WTO vs. TRAINS: A quantitative comparison of time-varying Ad-Valorem Equivalents for non-tariff trade measures

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Abstract

In the realm of trade economics, Non-Tariff Measures (NTMs) have gained considerable attention as their prevalence has grown and their impacts on trade and other economic outputs are explored in the literature. NTM incidence data are widely employed to estimate Ad Valorem Equivalents (AVE) to quantify the effects of NTMs on international trade. Currently, most studies rely on one of two different NTM databases: TRAINs from UNCTAD (United Nations Conference on Trade and Development) and WTO (World Trade Organization) notifications from the Integrated Trade Intelligence Portal (ITIP). This research estimates time varying AVEs from both datasets, compares results from the two sources, and creates a novel NTM database by combining information from WTO and TRAINS. Static analyses typically favor TRAINS because it records NTM data with a high degree of precision for select countries and snapshots of time. However, TRAINS is constrained by its limited coverage of countries and years. Given that TRAINS captures a snapshot of current NTMs, irregular data collection poses challenges for time-based analysis. Conversely, WTO notification data offer broader country and time coverage but lack withdrawal date information, specifically for measures such as Sanitary and Phytosanitary (SPS) and Technical Barriers to Trade (TBT). In addition, discrepancies between the notification year provided in the data and the actual implementation year of the NTM, along with the possibility that countries may not always notify correctly, can introduce biases in AVE estimation that can lead to potential measurement errors. While the existing literature discusses the merits and drawbacks of each database, overall performance in quantitative analysis remains unexplored. This study fills this gap by quantitatively evaluating whether AVE estimates derived from both databases align when using the price-based method proposed by Ing and Cadot (2016) and Kravchenko et al. (2022). In addition to the two primary NTM databases, we use trade data from the World Integrated Trade Solution (WITS) and other country gravity characteristics from the Centre for Prospective Studies and International Information (CEPII). We specifically focus on comparing the mean and variance in AVEs obtained from both databases. Given the accuracy of AVE estimates from the UNCTAD database, our focus examines the potential measurement error inherent in estimating AVEs from the WTO notification database. In addition, by estimating the measurement error in the AVEs, we aim to understand its sources and identify the countries and products where it is most pronounced. We find that the measurement error, primarily present in the WTO notifications database, likely stems from countries not notifying correctly or other assumptions made when using the data. Furthermore, this study develops a comprehensive database integrating NTM incidence information from both WTO and UNCTAD to enhance coverage across years and countries, providing improved data for future research.

I. Introduction

In recent years, economists have increasingly focused on non-tariff measures (NTMs) as crucial elements affecting international trade barriers. While the use of traditional tariffs has declined, implementation of NTMs has surged (Orefice, 2017). Recognizing their growing significance, numerous studies have analyzed the effects of NTMs not only on trade but also on various economic outcomes. However, quantifying the impact of NTMs has posed challenges due to their heterogeneity and less straightforward effects compared to tariffs. As defined by DITC et al. (2010), NTMs consist of “policy measures other than ordinary customs tariffs that can potentially have an economic effect on international trade in goods, changing quantities traded, or prices or both". The inherent ambiguity of this definition stems from the diverse range of policies classified as NTMs. While NTMs impact trade similarly to tariffs, they operate through different market channels. NTMs typically impose specific requirements for products to be sold in domestic markets, often aimed at reducing market imperfections by standardizing products, mitigating externalities such as risks to human and animal health, and addressing information asymmetries. Consequently, NTMs often introduce additional trade costs that can impact both prices and trade quantities between countries (Ferrantino, 2006; Cadot, Gourdon, and Van Tongeren, 2018). To better understand the effect of NTMs, economists have typically quantified these measures using Ad Valorem Equivalents (AVEs). An AVE is the tariff rate that would have an equivalent effect on the imported quantity as the non-tariff measure, making them comparable (Disdier, Fugazza et al., 2020). By integrating AVEs into trade policy studies, we can effectively account for the effect of NTMs. Presently, AVEs are derived from NTM incidence databases, which track implemented NTMs by year, country, and type of measure. In response to escalating concerns regarding NTM effects, international organizations have invested substantial efforts in creating inventories of applied NTMs by importing countries. Numerous databases offer qualitative insights into NTM implementation and incidence. Of these sources, the UNCTAD TRAINS database and the WTO notification database are frequently employed when estimating AVEs. Despite both databases cataloging existing NTMs, their data collection methods differ, leading to potential discrepancies in AVE estimates. While the TRAINS database offers more precise information about implemented Non-Tariff Measures, its use is constrained by limited data availability across countries and time periods. Consequently, many studies resort to estimating static values of Ad-Valorem Equivalents (AVEs) (Beghin, Maertens, and Swinnen, 2015; Cadot and Gourdon, 2016; Cadot, Gourdon, and Van Tongeren, 2018). Conversely, WTO notifications afford broader coverage across countries and time frames, yet they pose a risk of containing less reliable information, particularly for econometric analyses. Despite this drawback, the superior temporal coverage provided by WTO notifications has enabled some studies to estimate time-varying AVEs, thereby extending the scope of analysis (Ghodsi et al., 2017; Ghodsi and Stehrer, 2022).

Although previous studies have explored qualitative differences between the two databases (Rau and Vogt, 2017; De Melo and Nicita, 2018), no studies, to our knowledge, have looked at the quantitative difference between the two. In this study, we aim to fill this gap by analyzing the statistical difference in the estimated Ad Valorem Equivalents (AVEs) from both databases. NTM incidence information provided by the UNCTAD database is more accurate than the WTO notifications because of the way data are collected. Hence, we seek to estimate the measurement error by using the WTO notifications. In addition, we will examine unconditional differences while exploring heterogeneity by product groups and product level, time periods, country characteristics, and methods of AVE estimation. The contribution of this paper is to offer enhanced insights into data utilization when estimating AVE, thus providing valuable guidance for future analyses, particularly those examining the effects of trade policy on international trade and other economic outcomes. By exploring the trade-offs associated with using one database over another, we also aim to lay the groundwork for future endeavors aimed at creating a unified database integrating information from both TRAINS and WTO notifications

Due to data constraints, primarily within the UNCTAD database, our analysis will concentrate on countries with data available for at least six consecutive years and present in both databases. We have chosen to focus initially on South American countries due to their relatively high time-coverage. Although we intend to analyze multiple countries, this initial paper draft will center solely on Brazil. Our analysis will estimate time-varying AVEs at the Harmonized System level 1 for two types of NTMs: Technical Barriers to Trade (TBT) and Sanitary and Phytosanitary Measures (SPS).

Before delving into the quantitative analysis, we will compare the two databases qualitatively and outline how the literature has quantified NTMs through AVE. Following this, we will provide an overview of the data used. Section IV will thoroughly explain our methodology, and the results will be presented in Section V.

II. Related Literature

In this section, we will present the existing NTM incidence databases and the AVE estimation method used in the literature. We additionally outline the benefits and limitations of NTM data while comparing the country and time coverages of TRAINS and WTO notifications.

II - I NTMs database

With the increasing concerns about the impact of NTMs, international organizations, and governments have dedicated significant resources to establishing databases on NTMs. Numerous sources provide qualitative insights into the implementation of NTMs. However, to effectively assess the effect of NTMs, it becomes imperative to convert qualitative information into quantitative estimates, which inherently requires making certain assumptions when using the data. In this section, we will present the existing data on NTMs and how they can be limiting when trying to understand their potential impacts on trade and prices.

Rau and Vogt (2017) offer a comprehensive overview of existing sources of NTM information. The paper identifies multiple types of sources, such as inventories and legislation, reviews of legislation, notifications, surveys, import refusals, and other sources.

National legislation inventories emerge as the most pertinent among the array of available databases. These inventories meticulously catalog national legislation wherein measures can be indexed within the MAST classification [1]. Notably, the TRAINS database, jointly developed by UNCTAD and ITC (International Trade Centre), stands out as a primary resource for researchers investigating NTM effects. This database meticulously gathers and classifies all legal texts issued by countries into NTMs, along with bilateral and plurilateral agreements. Indeed, it stems from an active collection of data contingent on independent regulatory review by the UNCTAD. However, it does not include private standards or international standards that are not part of national legislation.

[1] The Multi-Agency Support Team group (MAST), established under UNCTAD, has been instrumental in shaping the International Classification of Non-tariff Measures (NTMs). This classification system is extensively used to categorize and grasp the diverse forms of NTMs impacting global trade.

Moreover, the TRAINS database offers information at the 6 Harmonized System (HS) code level for 103 countries. It furnishes details on the implementing country, affected nations, regulation and product details, and the date of implementation and withdrawal. Data collection began in 1994, but the TRAINS database underwent restructuring in 2006, with most current NTM data collected post-2008 (UNCTAD, 2018). The notable strengths of this database include its traceability, comparability (across countries), transparency, and open accessibility to data. However, a significant limitation arises from the uneven collection of NTM data across countries on an annual basis, posing a potential challenge in accurately estimating Ad-Valorem Equivalents (AVEs) for all nations and over time. In panel-type analysis, only countries with multiple years of data collection can be effectively incorporated, highlighting a constraint in the coverage of estimated AVEs across diverse nations.

Another valuable source of NTM data is WTO notifications. As members of the WTO, countries are required to notify the implementation of non-tariff measures to enhance the predictability and transparency of trade policies. The current WTO notification data encompasses NTMs for 140 countries (WTO members) since 1979, providing information on the type of NTMs at the HS6 level, product and regulation details, the date of notification, and occasionally the year of withdrawal (excluding TBT and SPS type notifications). While this dataset covers more countries and periods than UNCTAD, the WTO adopts a passive approach to gathering notifications submitted by countries. Indeed, some countries do not always notify the WTO when directly implementing NTMs, which could create a gap between the implementation and the notification years. Consequently, NTM notifications often experience delays and occasional omissions. Therefore, this database often complements the TRAINS database in economic analyses. Nonetheless, some studies leverage it for its broader country and temporal coverage.

Furthermore, business surveys and complaint portals serve as another possible source of NTM data, offering insights from a business perspective. Examples include the ITC NTM surveys and the EU market access database. However, survey data often represent the views of firms affected by NTMS and, consequently, are more inclined to highlight

NTMs perceived as restrictive, while potentially overlooking those that have minimal impact. Hence, such data must be interpreted with caution, considering the inherent biases and limitations associated with the perspective of surveyed businesses. We do not focus on those databases in this analysis, as they tend to be country-specific.

II - II Limitations with NTMs database

Despite the extensive amount of information on NTMs, those databases show common limitations when using them in quantitative studies. De Melo and Nicita (2018) mentions six crucial aspects to consider when using data, such as the TRAINS or the WTO notifications databases. They are as follows: comprehensiveness, lack of precision, dimensionality of the data, time dimension, product-specific requirements, and endogeneity. Comprehensiveness refers to omissions and double counting. As previously seen, there are multiple sources of the NTM databases (at the national and international level), which can often lead to missed information. Double counting, on the other hand, may occur when the same NTM legislation is reported twice under different titles. The lack of precision arises from the qualitative nature of the data, making it challenging to deduce the level of stringency of trade regulations. Indeed, the data fails to elucidate the significance of measures in terms of the importance of traded volume and sector economics. Dimensionality poses challenges in disentangling the econometric effects of individual measures on products due to the heterogeneous nature of measures classified as non-tariff measures (specifically at the HS6 level). Often, the consequent collinearity across NTMs necessitates the aggregation of measures into broader categories. Issues in the time dimension arise from data collection. Conducting time series analyses is hindered by inaccuracies in the dates of implementation and withdrawal of the measure. In WTO notification data, WTO members are only required to notify new measures, potentially omitting long-existing NTMs (as withdrawal data are not always present). In the TRAINS database case, as it is a snapshot of existing NTMs at data collection time, we can only use data that are collected for successive years. Product-specific requirements refer to the aggregation of products at different HS code levels when analyzing the effects of NTM. We need to be careful when aggregating or disaggregating the effect of NTMs. Finally, Endogeneity poses challenges in assessing the causal effects of NTMs on trade flows or prices, with reverse causality being a significant concern. Countries may overcontrol domestically important sectors, leading to excessive NTM implementation in sectors with significant trade flows. We will go through this specific issue in detail in the method section.

