A Pragmatic Approach to Estimating Nondiscriminatory
Non-tariff Trade Costs

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Abstract

Despite the growing importance of non-tariff measures (NTMs) in trade policy, many common methods for estimating their costs exhibit significant challenges in terms of data requirements or do not isolate the effects of specific NTMs. I propose an extension to existing approaches that mitigates these limitations. Following earlier work by Fontagné et al. (2011), I estimate a measure of the aggregate nondiscriminatory trade costs present in each country. Then, in a second stage, I econometrically decompose the estimated trade costs into individual components such as the costs associated with specific NTMs. Additionally, the second stage allows for the identification and removal of non-cost factors that erroneously contributed to the aggregate cost estimates. The methodology provides a means by which to estimate the effects of specific NTMs using widely available data and standard econometric techniques. I test the methodology using a typical gravity dataset and detailed NTM data. The results provide specific cost estimates for SPS measures and TBTs across many sectors and demonstrate that aggregate measures of non-discriminatory trade costs can significantly reflect non-cost factors.

Keywords: trade, non-tariff measures, gravity

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1 Introduction

In recent years, trade policy has increasingly targeted issues related to non-tariff measures (NTMs). Tariff reductions, which had long been the primary focus of trade policy, have become relatively less important as MFN rates have fallen, leaving little room for additional tariff liberalization. These trends have left NTMs such as sanitary and phytosanitary (SPS) measures and technical barriers to trade (TBTs) as the primary types of trade costs faced by most goods and services. However, despite these trends in trade policy, estimating measures of the costs of NTMs remains a challenge.

While many different approaches for estimating the effects of NTMs have been proposed in recent years, most exhibit data or methodological requirements that limit their use in many situations. In some cases, these approaches rely on specialized product-specific, micro-level data that cannot be easily applied to other products or NTMs. In other cases, the methods require access to uncommon macro-level data such as reliable price information or domestic shipments in different markets that may not be widely available. Some approaches require specialized methodologies that can not be easily replicated or adapted to new applications. Finally, many approaches estimate broad NTM-related trade costs that do not necessarily identify the effects of specific NTMs that may be of interest. In this paper, I propose an approach that mitigates these limitations. First, it uses publicly available data and easily implementable econometric procedures. Second, it provides an economically sound way to identify the effects of specific NTMs. For these reasons, it represents a methodology that is well suited for broad use in trade policy analysis where the NTMs of interest are unique in each scenario and specialized data may not be readily available. As an example of its usefulness for modern trade policy, a similar approach was employed in the U.S. International Trade Commission's analysis of the U.S.-Mexico-Canada agreement (USITC, 2019) to estimate the impacts of several types of influential NTMs including intellectual property rights, data transfer provisions, and cross-border services barriers.

Many different types of approaches have been proposed for estimating the effects of NTMs. Some of this research, such as that by Dean et al. (2009), estimates the effects of NTMs by analysing prices. Such an approach provides a direct way of identifying the effects of NTMs on costs but relies on the availability of pricing data, which can be prohibitive in many situations. Because of these limitations, most modern approaches have focused on trade values instead of prices, which

are more readily available but provide a less direct means of estimating the ad valorem equivalent (AVE) costs of policies. As a result, econometric models for identifying costs have had to follow suit, often becoming increasingly complex and specialized.

For many years, research into the impacts of NTMs on trade has been hamstrung by the limited availability of data on specific types of NTMs. For example, maximum residue limits (MRLs), which are agricultural standards that limit the amount of pesticide that can appear on a crop, have been a common target of study because they are one of few prominent NTMs to exhibit clearly defined, continuous, and bilaterally quantifiable requirements (c.f. Winchester et al. (2012) and Xiong and Beghin (2014)). However, despite the useful insight these studies can provide on MRLs specifically and—to some extent—NTMs more broadly, there are few other types of measures that similarly well suited for direct analysis. Fortunately, in recent years, significant effort has been expended to increase the availability of granular NTM information. For example, UNCTAD and its collaborators have produced a classification scheme and extensive database of individual NTMs affecting goods trade (UNCTAD, 2019). This database covers 16 different types of NTMs such as SPS, TBT, customs procedures, price controls, and export subsidies at the product level for a significant number of countries. Similarly, the OECD (Grosso et al., 2015) and and World Bank (Borchert et al., 2012) have produced detailed indices cataloging the NTMs affecting services trade.

