table 13 presents summary statistics of the AVEs estimated for NTMs imposed on imports. Both positive and negative AVEs are included. On average, all NTMs are trade restrictive, except for SPS measures, TBTs and SSG. For instance, SPS measures on average work as a subsidy or a negative tariff of -0.21%, while TBTs are comparable to a negative tariff of -0.01%. The average AVE of trade restrictive SPS is above 22% while the average AVE of trade enhancing SPS is below 20%. While the number of bilateral sectors facing trade restrictions by TBTs (3,407) is slightly larger than those hampered by SPS (3,300), the average positive AVE of TBT is only about half the magnitude of the average positive AVE of SPS measures. This could indicate that SPS measures lead to bigger price increases of imported products than TBT do.

[40] Note that by definition of trade policy channels $\tau_{1jks} = \tau_{2kjs}$.

Table 13 / AVE statistics on 16 non-services WIOD sectors

τ_{1ijh}	Sample Mean	Mean AVE>0	No. AVE>0	Mean AVE<0	No. AVE<0
SPS	-0.21	22.24	3300	-19.22	4098
STC(SPS)	1.80	85.09	1023	-43.13	935
TBT	-0.01	12.18	3407	-5.51	7594
STC(TBT)	6.81	107.62	3164	-56.08	2928
ADP	20.29	156.49	4804	-72.52	3121
CVD	3.41	107.83	1651	-74.31	1207
QRS	4.38	86.80	2060	-32.80	1992
SG	3.08	114.00	987	-35.28	928
SSG	-0.50	54.72	86	-49.85	355
AHS	4.21				
TRI	43.26	102.98	16199	-61.77	8870

Source: wiiw calculations

While number of bilateral trade flows stimulated by TBTs and SPS measures is larger than the amount of trade flows being hindered by these measures, STCs raised against TBTs and SPS measures show the opposite pattern. The average positive AVE of STCs is substantially large. TBT and SPS are usually unilateral regulations imposed against all trading partners. However, an STC is discriminatory and specific exporters raise concerns against given TBTs or SPS measures. In line with the recent findings in the literature on the restrictiveness of STCs (e.g. Fontagné et al. 2015), we find higher magnitudes for STCs compared to SPS measures and TBTs; however, the results in Table 13 also point towards trade promoting effects. Descriptive statistics of AVE results suggest trade-impeding effects of all other trade policy measures, resulting in a positive average bilateral restrictiveness index (BRI).

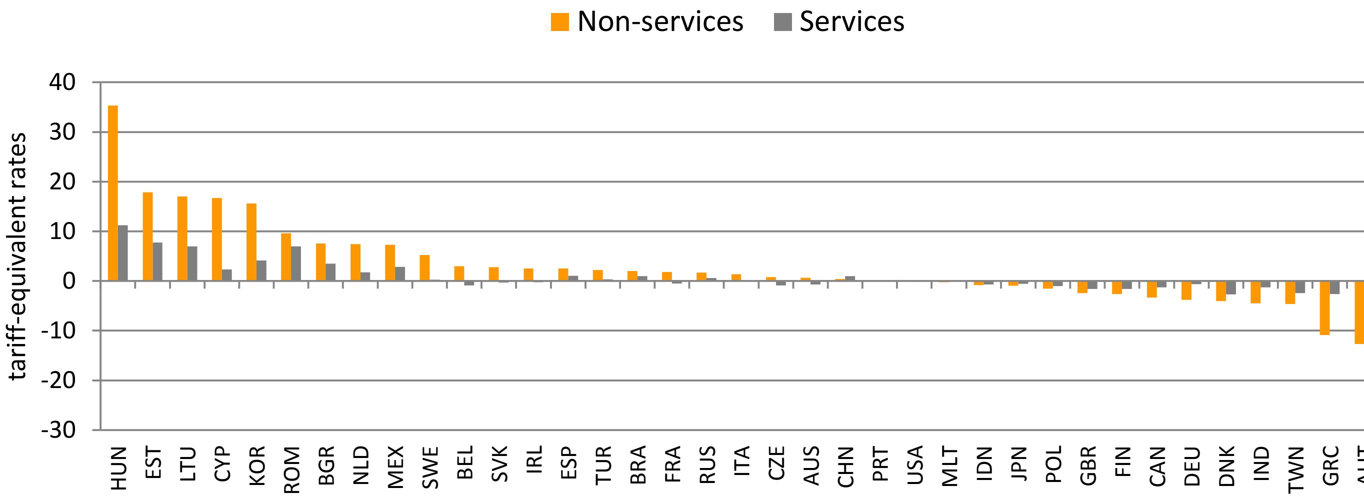
6.3.2. Accumulated trade policy measures

Next, we present indirect bilateral restrictiveness indices (τ_{3ijh}) levied against inputs of production along GVCs expressed in percentages of import prices. These results are country aggregates using simple averages over all sectors. Figure 15 depicts the average BRI_3 (i.e. the summation of AVEs of all trade policy measures) accumulated along previous stages of production of intermediate inputs crossing different borders and used in a given exporting country BRI_3.