II - III NTMs effect quantification

As seen in the previous section, we presented the existing NTM databases, which are purely qualitative. These data do not provide any quantitative information on the stringency of the measures. To provide a better indicator of the trade effects of NTM, researchers have quantified them through AVE using various approaches: inventory approach, price gap, and econometric approaches. In this paper, we will focus on econometric approaches as they provide the inferred effects of an additional NTM on trade.

In the literature, two main econometric approaches have been employed: quantity-based and price-based. Both approaches leverage gravity models to discern the impact of NTMs on either imported quantity or price. Bilateral trade quantities or prices are regressed against importer-exporter characteristics and trade barrier variables, including tariffs and non-tariff measures.

The quantity-based approach examines the impact of additional NTMs on traded volume, converting it into trade costs using elasticities of substitution. This method assesses whether the implementation of NTM results in changes in trade flow. Conversely, the price-based approach analyzes the effect of additional NTMs on prices, expecting to observe price changes if the NTM is associated with additional costs. This approach seeks evidence indicating that NTMs result in domestic prices being higher than they would be in the absence of NTMs (Cadot and Gourdon, 2016). Past studies have employed both quantity-based (e.g., (Looi Kee, Nicita, and Olarreaga, 2009; Essaji, 2008; Beghin, Maertens, and Swinnen, 2015; Ghodsi and Stehrer, 2022)) and price-based approaches (e.g., (Cadot and Gourdon, 2016; Ing et al., 2016; Cadot, Gourdon, and Van Tongeren, 2018; Kravchenko et al., 2022)). The choice between the two is often made based on the available data and the models' specifications. While both approaches have merits and limitations, we will concentrate solely on the price-based approach for the purposes of this study. Further details regarding the price-based approach and the estimation of AVEs will be provided in the Methods section.

II - IV Comparing WTO and UNCTAD

As demonstrated in earlier sections, the two databases employ different collection methods. Hence, we believe that they might yield different estimates of AVE. While we hold the view that the TRAINS database offers a more precise estimation of AVE, its restricted country and time coverage present challenges in estimating a time-varying AVE.

Indeed, from 2010 to 2019, the WTO data cover a total of 120 countries for Technical Barriers to Trade (TBT) and 103 countries for Sanitary and Phytosanitary Measures (SPS), whereas UNCTAD covers only 92 countries for both TBT and SPS. Figure 1 illustrates the number of observed countries in each dataset per year. [2]It is evident that WTO notification provides considerably broader country coverage than the UNCTAD data. Figure 2 and 3 provide the counts of observed distinct years from 2010 to 2020. While country coverage may pose challenges when estimating specific country effects, time coverage may present obstacles when estimating time-varying AVEs.

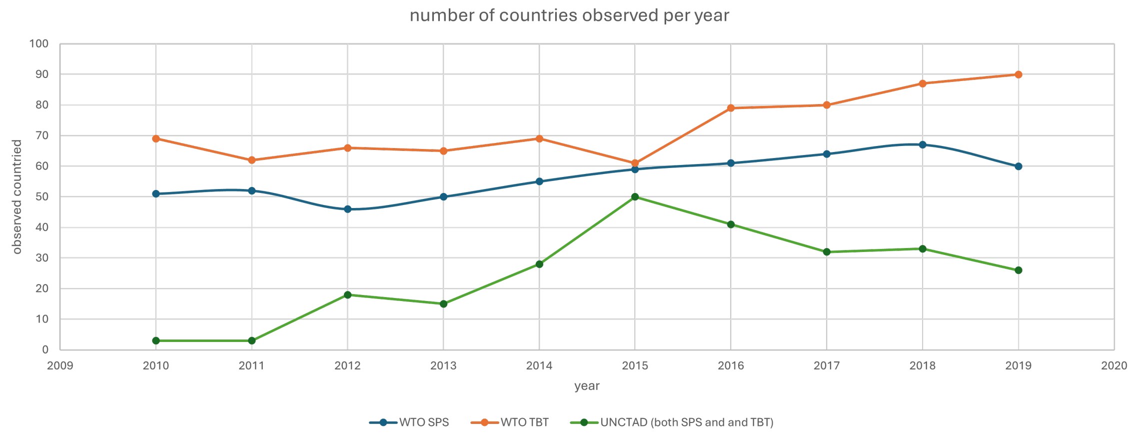

Figure 1: Country and time coverage of both TRAINS and WTO notifications

[2]In the TRAINS database, country coverage denotes the number of distinct countries for which UNCTAD has collected NTM data for a specific year. Conversely, in the WTO data, country coverage represents the number of distinct countries that have notified the implementation of an NTM during a specific year.

To date, most studies have focused on estimating static AVE of NTMs using UNCTAD data Essaji (2008); Looi Kee, Nicita, and Olarreaga (2009); Kee and Nicita (2022). While some papers have attempted to estimate time-varying AVE, they have been limited to countries with data collected over multiple years. For instance, Niu et al. (2018) and Niu et al. (2020) estimates AVE from 2003 to 2015 with a three years interval.

In contrast, the WTO notification database provides broader coverage across both countries and time periods. Indeed, several papers have utilized WTO notifications to estimate time-varying AVE for multiple countries Ghodsi and Stehrer (2022); Adarov and Ghodsi (2023). However, this data comes with several caveats. Firstly, there are instances of missing HS codes in the data, posing challenges when attempting to discern the effects of NTMs at the product code level. To address this issue, we followed Ghodsi, Reiter, and Stehrer (2015) recommendations by retrieving HS codes using product information. Further elaboration will be provided in the data section. Secondly, the WTO notifications are susceptible to self-notification bias, given that countries are responsible for reporting their NTMs, with no external verification process. While this may be mitigated by other countries reporting NTMs through trade concerns, discrepancies in the timing of notification and NTM implementation can arise. Currently, the available data include information on both the date of implementation and the date of notification. However, there are instances where the date of implementation is missing, necessitating the use of the date of notification instead. Finally, it is important to note that WTO notifications do not consistently record instances when an NTM is withdrawn. This issue is particularly pronounced for NTMs falling under the categories of Sanitary and Phytosanitary Measures (SPS) and Technical Barriers to Trade (TBT), where no withdrawal records are available in the data.

These limitations inherent in WTO notifications are believed to introduce measurement errors in AVE estimation. We will elucidate our strategies for circumventing these issues through assumptions outlined in the data section.

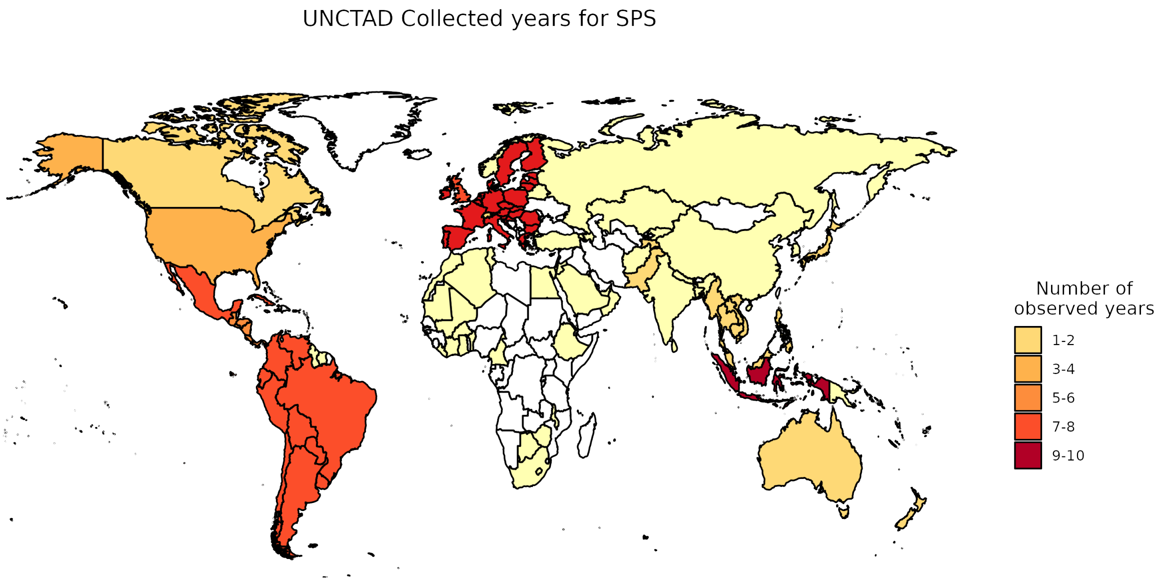

Figure 2: UNCTAD NTM (SPS) data country and time coverage

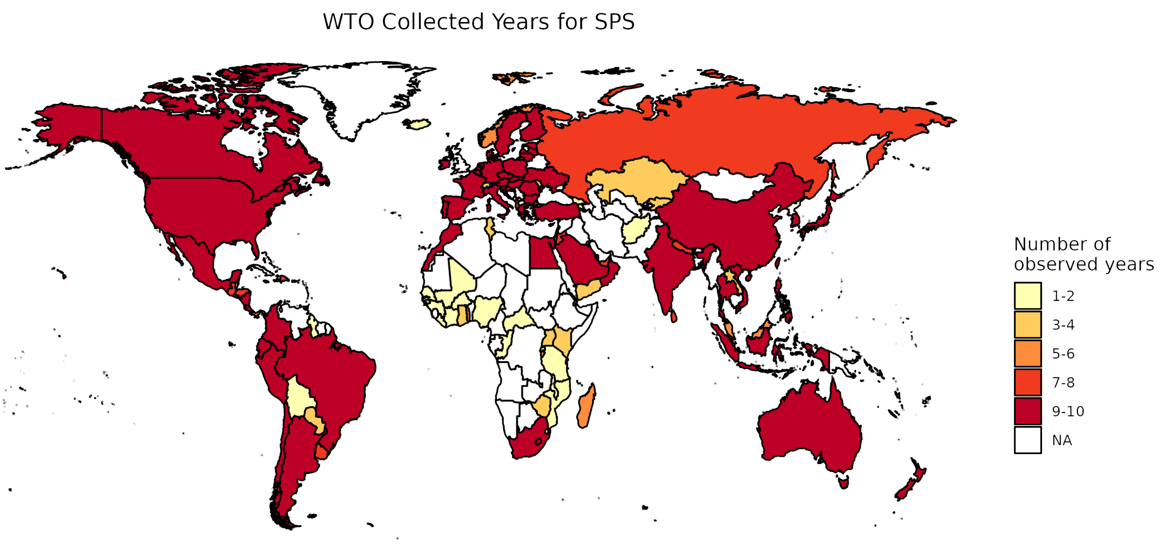

Figure 3: WTO NTM (SPS) data country and time coverage

III. Methods

In this section, we outline the methodology for estimating the Ad Valorem Equivalents (AVE) using a price-based approach with both the TRAINS and WTO NTM databases. We begin by detailing the procedure for calculating the AVE. Subsequently, we address endogeneity issues and propose an alternative model incorporating instrumental variables. We then compare the AVE obtained from TRAINS and WTO to see whether the two estimates are statistically different.

III - I Empirical model estimation

The method employed in this paper draws from the price-based approach used by Cadot and Gourdon (2016) and Kravchenko et al. (2022). We express price as a function of gravity variables, tariffs, and Non-Tariff Measures (NTMs), along with fixed effects.

Let us represent the importing country (here Brazil) by i and all exporting countries by j, in period t and for product k.

$$\begin{aligned}\ln p_{ijkt} = {} & \beta_1\delta_i + \beta_2\delta_j + \beta_3\rho_k + \beta_{\theta_{ijt}}\theta_{ij} + \beta_{4k}NTM^{SPS}_{ijkt} + \beta_{5k}NTM^{TBT}_{ijkt} + \beta_{6ik}(NTM^{SPS}_{ijkt} \times \delta_i) \\ & + \beta_{7ik}(NTM^{TBT}_{ijkt} \times \delta_i) + \beta_{8k}ln(1 + tariff_{ijkt}) + \beta_7\tau_t + \varepsilon_{ijk}\end{aligned} \tag{1}$$

Where the variables are defined as follows:

p_{ijkt} : price specific to importer i and exporter j product k in year t

δ_i : importer fixed effect

δ_j : exporter fixed effect

τ_t : time fixed effect

ρ_k : product fixed effect

θ_{ij} : gravity characteristics between importer i and exporter j (distance, contiguity, landlocked, com

NTM^{SPS}_{ijk} : count of imposed SPS measures by country i on imports from j on good k

NTM^{TBT}_{ijk} : count of imposed TBT measures by country i on imports from j on good k

$tariff_{ijk}$: applied tariff imposed by country i on imports from j on good k

ε_{ijkt} : error term

In this model, importer, exporter, and product fixed effects help mitigate omitted variable bias by accounting for unobserved heterogeneity across these dimensions. However, in contrast to the approach taken by Cadot and Gourdon (2016) and Kravchenko et al. (2022), we further incorporated a time-fixed effect into our model. This additional fixed effect enables us to capture and account for unobserved variations over time that apply to all countries and trading partners, thereby reducing the potential for omitted variable bias.