The availability of NTM data does not solve all methodological problems associated with the measurement of NTM trade costs. One notable challenge is the nondiscriminatory nature of most NTMs. For example, while workhorse gravity models can easily include discriminatory (bilateral) NTMs, many important NTMs are applied equivalently to all foreign imports, regardless of the exporter. Because of this, typical gravity models—which are one of the premier methods for estimating trade costs—often cannot identify the effects of nondiscriminatory NTMs. Structural gravity models require the inclusion of multilateral resistance terms (MRTs) that are typically modeled as importer and exporter fixed effects. Under most standard specifications, these terms capture the effects of nondiscriminatory trade policies like NTMs, thereby precluding the direct inclusion of nondiscriminatory policies in the model. Heid et al. (2017) describe a useful method for overcoming this issue by including data on intra-national trade (domestic shipments). Doing so allows for the interaction of nondiscriminatory trade policies with an indicator for international trade, which effectively separates the nondiscriminatory policies from the country fixed effects.

Novy (2013) describes an alternative gravity approach for using intranational trade data to estimate aggregate trade costs—including NTM costs—at the bilateral level using ratios of international to intranational trade to indirectly infer barriers. However, both approaches rely on the inclusion of intra-national trade data, which can be a prohibitive challenge in many cases as such information is often not available for many sectors or time periods.

One alternative method for measuring the effects of nondiscriminatory NTMs is to conduct the analysis at the country-level. One of the most prominent approaches is that of Kee et al. (2009), which analyzes the impacts of NTMs on aggregate imports. Following the log-linear models of Leamer (1988, 1990), Kee et al. estimate the effects of "core" NTMs and export subsidies on imports at the tariff line. These estimates are used to generate AVE trade costs and other restrictiveness indices. Other work has build on this methodology, including that of Niu et al. (2018), who replicate the earlier analysis using multiple years of data to study the costs of NTMs over time. However, there are drawbacks to using a unilateral approach. The most notable is the inability to control for many bilateral aspects of trade. For example, Kee et al. (2009) attempt to partially control for these factors by including country-level, gravity-inspired variables such as the average distance between each importer and the rest of the world or whether importers are islands. However, such an approach is unable to accurately capture the full influences of well established bilateral determinants like trade agreements, language and other cultural similarities, and distance. For this reason, a gravity model approach has advantages.

Some authors have proposed gravity approaches in which structural components of the model are allowed to absorb the effects of multiple factors including NTMs. These components are then used to infer trade costs associated with the NTMs. This approach originated with the work of Park (2002), who used the residuals from a gravity model to derive an associated, unobserved trade cost. Fontagné et al. (2011) improved upon this approach by using the importer fixed effects in a structural gravity model instead of residuals.[1] Fontagné et al.'s method represents a theory-consistent and practical means of estimating a broad measure of the relative frictions faced by exporters in each importing country. However, the approach has two significant limitations. The first is that it does not identify the effects of any specific NTMs, only an aggregate AVE trade cost for each country. The second is that it does not control for other non-cost factors that may affect

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[1]See Fontagné et al. (2016) for a more recent application of this methodology.

the estimated fixed effects and, therefore, the estimated AVE costs. For example, the approach may incorrectly attribute a lack of foreign imports to high trade barriers when it is instead a result of high domestic production and limited demand for foreign produced products. Under both cases, the importer fixed effect would be relatively small and imply a high AVE, making it difficult to distinguish between the two possible scenarios.