Despite positive indirect accumulative tariffs on inputs, average BRI_3 are negative for many countries. This suggests that producers in these countries benefit from trade policy measures that promote the trade of their inputs of production along previous stages of GVC crossing different borders. In fact, the BRI_3 on intermediate inputs of Slovenian exporters of non-services is equivalent to a -15.7% tariff. This means that trade policy measures imposed globally reduced the price of intermediate inputs used in Slovenian non-services sectors by around 15.7% during the period 1995-2009. Slovenia is followed by, Latvia (-13.6%), Luxemburg (-13.2%), Austria (-12.7%), Greece (-10.9%), and Taiwan (-4.6%). It is worth to note that the BRI_3 of global trade policy measures on services inputs for the rest of the world economy (RoW) is -11.2% while on non-services inputs of production it is about -26.2%.

On the other side of the spectrum, Hungarian suppliers incur larger losses for more expensive inputs of both services and non-services sectors due to trade-restrictive policies globally. Normal tariffs induced only around 0.87% accumulated costs crossing different borders during the period 1995-2009 to the Hungarian intermediate inputs of non-services sectors. This suggests that global NTMs induced 34.45% to Hungarian non-services sectors on average, resulting in an average BRI_3 on Hungarian inputs of 35.32%. Following Hungary, the five highest ranked BRI_3 in non-services are found for Estonia (17.9%), Lithuania (17.04%), Cyprus (16.7%), South Korea (15.6%), and Romania (9.6%).

Figure 15 / Country average restrictiveness on imported inputs (BRI_3)



Note: Country ranking by average BRI_3 across all sectors.

No tariffs are levied against trade flows of services. However, service providers are indirectly affected by policy measures imposed against non-services inputs. In general, services are less affected as they do not face direct impacts. For a few economies, service inputs are on average promoted by global trade policy measures, while inputs for the manufacturing industry have become more expensive due to NTMs.

Looking at the effects of the respective trade policy measures accumulated on the inputs of production along GVCs crossing different borders by industry we find that TBTs improve the cost efficiency of intermediate inputs for the production of 'basic metals', 'transport equipment', and 'machinery', showing negative average accumulated AVEs. In addition to these three sectors, SPS measures largely decrease the costs of inputs for the 'pulp and paper' industry. In general, many sectors enjoy benefits of lower costs of intermediate inputs induced by both TBTs and SPS measures. However, fewer sectors are affected by trade promotion induced by STCs raised against TBTs and SPS measures. This indicates the restrictive nature of STCs causing higher trade costs, as referred to in the firm-level study by Fontagné et al. (2015).

An interesting pattern emerges for the upstream sectors enjoying the lowest BRI_3, i.e. trade-promoting effects of NTMs for imported inputs of production, led by the industry for 'coke, petroleum and nuclear fuel'. For 'energy', 'other mineral', and 'mining' sectors we also observe average negative BRI_3, while accumulated tariffs on their inputs T_3 are always increasing the costs of production. 'Inland transport' and 'private households' are the only two services sectors other than 'energy' enjoying lower costs of intermediate inputs due to global trade policy measures imposed on non-services goods.

6.3.3. The impact on labour productivity

The higher cost of intermediate inputs does not necessarily harm production. As argued earlier, NTMs increasing quality along GVC, could result in higher prices, but simultaneously upgrade the quality of the final product or production process, potentially resulting in higher gross output or higher value-added. In this section, the relation between the three outlined channels of NTM transmission and productivity growth is studied.

As discussed above, BRI_3 indicate the extent to which intermediate inputs are affected by global trade policy measures. From a simple Cobb-Douglas production function $Y_{iht} = \Psi_{iht} K_{iht}^{\alpha} L_{iht}^{\alpha}, \Psi > 0, 0 < \alpha < 1$

(where, Y, Ψ, K, and L refer to gross output, productivity (TFP), capital, and labour, respectively), we can obtain labour productivity growth, by taking first differences of the logarithmic labour intensive form :

$$\Delta y_{iht} = \Delta\psi_{iht} + \alpha\Delta k_{iht} \tag{33}$$

where y_{iht} and k_{iht} are logarithmic forms of output to labour (productivity) and capital to labour ratios, respectively, and $\Delta\psi_{iht}$ is the technological progress of industry h in country i at time t, which we hypothesise to be a function of trade policy and the share of high-skilled labour in the given industry $\Delta\psi_{iht} = \gamma_0 TP_{ijht} + \gamma_1 HS_{iht}$.