We run this model twice using either the TRAINS database or the WTO notification database to account for NTM_{ijk}^{SPS} and NTM_{ijk}^{TBT}. In addition, we estimate the regression for each product level k. Although k can represent HS6 levels, our current model employs the broader product level HS1 due to computational limitations.

III - II Estimation of Ad Valorem Equivalents

To derive the Ad Valorem Equivalent (AVE), we follow the method proposed by Cadot and Gourdon (2016), which involves using the previously estimated marginal effects of NTMs. Specifically, we can express the change in p_{ijkt} after an additional unit of NTM as:

$$\Delta \ln(p_{ijkt}) = \ln\left(\frac{p_{ijkt}(NTM_{ijkt}^{SPS})}{p_{ijkt}(NTM_{iikt}^{SPS} - 1)}\right) = \beta_{4k} + \beta_{6ik}\delta_i \tag{2}$$

We then get the marginal AVE on NTM imposed as (multiply by 100 to get percentages):

$$\text{AVE}_{ik}^{SPS} = \frac{\Delta \ln(p_{ijkt})}{p_{ijkt(NTM_{iikt}^{SPS}-1)}} = [\exp\left(\beta_{4k} + \beta_{6ik}\delta_i\right) - 1] \times 100 \tag{3}$$

This latter represents the mean AVE for a product k and an importer i. Using the previous equation, we can obtain the effect of the total number of NTMs imposed by country i at time t.

$$\text{AVE}_{ikt}^{SPS} = \left[\exp\left(\beta_{4k} \times NTM_{ijkt}^{SPS} + \beta_{6ik}\delta_i \times NTM_{ijkt}^{SPS}\right) - 1\right] \times 100 \tag{4}$$

We obtain two types of AVE estimates, one from WTO notifications and one from TRAINS NTM data estimates.

III - III Accounting for Endogeneity

Although the previous model provides an estimation of AVE, it fails to address the endogeneity inherent in Non-Tariff Measures (NTMs) and tariffs concerning trade volume and prices. Notably, a reverse causality emerges wherein the significance of the traded good may lead to trade policy implementation. Indeed, factors like import penetration in industries influence NTM protection. When import penetration increases, it can lead to policies that use NTMs to protect trade (Trefler, 1993; Lee and Swagel, 1997).

Although endogeneity poses a concern, we might assume that any bias resulting from it affects both the estimation with TRAINS data and WTO notification data similarly (in the same direction). If this is the case, adjusting for endogeneity might not be necessary. However, employing instrumental variables (IVs) becomes essential if the magnitude and the direction of the bias differ between the two models.

Papers have addressed this issue using instrumental variables (IVs), with a common approach being the use of NTMs imposed by neighboring countries (Looi Kee, Nicita, and Olarreaga, 2009; Cadot, Gourdon, and Van Tongeren, 2018; Kravchenko et al., 2022; Kee and Nicita, 2022). We will, therefore, proceed with a two-step regression, where we first regress Brazil's NTM implementation on its neighbors' implementation, and then incorporate the predicted NTMs into the equation (1).

In the context of our analysis, we would want to use countries such as Argentina or Uruguay to account for Brazil's NTMs. However, this poses a problem when countries are all part of a regional trade bloc with common external tariffs and NTMs. Indeed, MERCOSUR could compel countries to harmonize their NTM application among its members. Therefore, we will opt for Brazil's neighbors outside of Mercosur (Ecuador, Chile, Peru, Colombia, and Bolivia).

While we would prefer to employ the same model (equation (1)) as presented in the previous section, we encounter multicollinearity issues. This arises because NTMs are often not specific to an exporter but are instead applied uniformly to all trading partners, being nondiscriminatory in nature. Hence, we will modify the previous model by removing exporter specificity and use the following model instead: The First step consists of regressing NTM imposed by country i by all the neighboring countries of i. Here, we call n all neighbouring countries, and j all the exporting countries that export to n.

$$NTM_{ikt} = \sum_{n=1}^{5} \sum_{j=1}^{J} \phi_{kj} NTM_{njkt} + \varepsilon_{ikt} \tag{5}$$

As we are losing exporter specificity, we weight each NTM variable by their level of imports (M_{kj}) from the exporting country j at the baseline time period[3] . Here, it consists of the first observed time period, 2012. We get the following weight:

$$\phi_{kj} = \frac{M_{kj,t=0}}{\sum_{j=1}^{J} M_{kj,t=0}} \tag{6}$$

We then use the estimated NTM at the product level k to determine the effects of the NTM on trade.

$$\ln P_{ikt} = \beta_0 \gamma_i + \beta_1 \rho_k + \beta_{2k} N\hat{T}M_{ikt}^{SPS} + \beta_{3k} N\hat{T}M_{ikt}^{TBT} + \beta_4 \tau_t \varepsilon_{ikt} \tag{7}$$

We can then use the coefficients to estimate the Ad Valorem Equivalents using equation (3).

IV. Data

IV - I Data used in the analysis

To run the models presented in the previous section, we need trade data on Brazil and its partnering countries from 2012 to 2016, disaggregated at the HS6 level. We acquired this information from the World Integrated Trade Solution (WITS) database. Trade value and trade quantity data were used to compute prices (unit value). In addition, Tariff data were sourced from the WITS TRAINS database, providing bilateral tariff information. Regional Trade Agreement (RTA) data were obtained from Blöthner and

[3]We weight both the NTM variable from country i and from the neighboring county n. We then lose the exporter specificity in our NTM variable.

Larch (2022), while country gravity variables were acquired from the CEPII database (Conte, Cotterlaz, and Mayer, 2022). We also gathered data from neighboring countries to Brazil to construct instrumental variables for our analysis. Upon assembling all requisite data, we constructed a panel dataset at the yearly and HS6 product levels, with bilateral trade and country characteristics. Subsequently, this dataset was merged with the NTM database for further analysis.

IV - II UNCTAD and WTO NTM databases

We use data from UNCTAD's TRAINS database and the WTO notifications obtained on the Integrated Trade Intelligence Portal (I-TIP). Both data provide the type of NTM, the count of applied NTM, the implementing country, the affected country, the regulation, and affected product details. While the UNCTAD database can be readily employed, the WTO notifications require certain assumptions and rectifications to align with our analysis. However, these assumptions could indeed contribute to measurement errors when estimating AVEs. We will use recommendations provided by Ghodsi, Reiter, and Stehrer (2015) to transform WTO data. First, to address missing HS codes, we leveraged the methodology outlined by (Ghodsi et al., 2017), who retrieved all missing HS codes using product descriptions and cross-referencing with other datasets. Consequently, we must fully recover all missing HS codes at the HS6 level. Additionally, we addressed the absence of withdrawal information by following the approach proposed by Ghodsi et al. (2017); Ghodsi and Stehrer (2022), wherein it is assumed that countries do not retract any NTMs once implemented. Thus, we assume that once an NTM is notified, it will remain implemented by the country, providing us with the cumulative count of NTMs at a specific year. Finally, it's important to note that in the WTO notification database, the observed NTMs are only those that are notified. Therefore, we assume that all notified NTMs are the only NTMs implemented.

Next, we merge each NTM database with the bilateral trade and country characteristic data. This process yields a bilateral panel dataset at the HS6 digit level, comprising prices, the count of NTMs imposed by an importer to an exporter, and other relevant variables.

IV - III Summary analysis: Comparing UNCTAD and WTO NTM data

Before comparing the AVE estimates, it is essential to look at the differences between the two datasets. Since potential measurement errors in estimating AVE may arise from the assumptions made when using the WTO notifications data, it is prudent to review them to see how reasonable they are.

To verify whether the assumption of no withdrawal of NTMs is overly restrictive in the WTO notification data, we identified, from the UNCTAD database, the countries that have permanently withdrawn an NTM from 2010 to 2020. Figure 4 shows the number of countries repealing an NTM, where only 7 countries had a permanent withdrawal of SPS, and 8 countries for TBT. Additionally, the blue bars represent the number of distinct HS codes affected by these withdrawals at the HS6 level, proportionate to the total number of HS codes affected by NTMs for that specific country (shown in orange). It appears that India has substantial HS6 coverage affected by NTMs withdrawn compared to the total number of HS6 codes affected by NTMs. However, for the remaining countries, the number of withdrawals is relatively small. This observation suggests that while withdrawals do occur, they may not be as common across all countries. This reinforces the notion that the assumption of no withdrawal of NTMs may not be overly restrictive for the majority of countries.

This preliminary analysis focuses specifically on Brazil. Thus, we aim to compare the HS codes affected by NTMs in both databases. Figures 5 and 6 depict the number of distinct HS codes (at HS6 levels) affected by NTMs over the years. Notably, for both TBT and SPS NTMs, the number of distinct HS codes affected appears to have increased over time, consistent with the assumption of no withdrawal. In the case of TBT NTMs, the number of distinct HS codes seems relatively similar between the two databases. However, concerning SPS NTMs, we observe a slightly larger gap, with more distinct HS codes affected by NTMs in the UNCTAD database compared to the WTO notifications.

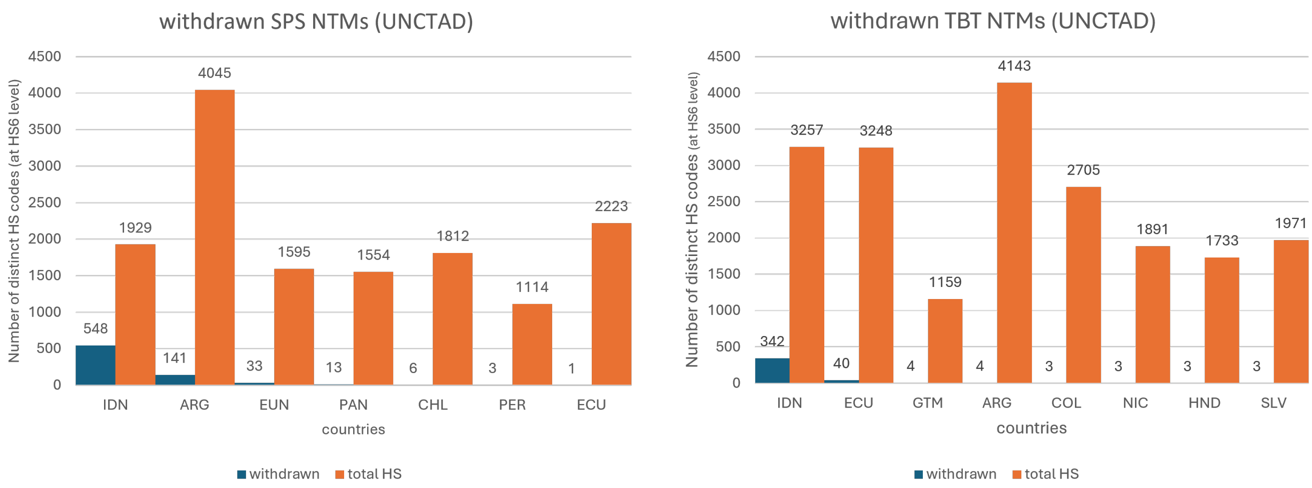

Figure 4: Number of distinct HS codes (at HS 6 level) IN the two databases

This difference could potentially be attributed to Brazil not notifying the WTO or to the challenges in identifying missing HS codes, with the latter scenario seeming more likely.