In this paper, I propose an extension to the methodology described by Fontagné et al. (2011) that addresses these two limitations. The extension is the addition of a second stage of analysis that decomposes the aggregate trade cost estimates produced by Fontagné et al.'s method into trade costs associated with specific NTMs and those connected to non-cost factors that are incorrectly interpreted as trade costs. The second stage analysis regresses the aggregate trade cost estimates against NTM policy data and additional controls. My proposed methodology maintains many of the features that make Fontagné et al.'s (2011) original approach attractive. It can be used with widely available public data and requires no complex econometric techniques beyond those that are standard in the gravity literature and present in common statistical programs. Additionally, the approach can be readily customized to model a wide range of nondiscriminatory trade costs and other types of non-cost controls to suit the needs of the analysis.

Similar two-stage approaches have been used in the past to study the factors underlying different gravity model estimates. Melitz (2008) examines the relationship between estimated country-level fixed effects and aspects of language such as literacy and linguistic diversity. Anderson and Yotov (2016) deconstruct exporter-importer fixed effects into individual trade cost variables for the sake of synthesizing fixed effect proxies for non-trading country pairs. Similarly, Agnosteva et al. (2019) estimate systematic "unexplained trade barriers" in exporter-importer fixed effects. Baier et al. (2019) econometrically decompose gravity estimates of specific FTAs to identify the determinants of FTA effects.

As a demonstration of my two stage methodology, I conduct an analysis of the trade costs associated with two prominent types of NTMs: SPS measures, and TBTs. As a control for demand factors that influence importer fixed effect estimates but should not be considered trade costs, I include each country's estimated exporter fixed effect and GDP per capita. Exporter fixed effects, which reflect the extent to which a country exports in a given sector, are included as a measure of the country's domestic production in that sector. Countries with large domestic production and

exports may import less due to a lack of residual demand for higher cost, foreign sourced products, which would result in smaller estimated fixed effects. GDP per capita is included in order to capture additional aspects of demand for foreign imports, particularly those related to a country's wealth.

The analysis finds that the concerns regarding the highlighted limitations are warranted. First, the non-cost factors have a significant impact on the estimates, indicating that the broad AVE cost estimates do reflect factors that should not be attributed to trade barriers. Second, despite SPS measures and TBTs being statistically significant components within the aggregate cost estimates for some (but not all) sectors, they represent only a small portion of the total estimated costs. This suggests that attributing aggregate trade cost estimates to common types of NTMs may over estimate their effects. For food and agricultural sectors, SPS measures represent an AVE trade cost of 7.3 percentage points but account for only 9.0 percent of the aggregate cost estimates in those sectors on average. In those same sectors, TBTs represent an AVE trade cost of 5.9 percentage points and reflect 6.8 percent of total estimated costs on average. Although it is possible that these NTMs have a significant impact on specific non-agricultural sectors, they do not have a notable effect on non-agricultural sectors overall. Together, these results provide compelling support for the usefulness of the second stage of analysis and demonstrate that the methodology can be an effective means by which to analyse nondiscriminatory international trade costs.

The remainder of the paper proceeds as follows. Section 2 describes the proposed methodology, including both the estimation and construction of nondiscriminatory trade costs from structure gravity models and the decomposition of the broad trade costs into specific components. Section 3 presents the demonstration of the methodology using real trade and NTM data. Section 4 concludes.

2 Methodology

To estimate the costs of specific NTMs, I propose a two stage procedure. In the first stage, a standard structural gravity model is estimated in order to produce importer(-year) and exporter(-year) fixed effect estimates. For the sake of brevity, I will refer to the structural fixed effects simply as importer and exporter fixed effects in what follows but note that in cases where estimation is based on panel data, time varying importer-year and exporter-year fixed effects should be used. Following the procedures described by Fontagné et al. (2011), aggregate cost estimates are derived using

the estimated fixed effects. It the second stage, the aggregate cost estimates are econometrically decomposed into the costs associated with specific NTMs and those associated with other factors. The ensuing cost estimates not only better measure the specific NTMs of interest but are also less reflective of factors that affect country fixed effects but are unrelated to trade frictions.