Since estimated AVEs of NTMs in a given industry are constant over the period, we analyse their impact on period-averaged annual productivity growth. Plugging the hypothesised productivity growth function into equation (33), and using initial productivity levels to account for convergence, we use the following growth model in our econometric analysis:

$$\overline{\Delta y_{ih}} = \beta_0 + \beta_1 y_{ih,95} + \beta_2\overline{\Delta k_{ih}} + \beta_3\overline{HS_{ih}} + \beta_4\overline{BRI_{1ih}} + \beta_5\overline{BRI_{2ih}} + \beta_6\overline{BRI_{3ih}} + \gamma_{ih} + \mu_{ih} \tag{34}$$

where $\overline{BRI_{1ih}} = \overline{\sum_{j=1}^{J}\frac{v_{ijh}^{m}}{\sum_{j=1}^{J}v_{ijh}^{m}}BRI_{ijh}}$ and $\overline{BRI_{2ih}} = \overline{\sum_{j=1}^{J}\frac{v_{ijh}^{x}}{\sum_{j=1}^{J}v_{ijh}^{x}}BRI_{jih}}$

where $\overline{\Delta y_{ih}}$ is the average annual labour productivity growth of industry h in country i from 1995 to 2009, $y_{ih,95}$ is the initial level of productivity in logarithmic form, $\overline{\Delta k_{ih}}$ is the average annual growth of the capital to labour ratio. $\overline{BRI_{1ih}}$ and $\overline{BRI_{2ih}}$ refer to the period averages of first and second channels of trade policy measures discussed before, respectively, which include the summation of all AVEs of NTMs and tariffs targeting imported and exported products. These channels are included in the regression as trade-weighted averages over all bilateral partners for each importing country: v_{ijh}^{m} (v_{ijh}^{x}) are the imports (exports) of industry h from (to) partner j to (from) country i, and J is the total number of trade partners to i. $\overline{BRI_{3ih}}$ refers to the third channel of trade policy (TP) comprising accumulated AVEs of NTMs and tariffs on inputs of industry h in country i during the same period. γ_{ih} denotes a set of industry and/or country-pair specific effects, and μ_{ih} is the error term. We consider two specifications of Equation (34). The first specification includes BRIs as the summation of AVEs for NTMs and tariffs. The second specification uses AVEs of all types of NTMs and tariffs instead of their summations as BRIs for each channel. Since the analysis is performed on cross sectional data, we use normal OLS for the estimation of equation (34) with robust standard errors to correct for possible heteroscedasticity.

6.3.4. Results

We consider services and non-services sectors separately. Due to production linkages, BRI_3 affects intermediate inputs of production of manufacturing sectors as well as services sectors, despite not being directly affected.

Table 14 presents the first specification estimation results. They indicate that there is no statistically significant impact of trade policy measures on productivity growth when including country fixed effects γ_i. However, when we include only sector fixed effects γ_h, trade policy seems to influence labour productivity growth of non-services sectors negatively through the second channel (BRI_2), which is targeting products destined for exports. A non-service industry facing more restrictive measures in a destination market (i.e. characterised by a larger AVE and BRI), experiences lower productivity growth.

When controlling only for sector fixed effects γ_h, productivity growth of services is negatively related to accumulated trade policy measures on imported products used as intermediate inputs in services sectors. Higher costs of intermediate inputs across different countries could result in lower productivity growth of services sectors.

Control variables show the expected effects on productivity growth. Including sector fixed effects γ_h, capturing variations across sectors within a country, we find insignificant coefficients for initial labour productivity in non-services. When including country fixed effects γ_i the initial productivity in non-services sectors turns statistically significant and negative pointing to convergence across countries. Sectors with a larger average share of high-skilled labour HS_{ih} experienced faster productivity growth. Statistically significant positive coefficients on changes of the capital to labour ratio indicate that labour productivity is on average enhanced by capital.

As discussed earlier, different types of trade policy measures have diverse impacts on trade flows for various reasons and consequently affect productivity differently. In Table 15, we present results of the second specification across various types of policy measures. Some of these trade policies do not have any statistically significant impact on labour productivity (at the 10% level of significance). They are therefore not presented in this table.

Controlling for fixed effects, trade-restrictive SPS measures imposed domestically are associated with higher labour productivity growth in terms of gross output. AVEs of SPS measures faced by non-services exporters do not significantly affect productivity growth. While the costs of SPS measures accumulated along previous stages of production do not seem to have an impact on non-services productivity growth, they affect productivity growth of services sectors in all specifications. In other words, the higher the AVEs for SPS measures on the inputs of production, the higher is the productivity growth in services.

TBTs imposed domestically affect productivity growth of non-services sectors. Controlling for both country and sector fixed effects, AVEs of TBTs accumulated on trade of commodities across borders, significantly reduce labour productivity growth in terms of value-added in service sectors, while not showing statistically significant effects on productivity growth in gross output of services, or in non-services.

When a non-service sector faces a STC(TBT) of the destination market with large AVEs, faster productivity growth in both value-added and gross output is observed when controlling for country-fixed effects. However, controlling for only sector-specific effects, additional costs on intermediate inputs induced by STC(TBT) along backward linkages of GVCs result in lower productivity growth in both services and non-services sectors. Effects of STC(SPS) transmitted via the third channel of imported intermediate inputs are similar to those of STC(TBT).

Accounting for sector-specific effects, antidumping (ADP) faced by non-service sectors is associated with higher productivity growth across different countries. However, when the costs of ADP are accumulated crossing borders in previous stages of GVC, this trade policy measure reduces the productivity growth in all sectors when controlling for both sector and country fixed effects,. Antidumping duties are implemented to counter the artificially low price of an exporting company. The results suggest that when an intermediate input becomes more expensive due to ADP, labour productivity of the sector goes down.