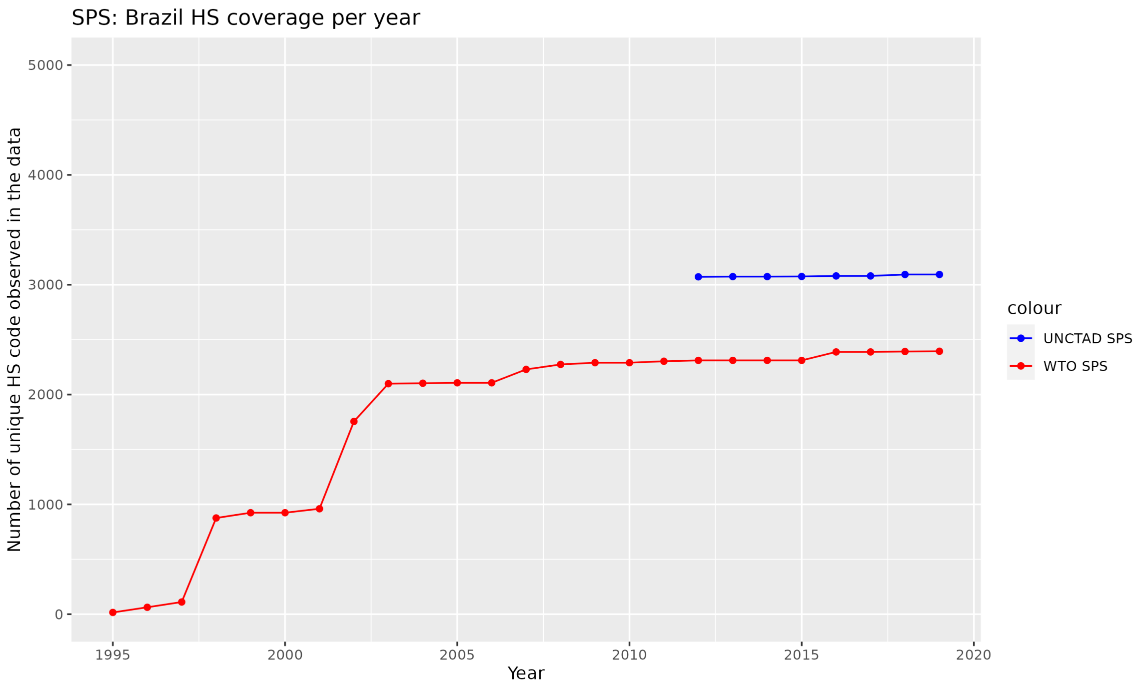

Figure 5: Number of distinct HS codes (at HS 6 level) iN the two databases (SPS)

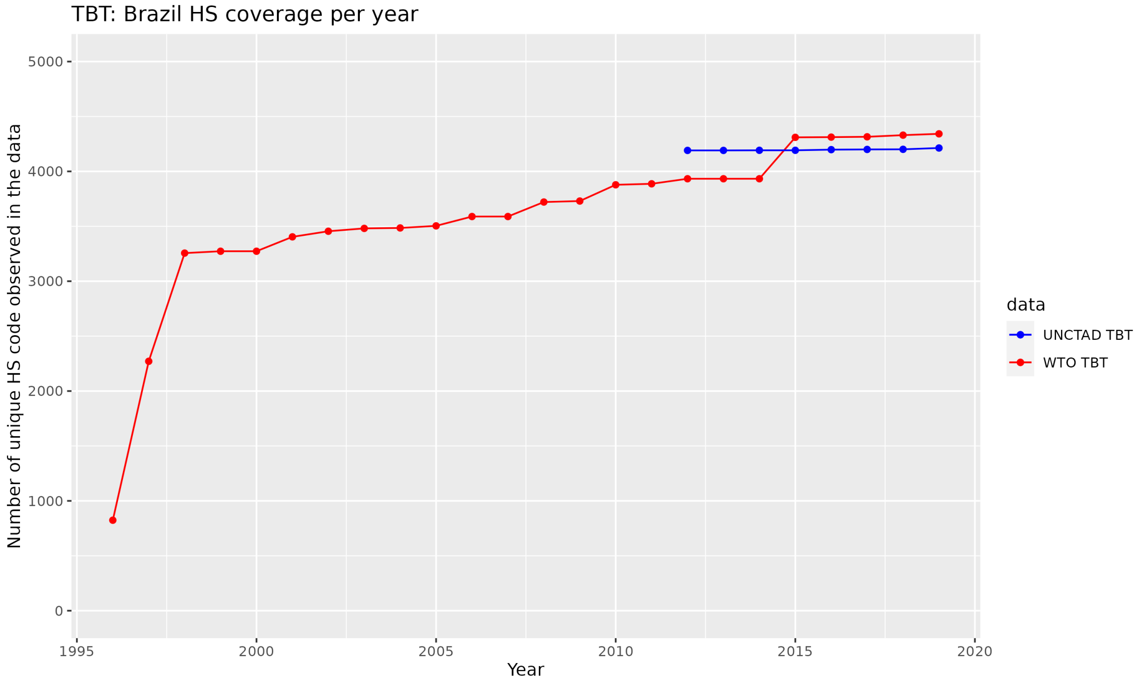

Figure 6: Number of distinct HS codes (at HS 6 level) iN the two databases (TBT)

Finally, we can examine the average number of NTMs imposed by Brazil at the product (HS 6-digit level), exporter, and year level by looking at the summary of the NTM variables in our panel data. Table 1 presents the mean, median, and quantiles of the observed counts of SPS and TBT in both databases. TBT measures seem to exhibit greater similarity between the two datasets compared to SPS measures. In addition, it is worth noting that the maximum counts of imposed NTMs appear to be much higher in the WTO data compared to the UNCTAD data. However, this discrepancy only pertains to a few observations.

Table 1: Summary statistics of observed counts of NTMs imposed by Brazil

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
UNACTD: number of observed SPS	0	0	2	4.633956	4	94
UNACTD: number of observed TBT	0	2	8	10.99333	14	97
WTO: number of observed SPS	0	0	0	9.114181	2	924
WTO: number of observed TBT	0	2	4	9.815389	14	273

Although there are still apparent differences between the two datasets, it is necessary to estimate AVEs to evaluate the impact of the assumptions made in the WTO notifications database.

V. Results

The model described in the Methods section is applied twice, using the two different sources of NTM data. We estimate the NTM effects at the HS1 digit level from 2012 to 2016 for Brazil and compare the resulting AVE from both datasets. In the first part of this section, we examine the resulting AVE using the model without accounting for endogeneity. Finally, we present the results obtained from using instrumental variables.

V - I AVE Estimates with endogeneity

The regression outputs of equation (1) using WTO notifications and TRAINS databases are summarized in Tables 2 and 3 of the Annex. These regressions provide coefficients for both TBT and SPS for each HS1 digit level (ranging from 0 to 9), which are then utilized to calculate the mean Ad Valorem Equivalents (AVEs). The mean estimates and confidence intervals for these AVEs are reported in Figures 7 and 8. The Figures report AVE for both UNCTAD (in blue) and WTO (in red) for each HS products codes.

In the case of SPS, it is observed that for HS0 to HS5, as well as for HS8 and HS9, the confidence intervals of the AVEs appear to intersect between the two databases, suggesting potential similarity between the datasets. However, for HS6, the intervals do not intersect, indicating possible differences. Similarly, in the case of TBT, the AVEs for products HS4, HS5, and HS9 also show non-intersecting confidence intervals, suggesting potential differences in estimates between the two databases.

The presented estimates reveal variations in means and variances between the two databases across different HS codes. While some HS codes yield similar AVE estimates, others exhibit significant differences between the databases. A possible explanation for this inconsistency could lie in the number of observed NTMs at the HS6 level for each HS1 level group. Figure 9 and 10 provide, for the two types of NTMs, the distinct number of NTMs applied at the HS6 level for each HS1 level group from 2012 to 2016. In the case of SPS, it's observable that for HS0 to HS3, WTO shows a higher number of applied NTMs. However, this might be attributed to the potential overcounting of NTMs in the WTO database (as we assume no repeal of the NTMs). Conversely, HS8 appears to have

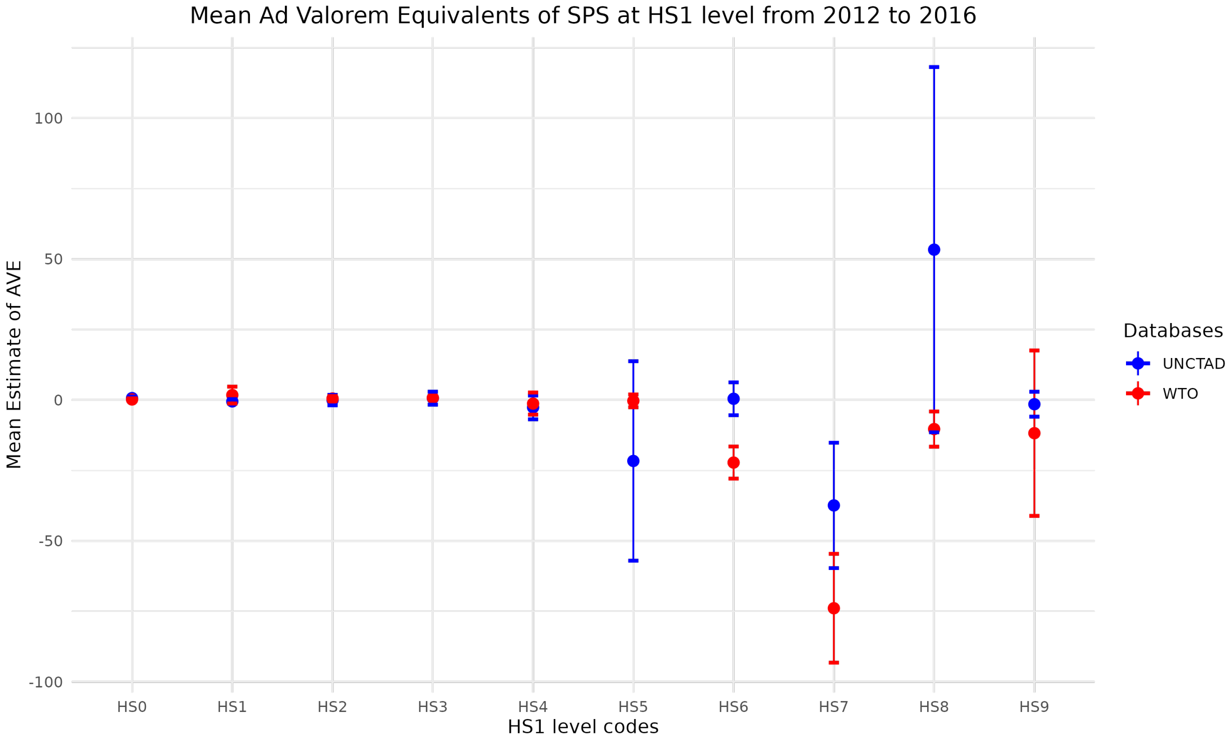

Figure 7: Estimated mean AVE (SPS) from both databases

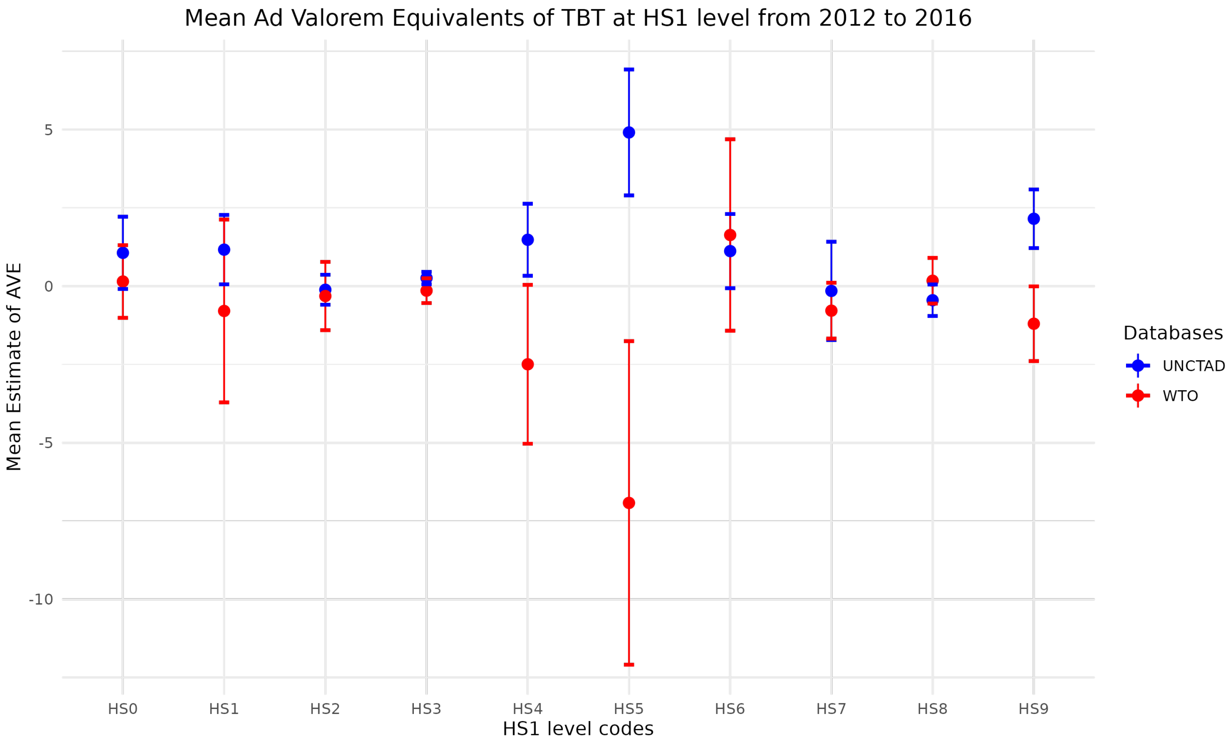

Figure 8: Estimated mean AVE (TBT) from both databases

a higher number of NTMs in the UNCTAD database. Hence, the discrepancy between the two databases may not really stem from the no-repeal assumptions, but from NTMs being imposed and observed in UNCTAD but not notified to the WTO. In the TBT case, it appears that the number of NTMs between the two databases is quite similar. Therefore, it's challenging to conclude that the number of applied NTMs is directly affecting the estimates. However, we could speculate that the gap in AVEs is once again due to certain NTMs not being notified for specific HS6 level codes. This speculation could hold particularly true for HS 5 and 9, where UNCTAD shows the highest number of imposed TBT measures. To further investigate the statistical differences between the two databases, we would need to conduct a bootstrap analysis and test whether the AVEs are statistically different in both means and variances.

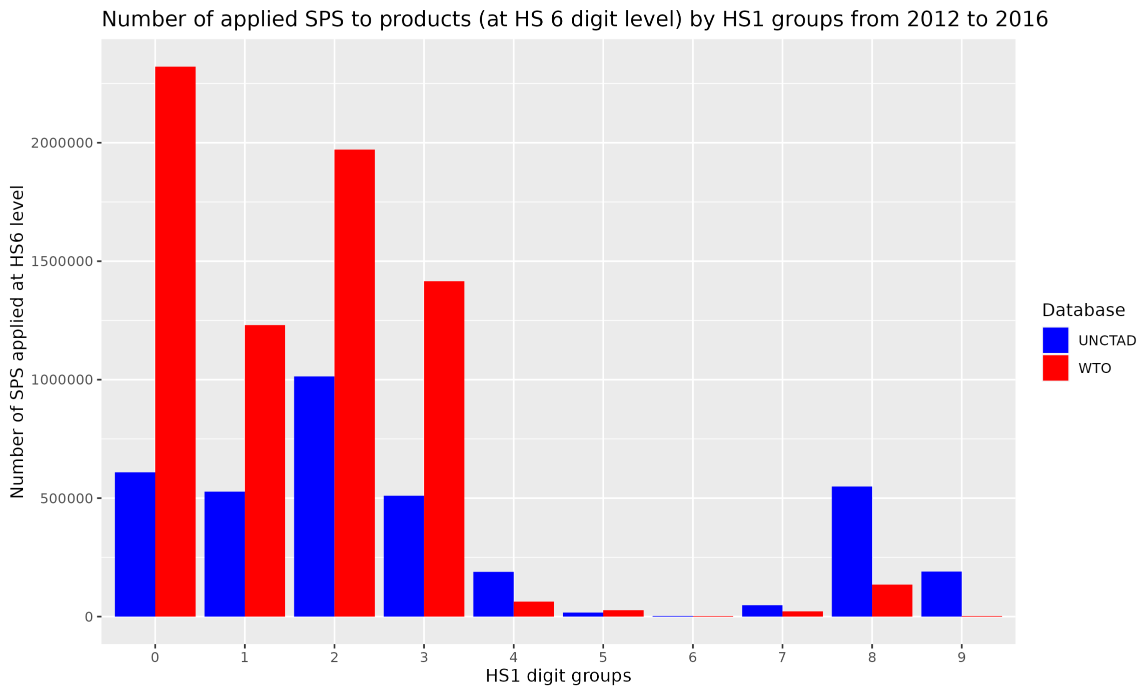

Figure 9: Number of distinct SPS applied to the HS6 levels for each HS 1 product code

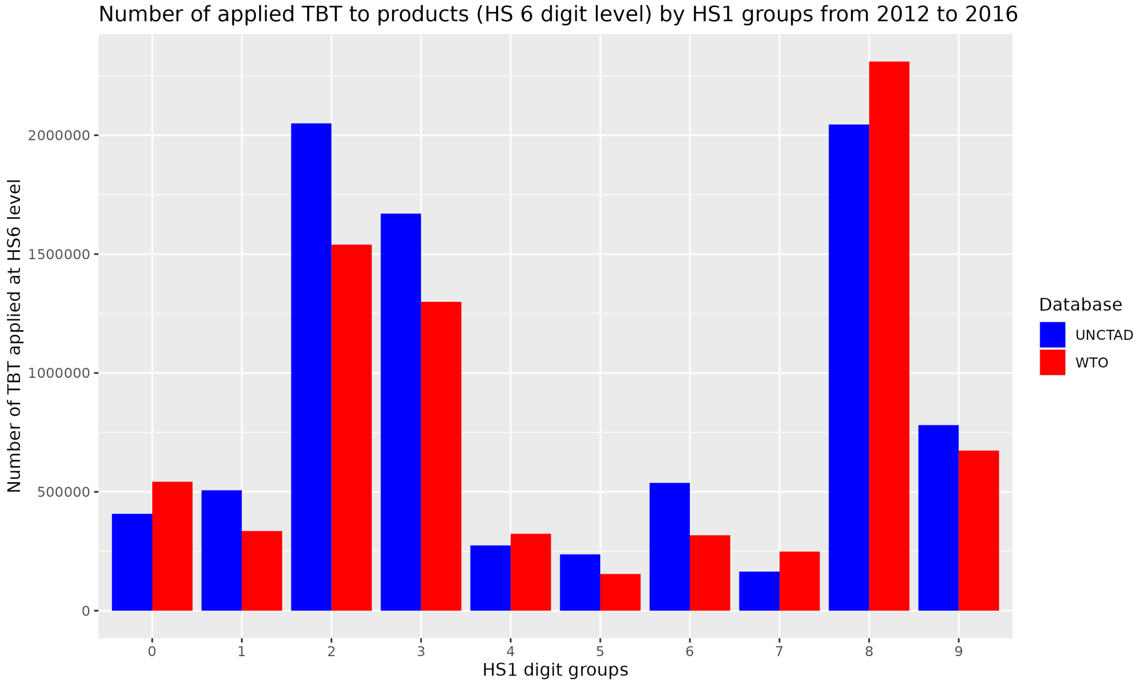

Figure 10: Number of distinct TBT applied to the HS6 levels for each HS 1 product code

V - II total AVE Estimates accounting for NTM counts

In this section, we present the total AVE effects, estimated from equation (4), which account for the total number of NTMs imposed by year. We present in figure 11 and 12 the estimated AVE for each HS1 group for the year 2012. As there is not much variation from one year to another, we present the results for other years in the annex. As observed, the gap between UNCTAD and WTO estimates has widened compared to the estimates from the mean AVE, as we account for NTMs implemented counts. This could be explained by the previous figures where, when more NTMs are applied in WTO data due to the no repeal assumption, we obtain much higher estimates for WTO total AVE. Conversely, the opposite case is also observed, where if there are more UNCTAD NTM counts, the estimates for UNCTAD AVE would be greater than WTO. Indeed, the count of NTMs becomes much more important when estimating total AVE effects, as it directly influences the magnitude of the estimated AVE. The measurement error stemming from the assumption of no NTM withdrawal also becomes more significant in this context, as it can lead to overestimation or underestimation of the total AVE effects.

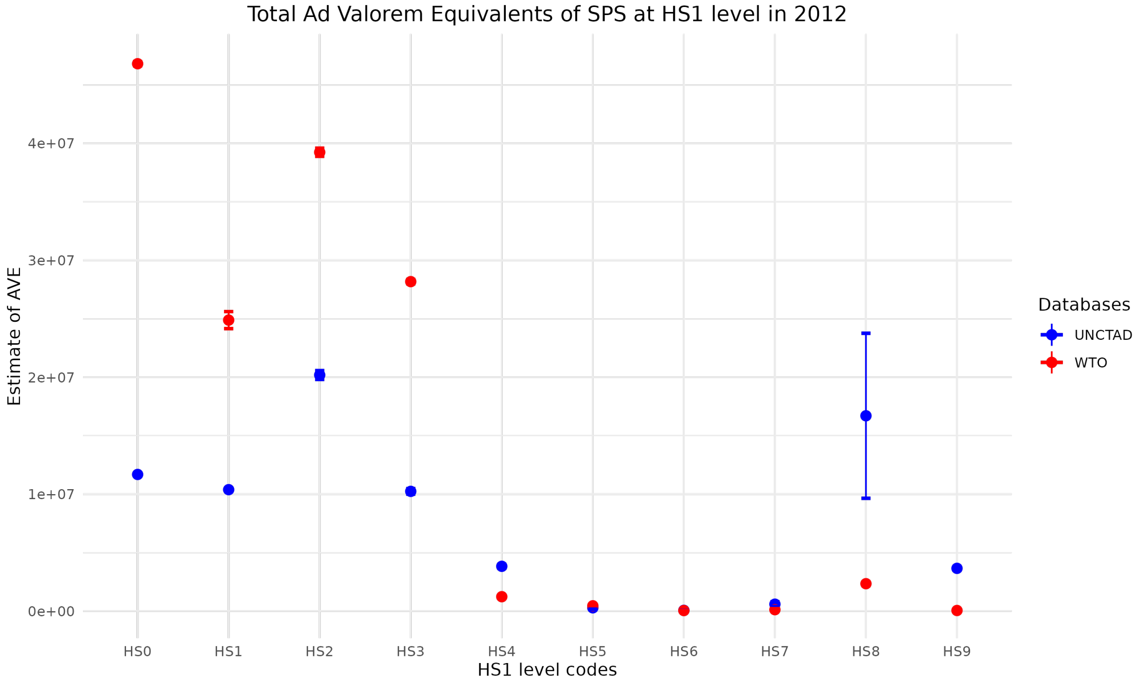

Figure 11: Estimated total AVE (counts of SPS) in 2012

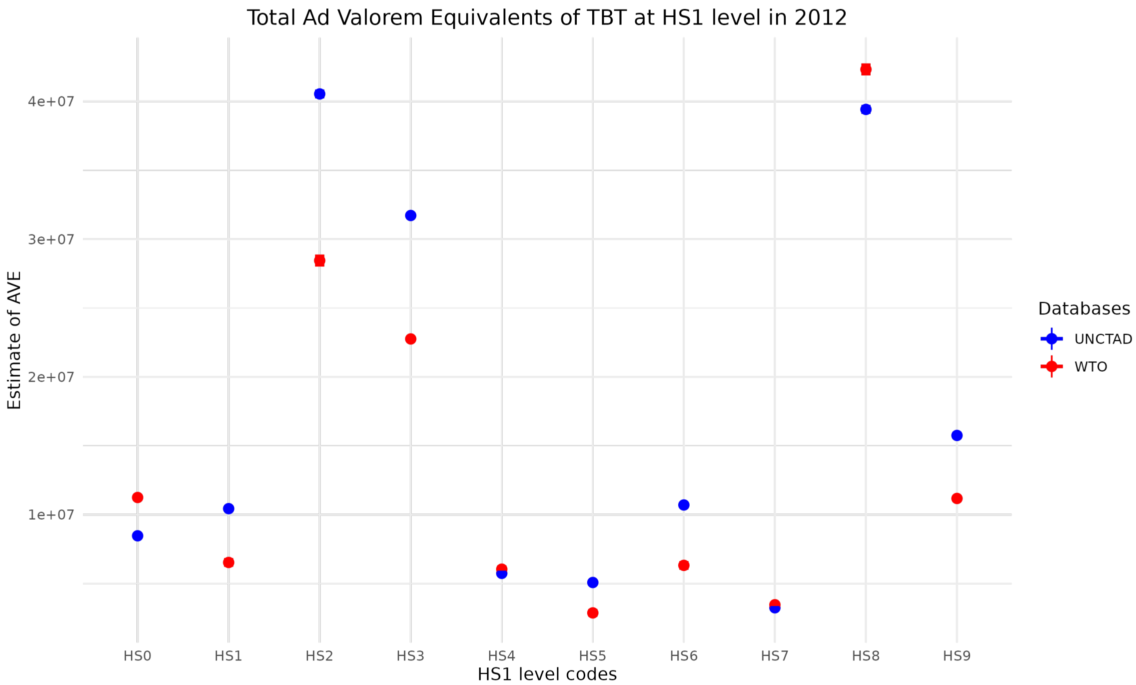

Figure 12: Estimated total AVE (counts of SPS) in 2012

V - III AVE Estimates using IVs

While the previous model appears to yield different AVE estimates between TRAINS and WTO, the observed gap might be due to endogeneity issues. If the bias, stemming from the reverse causality, affects both estimates differently, it could explain the observed discrepancy. Therefore, we plan to conduct the same analysis using instrumental variables (IVs). The results for this section will be added in the future.