Excluding country fixed effects, non-services sectors protected by imposed countervailing duties (CVD) show lower productivity growth. However, effects of CVD accumulated along previous stages of production are associated with higher productivity growth. Usually CVD are imposed to counter export subsidies. An intermediate input that was first subsidised but subsequently targeted by CVD increases the productivity of the importing sector.

Regarding the transmission of trade policy effects via imported intermediates, quantitative restrictions (QRS) seem to have similar effects on productivity growth as CVD when controlling only for sector fixed effects. However, when only country fixed effects are included, the impact of trade costs of QRS accumulated on backward linkages of GVC are correlated with lower productivity growth in services sectors across different countries. Safeguards (SG) and special safeguards (SSG) do not exhibit any statistically significant impact through direct channels, i.e. (S)SG imposed on imported or exported goods. One reason could be that they are designed to protect domestic industries temporarily and should not influence long-run productivity growth of sectors. However, when the costs of these measures are accumulated along GVCs, results suggest that they might influence productivity growth. Tariffs, as traditional trade policy tool, have a direct negative influence on productivity growth of the protected sector in all specifications. In particular, the burden of higher costs resulting from tariffs accumulated on their intermediate inputs is manifested in lower productivity growth.

6.4. Conclusions on the importance of NTMs in global value chains

In this chapter, we presented a framework to quantify effects of NTMs on prices and quality along global value chains. In a multi-step procedure, we estimate (i) bilateral import demand elasticities using detailed 6-digit bilateral trade flows, and (ii) bilateral ad-valorem equivalents (AVE) of seven types of NTMs and two forms of specific trade concerns (STC) notified to the WTO. These were used to derive (iii) cumulative indirect bilateral-trade restrictiveness indices (BRI_3) for inputs of production using WIOD and to evaluate (iv) the impact on labour productivity growth.

Results point towards a positive impact of SPS regulations further up the value chain on the performance of services sectors. In addition, non-service sectors protected by SPS measures enjoy higher labour productivity growth with respect to gross output. The opposite is observed in the case of trade costs associated with TBTs. Finally, the diverse effects of different types of NTMs are in line with the existing literature on complexity of NTMs as trade policy tools.

Table 14 – Three BRI channels' impact on productivity growth

Sectors:	**Non-services**						**Services**					
Dep. Var.:	$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$			$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$		
$y_{ih,95}$	-0.018***	-0.0005	-0.019***	-0.0060*	0.0027	-0.016***	-0.0042**	0.0086**	-0.019***	-0.00077	0.012***	-0.018***
	(0.0032)	(0.0033)	(0.0047)	(0.0035)	(0.0032)	(0.0046)	(0.0019)	(0.0035)	(0.0041)	(0.0019)	(0.0028)	(0.0033)
$\overline{HS_{ih}}$	0.17***	0.37***	0.16***	0.10**	0.35***	0.10**	-0.020***	0.18***	0.020	-0.030***	0.18***	0.022
	(0.042)	(0.045)	(0.046)	(0.045)	(0.044)	(0.044)	(0.0076)	(0.027)	(0.016)	(0.0082)	(0.027)	(0.017)
$\overline{\Delta k_{ih}}$	0.14***	0.14***	0.15***	0.11***	0.11***	0.11***	0.13**	0.17***	0.089*	0.12***	0.15***	0.077***
	(0.026)	(0.037)	(0.026)	(0.034)	(0.040)	(0.039)	(0.050)	(0.062)	(0.050)	(0.027)	(0.038)	(0.023)
$\overline{BRI_{1ih}}$	0.00000034	-0.000057	-0.000011	-0.0000030	-0.000069	-0.000025						
	(0.000023)	(0.000053)	(0.000023)	(0.000025)	(0.000055)	(0.000023)						
$\overline{BRI_{2ih}}$	0.000017	0.000048***	0.0000094	0.000012	0.000050***	0.0000063						
	(0.000014)	(0.000013)	(0.000013)	(0.000014)	(0.000014)	(0.000011)						
$\overline{BRI_{3ih}}$	-0.00024	-0.00032	-0.00031	-0.00018	-0.00022	-0.00010	-0.00020	-0.0029***	0.000070	-0.00058	-0.0029***	-0.00021
	(0.00024)	(0.00024)	(0.00024)	(0.00027)	(0.00025)	(0.00025)	(0.00049)	(0.00065)	(0.00046)	(0.00049)	(0.00066)	(0.00046)
N	632	632	632	632	632	632	710	710	710	710	710	710
R^2	0.827	0.182	0.842	0.797	0.170	0.826	0.798	0.149	0.844	0.779	0.185	0.847
adj. R^2	0.814	0.154	0.826	0.782	0.141	0.808	0.785	0.122	0.829	0.765	0.159	0.832
AIC	-2,487.3	-1,505.3	-2,546.1	-2390.8	-1500.2	-2487.2	-2735.6	-1713.5	-2916.0	-2683.2	-1756.5	-2943.1
BIC	-2,460.6	-1,478.6	-2,519.4	-2364.1	-1473.5	-2460.5	-2717.4	-1695.3	-2897.8	-2664.9	-1738.2	-2924.8
γ_i	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
γ_h	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Robust standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 15 / Direct and Indirect Policy Measures Impact on Productivity Growth

Sectors:	**Non-services**						**Services**					
Dep. Var.:	$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$			$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$		
$y_{ih,95}$	-0.020***	-0.013***	-0.020***	-0.011***	-0.0076**	-0.019***	-0.0050***	-0.000085	-0.019***	-0.0018	0.0050	-0.018***
	(0.0034)	(0.0039)	(0.0047)	(0.0034)	(0.0036)	(0.0048)	(0.0019)	(0.0043)	(0.0043)	(0.0019)	(0.0033)	(0.0033)
$\overline{HS_{ih}}$	0.16***	0.38***	0.16***	0.11**	0.35***	0.11**	-0.020**	0.16***	0.021	-0.026***	0.16***	0.025
	(0.042)	(0.043)	(0.047)	(0.043)	(0.041)	(0.045)	(0.0078)	(0.026)	(0.016)	(0.0084)	(0.026)	(0.017)
$\overline{\Delta k_{ih}}$	0.14***	0.14***	0.14***	0.10***	0.11***	0.11***	0.12**	0.15**	0.090*	0.12***	0.14***	0.078***
	(0.027)	(0.034)	(0.026)	(0.036)	(0.041)	(0.039)	(0.050)	(0.062)	(0.051)	(0.027)	(0.039)	(0.023)
$\overline{SPS_{1ih}}$	0.00018	0.00038	0.00013	0.00031**	0.00055**	0.00024*						
	(0.00013)	(0.00025)	(0.00014)	(0.00014)	(0.00025)	(0.00014)						
$\overline{TBT_{1ih}}$	-0.000054	-0.000010	-0.000058	-0.00013*	-0.000075	-0.00013*						
	(0.000063)	(0.00012)	(0.000061)	(0.000075)	(0.00014)	(0.000068)						
$\overline{TBTSTC_{1ih}}$	0.00085	0.0011*	0.00086	0.0012	0.0015	0.0013						
	(0.00053)	(0.00066)	(0.00055)	(0.0010)	(0.0011)	(0.00097)						
$\overline{CV_{1ih}}$	-0.000052	-0.00036***	-0.000066	-0.000039	-0.00036***	-0.000072						
	(0.000063)	(0.00011)	(0.000067)	(0.000071)	(0.00011)	(0.000076)						
$\overline{T_{1ih}}$	-0.0011***	-0.0028***	-0.0012**	-0.0013***	-0.0027***	-0.0013**						
	(0.00040)	(0.00097)	(0.00047)	(0.00048)	(0.0010)	(0.00056)						
$\overline{SPS_{2ih}}$	0.00017	-0.00017	0.00040	0.00055*	-0.00029	0.00033						
	(0.00028)	(0.00067)	(0.00031)	(0.00032)	(0.00067)	(0.00030)						
$\overline{TBTSTC_{2ih}}$	0.00011**	0.00011	0.000097**	0.00011*	0.00010	0.000096*						
	(0.000057)	(0.000081)	(0.000049)	(0.000060)	(0.000085)	(0.000051)						
$\overline{ADP_{2ih}}$	-0.0000026	0.000037***	-0.000010	-0.0000074	0.000042***	-0.0000078						
	(0.0000099)	(0.000014)	(0.0000083)	(0.000012)	(0.000016)	(0.0000084)						
$\overline{CV_{2ih}}$	0.00022**	0.00010	0.00014	0.00018	0.000097	0.00010						
	(0.00011)	(0.00026)	(0.00011)	(0.00011)	(0.00025)	(0.00012)						
$\overline{T_{2ih}}$	-0.00016	-0.0034***	-0.0011	-0.00030	-0.0031**	-0.00086						
	(0.00061)	(0.0013)	(0.00081)	(0.00067)	(0.0013)	(0.00090)						