VI. Conclusion and next steps

In conclusion, the observed disparity in AVE between the two databases fluctuates notably across different HS code categories at a one-digit level. This discrepancy could potentially be attributed to some NTMs not being notified to the WTO but appearing in the UNCTAD database. In addition, the observation that NTM counts matter more when estimating total NTM effects underscores the significance of the assumption of no withdrawal, making it more likely to introduce measurement errors. But the counts seem to be less important when only measuring average AVE. This suggests a nuanced relationship that warrants deeper investigation. Future analysis should focus on comparing these estimates using instrumental variables (IVs) across various HS code levels to understand this discrepancy better. It is also imperative to extend the comparison beyond mean values and delve into the variances while using more robust statistical techniques such as bootstrapping.

In future analyses, we aim to broaden this investigation to include various HS code levels and incorporate countries beyond Brazil. As highlighted by Ing, Cadot, and Walz (2018), certain countries demonstrate a higher propensity to notify NTMs to the WTO compared to others, influenced by differing levels of transparency across nations. This disparity could potentially lead to varying gaps between the AVE estimates derived from the two databases, particularly in countries that are less transparent in their notification practices, resulting in increased measurement errors when estimating AVEs from WTO notifications.

Lastly, the idea of combining datasets from both the WTO and UNCTAD into a single database presents an intriguing solution. This merger would expand country and time coverage while reducing potential measurement errors, allowing for a more thorough analysis. Such a unified database holds the promise of revealing deeper insights into the underlying dynamics of trade economics, ultimately enhancing our understanding of global trade patterns and trends.

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Annex

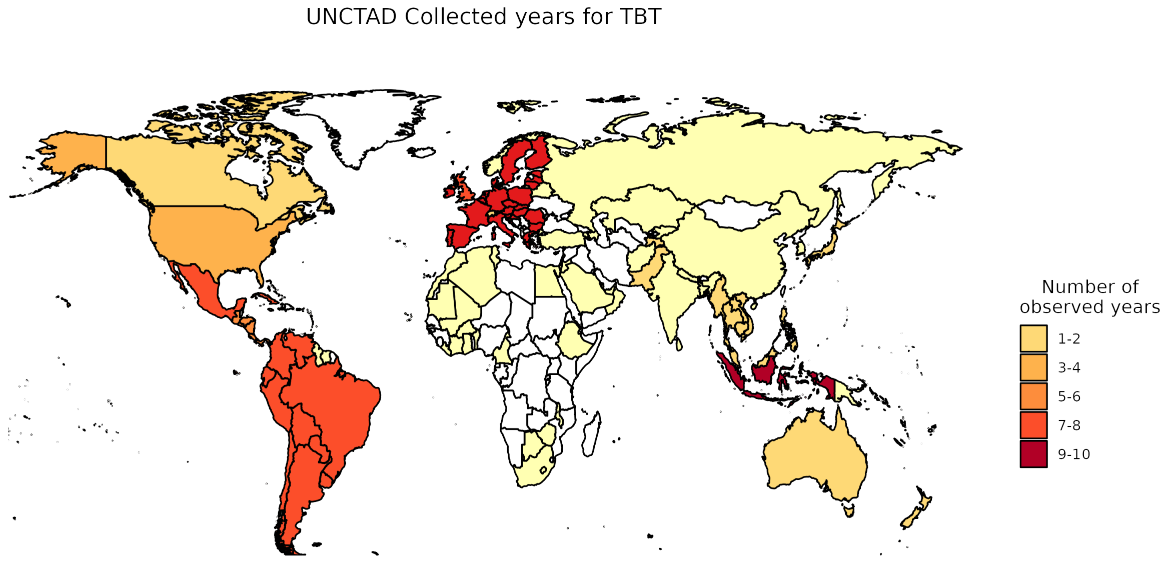

Figure 13: TBT: UNCTAD NTM data country and time coverage

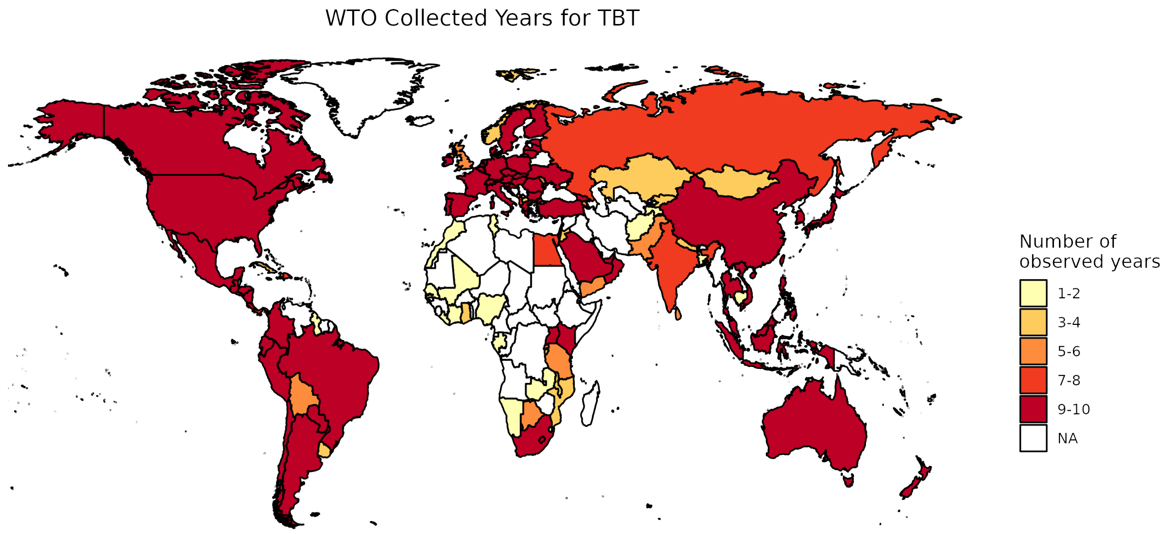

Figure 14: TBT: WTO NTM data country and time coverage

Table 2: UNCTAD: regression results

	H0	H1	H2	H3	H4	H5	H6	H7	H8	H9
Dpt Vars.					UNCTAD log(price)					
Constant	70.73 (75.09)	-0.2396 (65.36)	-60.44 (116.6)	44.40 (55.81)	-6.149 (61.80)	-154.3 (133.9)	-16.29 (67.01)	-34.35 (57.56)	51.93 (37.98)	62.13 (83.00)
log(dist)	-7.538 (8.873)	0.0381 (7.724)	7.172 (13.78)	-4.666 (6.594)	0.8782 (7.302)	18.91 (15.82)	2.283 (7.918)	4.470 (6.801)	-5.760 (4.488)	-6.775 (9.808)
contig	3.903 (4.691)	-0.5733 (4.082)	-3.173 (7.278)	2.746 (3.484)	-0.4392 (3.855)	-9.380 (8.354)	-0.8277 (4.179)	-2.777 (3.591)	3.177 (2.369)	3.687 (5.179)
comlang_off	1.925 (2.607)	-0.3320 (2.263)	-1.803 (4.043)	0.2445 (1.949)	0.1522 (2.157)	-9.999 (8.156)	-0.6746 (2.317)	-1.561 (2.013)	0.9357 (1.324)	1.426 (2.886)
rta	-0.2075 (0.1348)	0.1274 (0.1361)	-0.1005 (0.1131)	0.0332 (0.0758)	0.0377 (0.0869)	-0.0188 (0.1212)	-0.0841 (0.0863)	-0.0624 (0.0784)	-0.1156* (0.0579)	0.0407 (0.1234)
ntm_SPS	0.0067* (0.0027)	-0.0051 (0.0040)	-0.0003 (0.0095)	0.0063 (0.0117)	-0.0267 (0.0222)	-0.2438 (0.2304)	0.0043 (0.0296)	-0.4684** (0.1813)	0.4274* (0.2156)	-0.0151 (0.0229)
ntm_TBT	0.0106. (0.0058)	0.0116* (0.0056)	-0.0011 (0.0024)	0.0026** (0.0010)	0.0147* (0.0058)	0.0479*** (0.0098)	0.0112. (0.0060)	-0.0015 (0.0080)	-0.0045. (0.0026)	0.0213*** (0.0047)
log(1+_tar)	0.0102 (0.0884)	-0.0173 (0.1645)	-0.0078 (0.0913)	0.0599 (0.0790)	0.2006 (0.2466)	0.0812 (0.1116)	-0.1442 (0.1069)	0.2553. (0.1343)	0.1330 (0.1032)	-0.2119* (0.1011)
Year2013	-0.0276 (0.0213)	-0.0052 (0.0181)	-0.0097 (0.0143)	0.0056 (0.0114)	0.0405** (0.0128)	0.0120 (0.0150)	0.0199. (0.0107)	0.0137 (0.0119)	0.0067 (0.0085)	-0.0100 (0.0167)
Year2014	-0.0075 (0.0214)	0.0162 (0.0181)	-0.0187 (0.0142)	0.0239* (0.0114)	0.0561*** (0.0128)	0.0380* (0.0151)	0.0108 (0.0107)	0.0135 (0.0119)	0.0139 (0.0085)	0.0303. (0.0167)
Year2015	-0.0894*** (0.0223)	-0.0577** (0.0183)	-0.0877*** (0.0144)	-0.0500*** (0.0115)	-0.0307* (0.0129)	-0.0405** (0.0152)	-0.0819*** (0.0107)	-0.0559*** (0.0120)	-0.0594*** (0.0086)	-0.0085 (0.0170)
Year2016	-0.1354*** (0.0227)	-0.0957*** (0.0186)	-0.1064*** (0.0146)	-0.0962*** (0.0117)	-0.0889*** (0.0131)	-0.1020*** (0.0154)	-0.0946*** (0.0107)	-0.0931*** (0.0122)	-0.0855*** (0.0086)	-0.0139 (0.0172)
Obs	16,951	21,447	63,759	86,346	65,925	40,154	84,932	91,114	226,434	68,084
R2	0.72989	0.61898	0.55659	0.50297	0.62047	0.44400	0.48747	0.47634	0.52367	0.50496
Adj. R2	0.71941	0.61110	0.55009	0.49945	0.61704	0.43493	0.48359	0.47213	0.52104	0.50082