Sectors:	Non-services						Services					
Dep. Var.:	$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$			$\overline{\Delta y_{ih}^{VA}}$			$\overline{\Delta y_{ih}^{GO}}$		
$\overline{TBT_{3ih}}$	-0.0013	-0.0055	-0.00066	-0.00086	-0.0034	0.00020	-0.0060	-0.011*	-0.0084**	0.0017	-0.0036	-0.0012
	(0.0023)	(0.0043)	(0.0026)	(0.0025)	(0.0041)	(0.0026)	(0.0041)	(0.0065)	(0.0033)	(0.0048)	(0.0061)	(0.0039)
$\overline{SPS_{3ih}}$	-0.0010	0.00047	-0.00082	-0.0015	-0.00049	-0.0012	0.0049***	0.010**	0.0046**	0.0028*	0.0074*	0.0028*
	(0.00089)	(0.0015)	(0.00094)	(0.0010)	(0.0015)	(0.0010)	(0.0017)	(0.0044)	(0.0020)	(0.0015)	(0.0040)	(0.0015)
$\overline{TBTSTC_{3ih}}$	-0.000019	-0.0023***	-0.000036	0.00077	-0.0017**	0.00063	0.0017	-0.0035***	0.0014	0.0014	-0.0035**	0.00095
	(0.00051)	(0.00061)	(0.00050)	(0.00064)	(0.00072)	(0.00061)	(0.0011)	(0.0013)	(0.00096)	(0.0011)	(0.0014)	(0.00096)
$\overline{SPSSTC_{3ih}}$	-0.00057	-0.0040*	-0.00094	-0.000066	-0.0047**	-0.00044	-0.00077	-0.024***	0.0019	0.0028	-0.018**	0.0060*
	(0.0015)	(0.0022)	(0.0016)	(0.0015)	(0.0022)	(0.0016)	(0.0034)	(0.0084)	(0.0032)	(0.0040)	(0.0084)	(0.0032)
$\overline{ADP_{3ih}}$	-0.00070	-0.00024	-0.00095*	-0.0011**	-0.00018	-0.00095*	-0.0017**	-0.0044***	-0.00061	-0.0027***	-0.0049***	-0.0014*
	(0.00052)	(0.00064)	(0.00054)	(0.00051)	(0.00064)	(0.00054)	(0.00068)	(0.0012)	(0.00052)	(0.0010)	(0.0014)	(0.00075)
$\overline{CV_{3ih}}$	0.00088*	0.0035***	0.00055	0.00092	0.0033***	0.00068	-0.00025	0.013***	-0.0022	-0.00063	0.012***	-0.0030*
	(0.00046)	(0.00071)	(0.00046)	(0.00059)	(0.00076)	(0.00057)	(0.0015)	(0.0032)	(0.0015)	(0.0017)	(0.0032)	(0.0018)
$\overline{QR_{3ih}}$	-0.00084	0.0019*	-0.00026	-0.0011	0.0017*	-0.00043	-0.0046***	0.0063*	-0.0016	-0.0051**	0.0069**	-0.0017
	(0.00068)	(0.00099)	(0.00072)	(0.00071)	(0.00100)	(0.00073)	(0.0017)	(0.0036)	(0.0019)	(0.0024)	(0.0033)	(0.0019)
$\overline{SG_{3ih}}$	-0.00040	-0.0071***	-0.0011	0.00016	-0.0062**	-0.00063	-0.0075**	-0.040***	-0.0052	-0.0041	-0.036***	-0.0021
	(0.0012)	(0.0026)	(0.0012)	(0.0013)	(0.0026)	(0.0013)	(0.0033)	(0.012)	(0.0036)	(0.0038)	(0.012)	(0.0042)
$\overline{SSG_{3ih}}$	-0.0080	-0.024	-0.0055	-0.0050	-0.027	-0.0040	0.0018	-0.038***	-0.0060*	0.010***	-0.033***	-0.00060
	(0.0081)	(0.015)	(0.0086)	(0.0066)	(0.018)	(0.0071)	(0.0032)	(0.0096)	(0.0034)	(0.0030)	(0.010)	(0.0036)
$\overline{T_{3ih}}$	0.0021	-0.0092*	0.00049	0.0064*	-0.0060	0.0043	-0.0037	-0.032***	-0.0022	0.0046	-0.020**	0.0088
	(0.0027)	(0.0052)	(0.0033)	(0.0034)	(0.0053)	(0.0037)	(0.0052)	(0.011)	(0.0065)	(0.0062)	(0.0099)	(0.0067)
N	632	632	632	632	632	632	710	710	710	710	710	710
R^2	0.838	0.315	0.852	0.817	0.284	0.837	0.805	0.252	0.847	0.787	0.272	0.850
adj. R^2	0.817	0.259	0.828	0.794	0.225	0.811	0.789	0.218	0.830	0.770	0.239	0.834
AIC	-2473.5	-1564.0	-2530.0	-2402.1	-1539.8	-2475.9	-2740.7	-1787.4	-2914.8	-2690.1	-1818.5	-2940.7
BIC	-2326.7	-1417.1	-2383.2	-2255.3	-1393.0	-2329.1	-2681.3	-1728.1	-2855.4	-2630.8	-1759.1	-2881.4
γ_i	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
γ_h	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Robust standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

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Appendix

Appendix 1 / Description of HS sections

Sections	*HS 2-digit (rev.2002)*	*Product group description*
I	HS 01-05	Live animals and products
II	HS 06-14	Vegetable products
III	HS 15-15	Animal and vegetable fats, oils and waxes
IV	HS 16-24	Prepared foodstuff; beverages, spirits, vinegar; tobacco
V	HS 25-27	Mineral products
VI	HS 28-38	Products of the chemical and allied industries
VII	HS 39-40	Resins, plastics and articles; rubber and articles
VIII	HS 41-43	Hides, skins and articles; saddlery and travel goods
IX	HS 44-46	Wood, cork and articles; basketware
X	HS 47-49	Paper, paperboard and articles
XI	HS 50-63	Textiles and articles
XII	HS 64-67	Footwear, headgear; feathers, artif. flowers, fans
XIII	HS 68-70	Articles of stone, plaster; ceramic prod.; glass
XIV	HS 71-71	Pearls, precious stones and metals; coin
XV	HS 72-83	Base metals and articles
XVI	HS 84-85	Machinery and electrical equipment
XVII	HS 86-89	Vehicles, aircraft and vessels
XVIII	HS 90-92	Instruments, clocks, recorders and reproducers
XIX	HS 93-93	Arms and ammunition
XX	HS 94-96	Miscellaneous manufactured articles
XXI	HS 97-97	Works of art and antiques

For details see: http://unstats.un.org/unsd/tradekb/Knowledgebase/HS-Classification-by-Section

Appendix 2 /Regional classification of countries

East Asia & Pacific

1	AU	Australia
2	BN	Brunei Darussalam
3	KH	Cambodia
4	CN	China
5	HK	China, Hong Kong SAR
6	MO	China, Macao SAR
7	FJ	Fiji
8	ID	Indonesia
9	JP	Japan
10	MY	Malaysia
11	MN	Mongolia
12	MM	Myanmar
13	NZ	New Zealand
14	PH	Philippines
15	KR	Republic of Korea
16	SG	Singapore
17	TW	Taiwan
18	TH	Thailand
19	VN	Viet Nam

Europe & Central Asia

20	AL	Albania
21	AM	Armenia
22	AT	Austria
23	AZ	Azerbaijan
24	BY	Belarus
25	BE	Belgium
26	BA	Bosnia and Herzegovina
27	BG	Bulgaria
28	HR	Croatia
29	CY	Cyprus
30	CZ	Czech Republic
31	DK	Denmark
32	EE	Estonia
33	FI	Finland
34	FR	France
35	GE	Georgia
36	DE	Germany
37	EL	Greece
38	HU	Hungary
39	IS	Iceland
40	IE	Ireland
41	IT	Italy
42	KZ	Kazakhstan
43	KG	Kyrgyzstan
44	LV	Latvia
45	LT	Lithuania
46	LU	Luxembourg
47	ME	Montenegro
48	NL	Netherlands
49	NO	Norway
50	PL	Poland
51	PT	Portugal
52	MD	Republic of Moldova
53	RO	Romania
54	RU	Russian Federation
55	RS	Serbia
56	SK	Slovakia
57	SI	Slovenia
58	ES	Spain
59	SE	Sweden
60	CH	Switzerland

Europe & Central Asia (ctd.)

61	MK	TFYR of Macedonia
62	TR	Turkey
63	UA	Ukraine
64	UK	United Kingdom

Latin America & Caribbean

65	AG	Antigua and Barbuda
66	AR	Argentina
67	AW	Aruba
68	BS	Bahamas
69	BB	Barbados
70	BZ	Belize
71	BO	Bolivia
72	BR	Brazil
73	CL	Chile
74	CO	Colombia
75	CR	Costa Rica
76	DM	Dominica
77	DO	Dominican Republic
78	EC	Ecuador
79	SV	El Salvador
80	GD	Grenada
81	GT	Guatemala
82	HN	Honduras
83	JM	Jamaica
84	MX	Mexico
85	MS	Montserrat
86	NI	Nicaragua
87	PA	Panama
88	PY	Paraguay
89	PE	Peru
90	KN	Saint Kitts and Nevis
91	LC	Saint Lucia
92	VC	St. Vincent and the Grenadines
93	SR	Suriname
94	TT	Trinidad and Tobago
95	TC	Turks and Caicos Islands
96	UY	Uruguay
97	VE	Venezuela

Middle East & North Africa

98	DZ	Algeria
99	BH	Bahrain
100	DJ	Djibouti
101	EG	Egypt
102	IR	Iran
103	IL	Israel
104	JO	Jordan
105	KW	Kuwait
106	LB	Lebanon
107	MT	Malta
108	MA	Morocco
109	OM	Oman
110	QA	Qatar
111	SA	Saudi Arabia
112	PS	State of Palestine
113	SY	Syrian Arab Republic
114	TN	Tunisia
115	AE	United Arab Emirates
116	YE	Yemen

North America

117	BM	Bermuda
118	CA	Canada
119	US	United States

South Asia

120	BD	Bangladesh
121	BT	Bhutan
122	IN	India
123	MV	Maldives
124	NP	Nepal
125	PK	Pakistan
126	LK	Sri Lanka

Sub-Saharan Africa

127	BJ	Benin
128	BW	Botswana
129	BF	Burkina Faso
130	BI	Burundi
131	CV	Cabo Verde
132	CM	Cameroon
133	CF	Central African Republic
134	TD	Chad
135	KM	Comoros
136	CG	Congo
137	CI	Côte d'Ivoire
138	ET	Ethiopia
139	GA	Gabon
140	GM	Gambia
141	GH	Ghana
142	GN	Guinea
143	GW	Guinea-Bissau
144	KE	Kenya
145	LS	Lesotho
146	MG	Madagascar
147	MW	Malawi
148	ML	Mali
149	MR	Mauritania
150	MU	Mauritius
151	MZ	Mozambique
152	NA	Namibia
153	NE	Niger
154	NG	Nigeria
155	RW	Rwanda
156	ST	Sao Tome and Principe
157	SN	Senegal
158	SC	Seychelles
159	SL	Sierra Leone
160	ZA	South Africa
161	SD	Sudan (Former)
162	SZ	Swaziland
163	TG	Togo
164	TZ	Tanzania
165	UG	Uganda
166	ZM	Zambia
167	ZW	Zimbabwe

Note: World Bank list of economies (July 2015), Montserrat not classified by the World Bank. Information on West Bank and Gaza used for Palestine.