Table 3: WTO: regression results

	H0	H1	H2	H3	H4	H5	H6	H7	H8	H9
	WTO	WTO	WTO	WTO	WTO	WTO	WTO	WTO	WTO	WTO
Dpt Var.	log(price)	log(price)	log(price)	log(price)	log(price)	log(price)	log(price)	log(price)	log(price)	log(price)
Constant	75.55 (75.10)	-3.056 (65.40)	-60.92 (116.6)	44.47 (55.81)	-7.269 (61.80)	-160.5 (133.9)	-15.92 (67.01)	-35.21 (57.56)	52.74 (37.98)	60.98 (83.01)
log(dist)	-8.098 (8.874)	0.0638 (7.725)	7.197 (13.78)	-4.661 (6.594)	1.025 (7.303)	19.52 (15.83)	2.245 (7.919)	4.572 (6.801)	-5.855 (4.488)	-6.552 (9.809)
contig	4.211 (4.691)	-0.5817 (4.083)	-3.183 (7.279)	2.744 (3.484)	-0.5177 (3.855)	-9.694 (8.356)	-0.8084 (4.179)	-2.831 (3.591)	3.226 (2.369)	3.564 (5.179)
comlang_off	2.090 (2.607)	-0.3381 (2.263)	-1.816 (4.044)	0.2440 (1.949)	0.1060 (2.157)	-10.31 (8.158)	-0.6645 (2.318)	-1.592 (2.013)	0.9609 (1.324)	1.354 (2.886)
rta	-0.2099 (0.1348)	0.1214 (0.1361)	-0.1028 (0.1131)	0.0324 (0.0758)	0.0373 (0.0869)	-0.0178 (0.1212)	-0.0847 (0.0863)	-0.0622 (0.0784)	-0.1145* (0.0579)	0.0478 (0.1234)
ntm_SPS	0.0017 (0.0020)	0.0173 (0.0149)	0.0053 (0.0045)	0.0076* (0.0033)	-0.0128 (0.0203)	-0.0031 (0.0117)	-0.2511*** (0.0374)	-1.343*** (0.3772)	-0.1090** (0.0356)	-0.1253 (0.1697)
ntm_TBT	0.0015 (0.0059)	-0.0079 (0.0150)	-0.0032 (0.0056)	-0.0014 (0.0020)	-0.0253. (0.0133)	-0.0717* (0.0283)	0.0162 (0.0154)	-0.0079. (0.0046)	0.0017 (0.0037)	-0.0121. (0.0062)
log(1+_tar)	0.0131 (0.0884)	-0.0101 (0.1645)	-0.0081 (0.0913)	0.0604 (0.0790)	0.1829 (0.2468)	0.0288 (0.1126)	-0.1439 (0.1069)	0.2477. (0.1344)	0.1294 (0.1033)	-0.2123* (0.1011)
Year2013	-0.0135 (0.0209)	-0.0081 (0.0181)	-0.0078 (0.0146)	0.0069 (0.0115)	0.0445*** (0.0130)	0.0121 (0.0150)	0.0190. (0.0107)	0.0140 (0.0119)	0.0066 (0.0085)	0.0021 (0.0177)
Year2014	0.0063 (0.0212)	0.0136 (0.0181)	-0.0141 (0.0163)	0.0251* (0.0118)	0.0610*** (0.0131)	0.0382* (0.0151)	0.0107 (0.0107)	0.0239. (0.0134)	0.0121 (0.0086)	0.0535** (0.0201)
Year2015	-0.0723*** (0.0216)	-0.0611*** (0.0182)	-0.0801*** (0.0194)	-0.0437*** (0.0125)	-0.0234. (0.0134)	-0.0233 (0.0167)	-0.0821*** (0.0107)	-0.0448** (0.0137)	-0.0639*** (0.0107)	0.0183 (0.0209)
Year2016	-0.1295*** (0.0288)	-0.0950*** (0.0282)	-0.0993*** (0.0242)	-0.0901*** (0.0131)	-0.0793*** (0.0143)	-0.0828*** (0.0168)	-0.0951*** (0.0108)	-0.0818*** (0.0139)	-0.0865*** (0.0113)	0.0288 (0.0254)
Obs	16,951	21,447	63,759	86,346	65,925	40,154	84,932	91,114	226,434	68,084
R2	0.72975	0.61890	0.55660	0.50296	0.62045	0.44381	0.48745	0.47636	0.52368	0.50483
Adj. R2	0.71927	0.61101	0.55010	0.49944	0.61702	0.43474	0.48357	0.47215	0.52106	0.50069