Appendix 3 / Income classification of countries

Low Income

1	BJ	Benin
2	BF	Burkina Faso
3	BI	Burundi
4	KH	Cambodia
5	CF	Central African Republic
6	TD	Chad
7	KM	Comoros
8	ET	Ethiopia
9	GM	Gambia
10	GN	Guinea
11	GW	Guinea-Bissau
12	MG	Madagascar
13	MW	Malawi
14	ML	Mali
15	MZ	Mozambique
16	NP	Nepal
17	NE	Niger
18	RW	Rwanda
19	SL	Sierra Leone
20	TG	Togo
21	TZ	Tanzania
22	UG	Uganda
23	ZW	Zimbabwe

Lower middle income

24	AM	Armenia
25	BD	Bangladesh
26	BT	Bhutan
27	BO	Bolivia
28	CV	Cabo Verde
29	CM	Cameroon
30	CG	Congo
31	CI	Côte d'Ivoire
32	DJ	Djibouti
33	EG	Egypt
34	SV	El Salvador
35	GE	Georgia
36	GH	Ghana
37	GT	Guatemala
38	HN	Honduras
39	IN	India
40	ID	Indonesia
41	KE	Kenya
42	KG	Kyrgyzstan
43	LS	Lesotho
44	MR	Mauritania
45	MA	Morocco
46	MM	Myanmar
47	NI	Nicaragua
48	NG	Nigeria
49	PK	Pakistan
50	PH	Philippines
51	MD	Republic of Moldova

Lower middle income (ctd.)

52	ST	Sao Tome and Principe
53	SN	Senegal
54	LK	Sri Lanka
55	PS	State of Palestine
56	SD	Sudan (Former)
57	SZ	Swaziland
58	SY	Syrian Arab Republic
59	UA	Ukraine
60	VN	Viet Nam
61	YE	Yemen
62	ZM	Zambia

Upper middle income

63	AL	Albania
64	DZ	Algeria
65	AZ	Azerbaijan
66	BY	Belarus
67	BZ	Belize
68	BA	Bosnia and Herzegovina
69	BW	Botswana
70	BR	Brazil
71	BG	Bulgaria
72	CN	China
73	CO	Colombia
74	CR	Costa Rica
75	DM	Dominica
76	DO	Dominican Republic
77	EC	Ecuador
78	FJ	Fiji
79	GA	Gabon
80	GD	Grenada
81	IR	Iran
82	JM	Jamaica
83	JO	Jordan
84	KZ	Kazakhstan
85	LB	Lebanon
86	MY	Malaysia
87	MV	Maldives
88	MU	Mauritius
89	MX	Mexico
90	MN	Mongolia
91	ME	Montenegro
92	MS	Montserrat
93	NA	Namibia
94	PA	Panama
95	PY	Paraguay
96	PE	Peru
97	RO	Romania
98	LC	Saint Lucia
99	RS	Serbia
100	ZA	South Africa
101	VC	St. Vincent and the Grenadines
102	SR	Suriname
103	MK	TFYR of Macedonia
104	TH	Thailand
105	TN	Tunisia
106	TR	Turkey

High income

107	AG	Antigua and Barbuda
108	AR	Argentina
109	AW	Aruba
110	AU	Australia
111	AT	Austria
112	BS	Bahamas
113	BH	Bahrain
114	BB	Barbados
115	BE	Belgium
116	BM	Bermuda
117	BN	Brunei Darussalam
118	CA	Canada
119	CL	Chile
120	HK	China, Hong Kong SAR
121	MO	China, Macao SAR
122	HR	Croatia
123	CY	Cyprus
124	CZ	Czech Republic
125	DK	Denmark
126	EE	Estonia
127	FI	Finland
128	FR	France
129	DE	Germany
130	EL	Greece
131	HU	Hungary
132	IS	Iceland
133	IE	Ireland
134	IL	Israel
135	IT	Italy
136	JP	Japan
137	KW	Kuwait
138	LV	Latvia
139	LT	Lithuania
140	LU	Luxembourg
141	MT	Malta
142	NL	Netherlands
143	NZ	New Zealand
144	NO	Norway
145	OM	Oman
146	PL	Poland
147	PT	Portugal
148	QA	Qatar
149	KR	Republic of Korea
150	RU	Russian Federation
151	KN	Saint Kitts and Nevis
152	SA	Saudi Arabia
153	SC	Seychelles
154	SG	Singapore
155	SK	Slovakia
156	SI	Slovenia
157	ES	Spain
158	SE	Sweden
159	CH	Switzerland
160	TW	Taiwan
161	TT	Trinidad and Tobago
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163	AE	United Arab Emirates
164	UK	United Kingdom
165	US	United States
166	UY	Uruguay
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