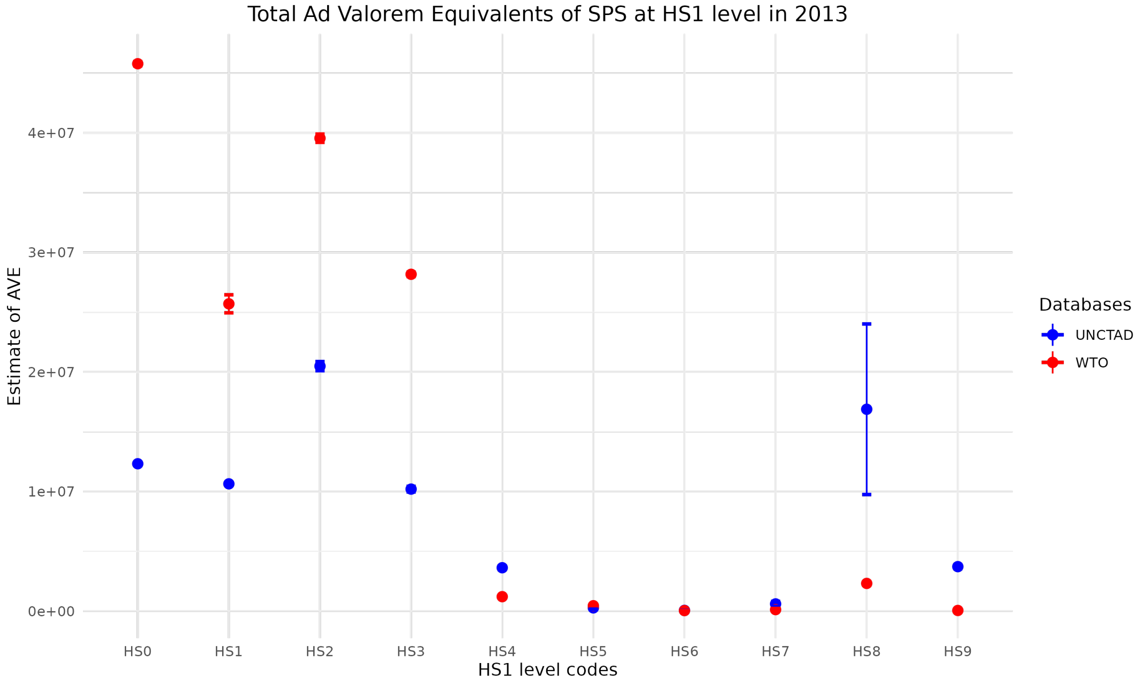

Figure 15: Estimated total AVE (counts of SPS) in 2013

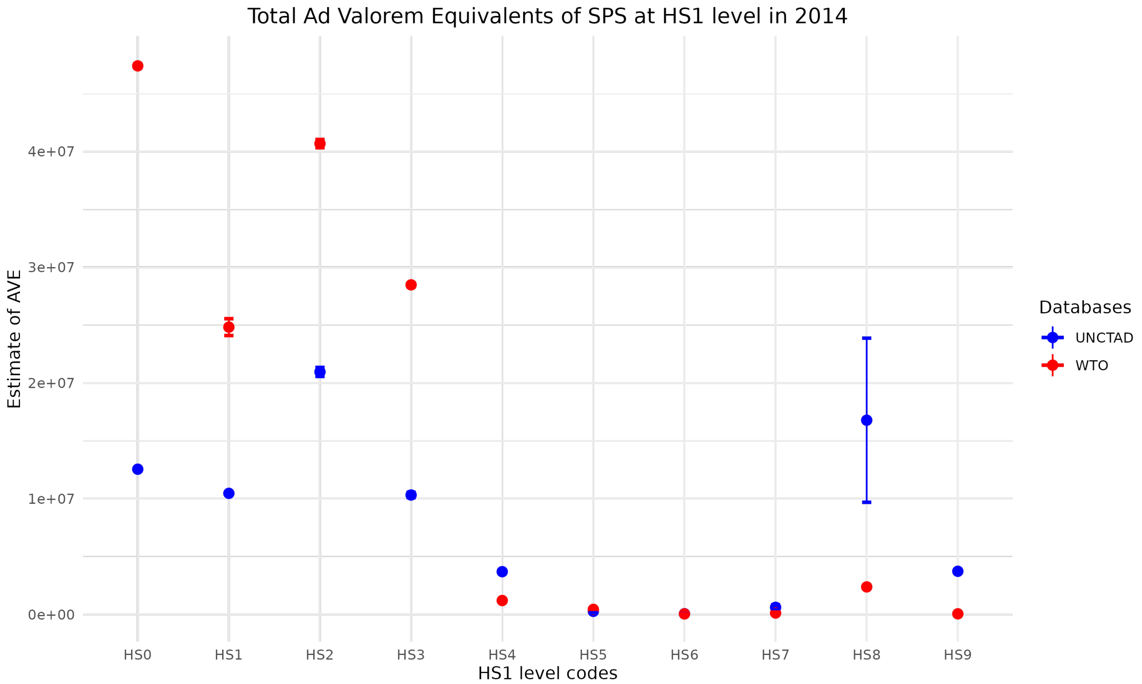

Figure 16: Estimated total AVE (counts of SPS) in 2014

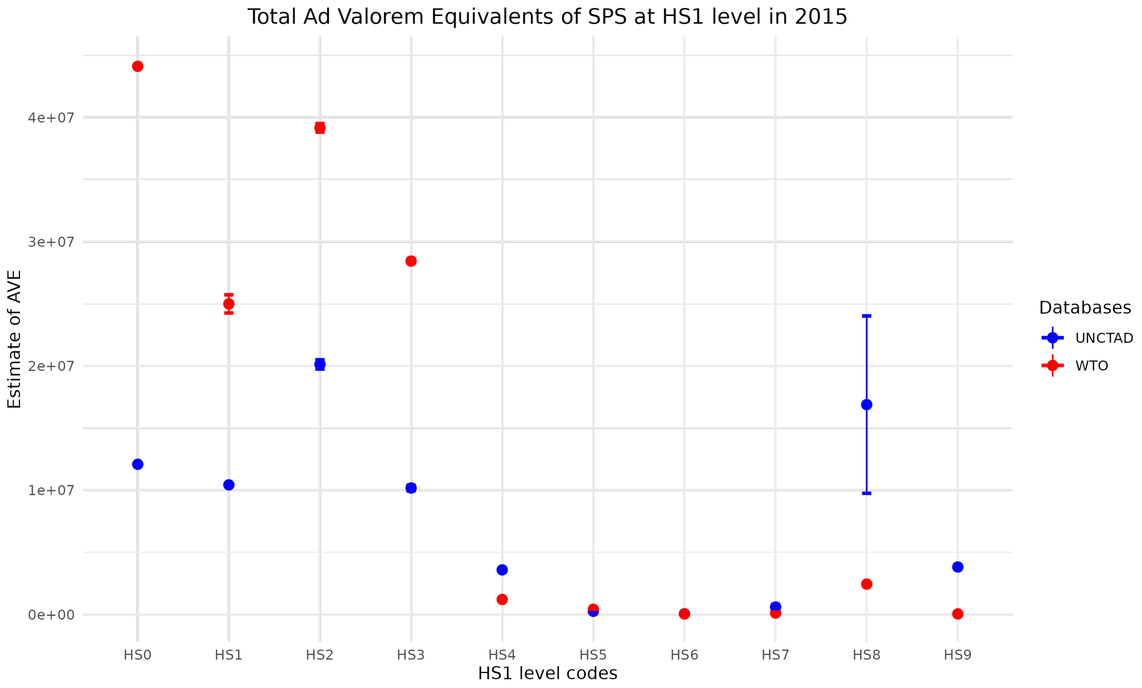

Figure 17: Estimated total AVE (counts of SPS) in 2015

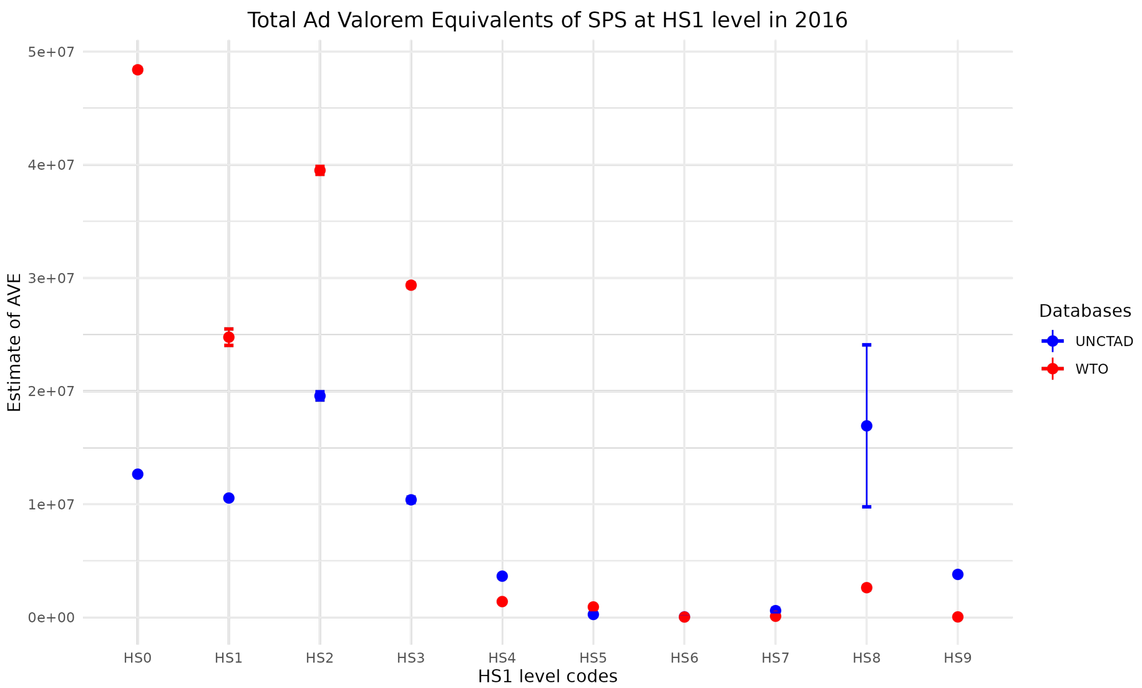

Figure 18: Estimated total AVE (counts of SPS) in 2016

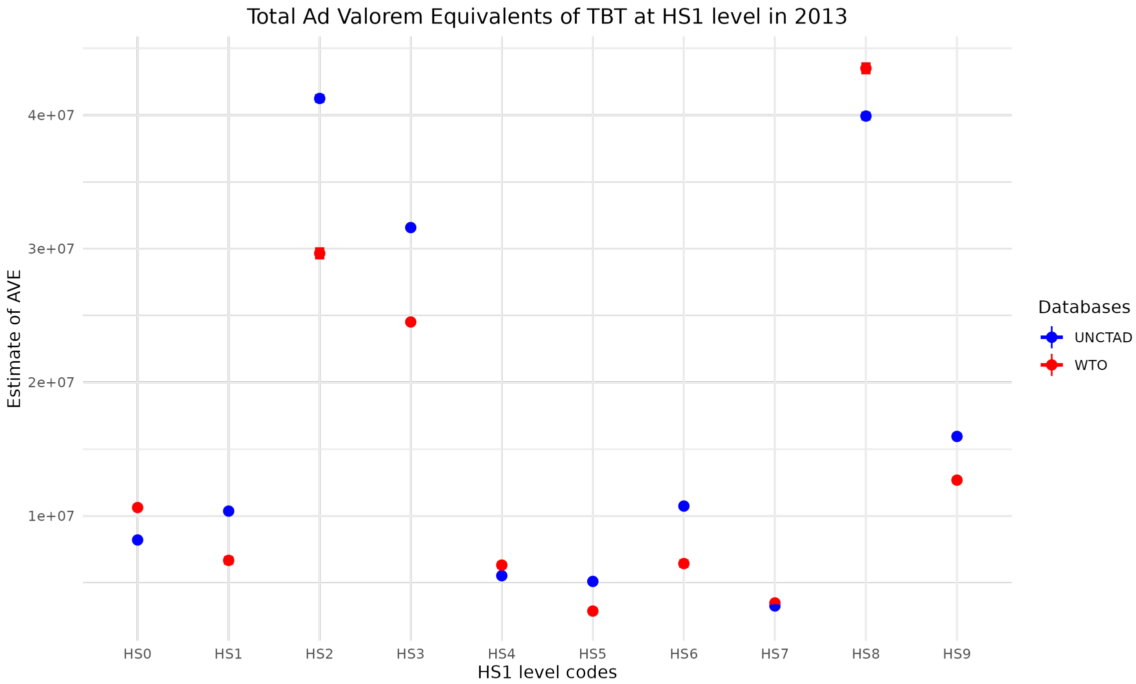

Figure 19: Estimated total AVE (counts of SPS) in 2013

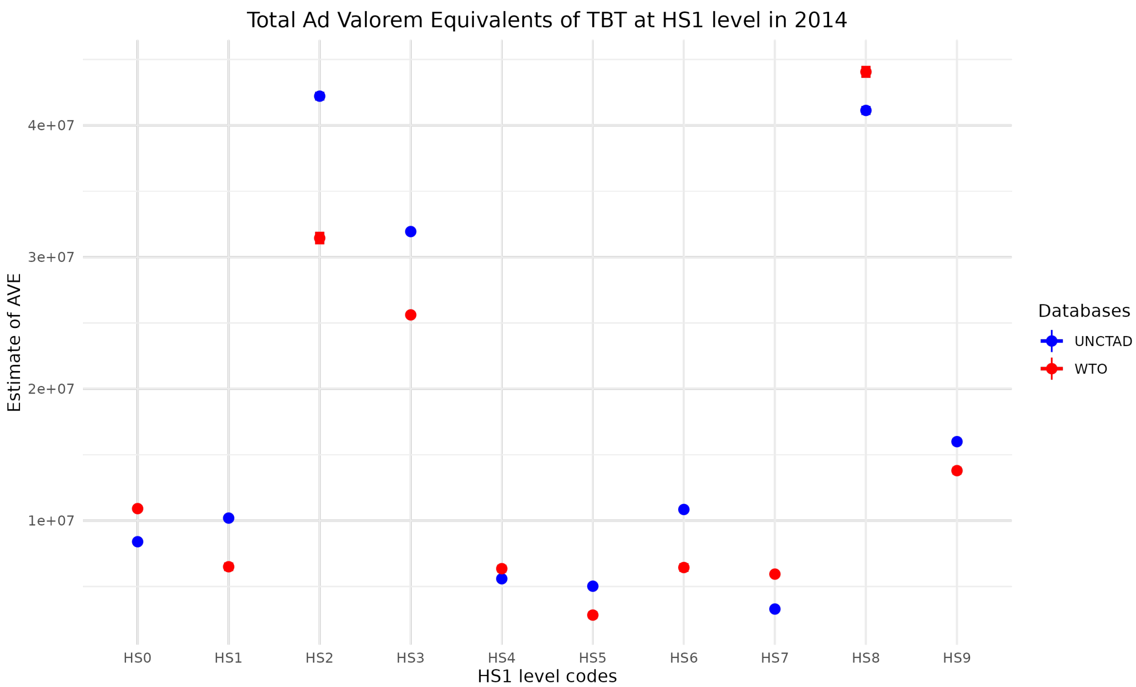

Figure 20: Estimated total AVE (counts of SPS) in 2014

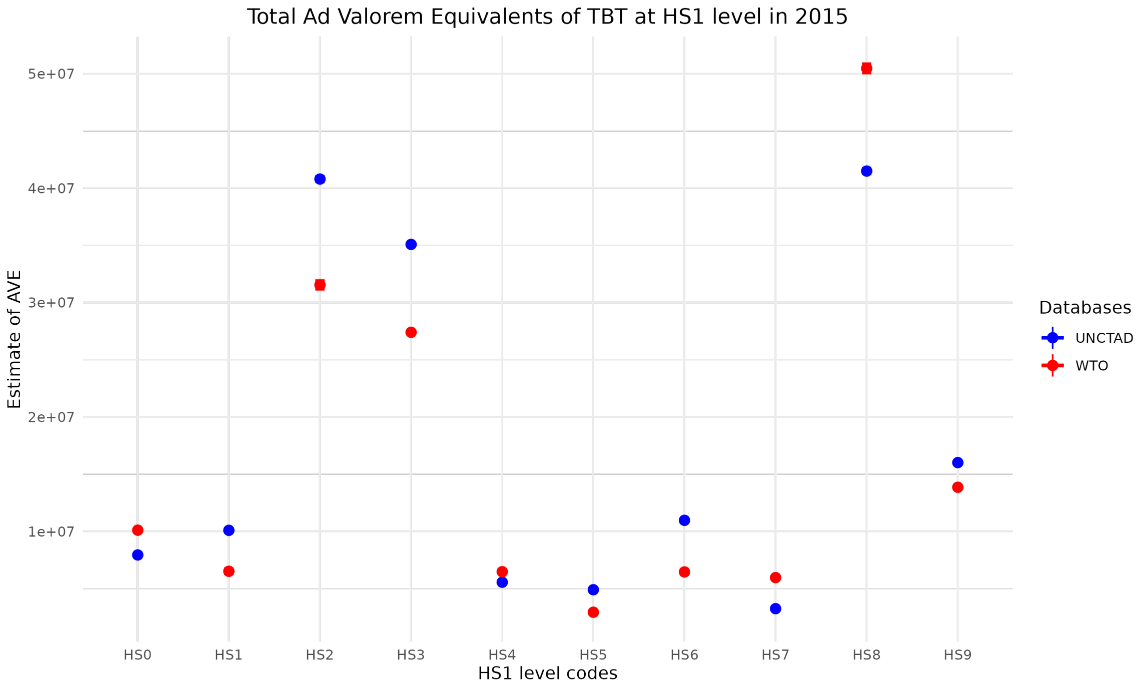

Figure 21: Estimated total AVE (counts of SPS) in 2015

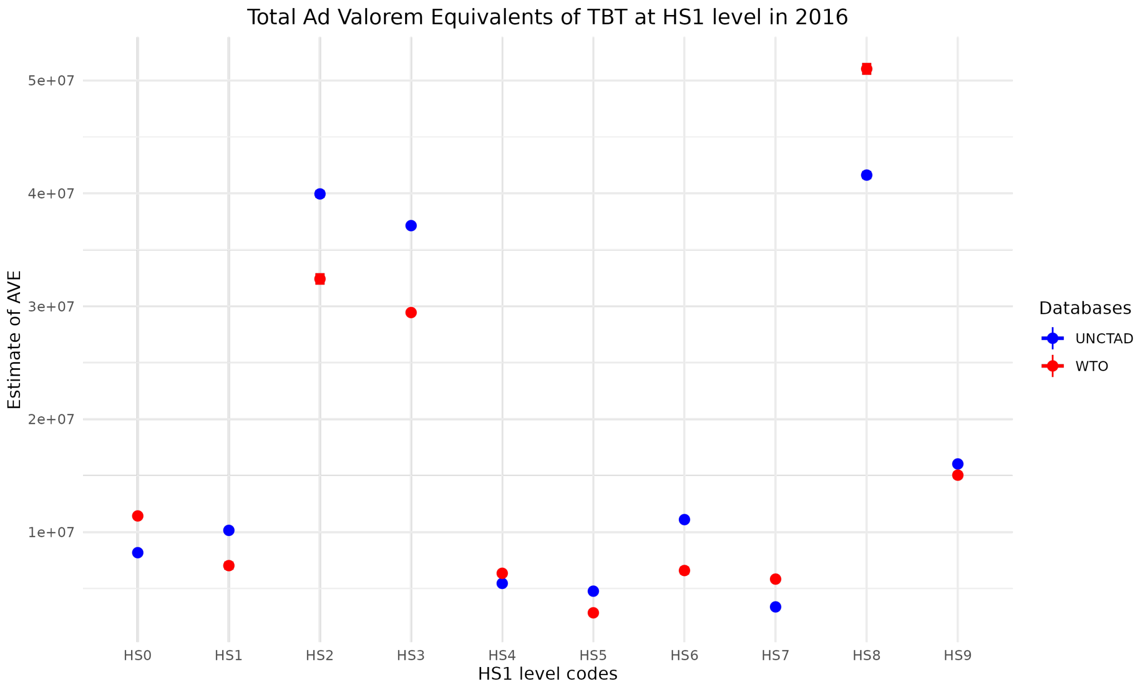

Figure 22: Estimated total AVE (counts of SPS) in 2016