2.1 Estimating Aggregate Nondiscriminatory Trade Costs

The canonical demand-side gravity model, as described by Anderson and van Wincoop (2003), is given by the following equations.

$$X_{ijt} = \frac{Y_{it} E_{jt}}{Y_t} \left(\frac{\tau_{ijt}}{P_{jt} \Pi_{it}} \right)^{1-\sigma} \tag{1}$$

$$\Pi_{it}^{1-\sigma} = \sum_j \left(\frac{\tau_{ijt}}{P_{jt}} \right)^{1-\sigma} \frac{E_{jt}}{Y_t} \tag{2}$$

$$P_{jt}^{1-\sigma} = \sum_i \left(\frac{\tau_{ijt}}{\Pi_{it}} \right)^{1-\sigma} \frac{Y_{it}}{Y_t} \tag{3}$$

X_{ijt} denotes the value of trade from exporter i to importer j in period t. Trade is a function of the exporter's output (Y_{it}), the importer's expenditures (E_{jt}), global output (Y_t), and trade frictions. Within the model, trade frictions are represented in three ways. There are bilateral trade frictions (τ_{ijt}), which reflect things that affect the ability for two particular countries to trade such as distance, cultural affinity, and preferential trade policies. The second and third trade costs are indexes of aggregate trade costs for the exporter (Π_{it}) and importer (P_{jt}), respectively. Finally, the three cost terms are augmented by the elasticity of substitution (σ).

The two aggregate trade cost indices, which are defined in equations (2) and (3), are the multilateral resistance terms (MRTs) that have become a hallmark of theoretically consistent structural gravity models. Anderson and van Wincoop (2003) first demonstrated the importance of these terms by showing that they were critical for grounding the oft used empirical model in theoretical foundations and correcting for pervasive biases. As Yotov et al. (2016) note, MRTs provide a means to capture relative remoteness and aggregate bilateral trade costs in theory-consistent, general equilibrium trade cost indices. Given the importance of these terms, Baldwin and Taglioni (2006) have called their omission the "gold medal mistake" of gravity modeling. In adapting the

theoretical model for econometric estimation, Anderson and van Wincoop solved for the MRTs directly using a custom iterative programming procedure. However, Feenstra (2004) found that the MRTs could be effectively introduced using importer and exporter fixed effects, which presented a much easier approach to estimating structural gravity models. The fixed effects approach has become the typical methodology for most gravity estimation.

The empirical gravity model used here follows these best practices and takes the following form (Yotov et al., 2016; Head and Mayer, 2014).

$$\frac{X_{ijt}}{Y_{jt}} = exp\{\boldsymbol{\alpha}\boldsymbol{z}_{ijt} + \mu_{it} + \nu_{jt}\} + \epsilon_{ijt} \tag{4}$$

As before, X_{ijt} denotes the value of trade from exporter i to importer j in period t. It is divided by the importer's GDP, denoted by Y_{jt}, in order to exogenously control for importer market size and expenditure (E_{jt}). Thus, the dependent variable is trade as a share of importer GDP. While this adjustment is not common in the recent gravity literature, doing so is consistent with the theoretical model and—as will be further motivated below—helps to remove the expenditure term from the estimated importer fixed effect. The independent variables on the right side of the equation are comprised of a collection of typical gravity covariates ($\boldsymbol{z}_{ijt}$) such as distance, common languages, and trade agreements that are intended to represent bilateral trade costs (τ_{ijt}). The exporter-year fixed effects denoted by μ_{it} represent both the outward MRTs (Π_{it}) and output (Y_{it}). The importer-year fixed effects denoted by ν_{jt} represent inward MRTs (P_{jt}). Finally, the term ϵ_{ijt} denotes an error term. The use of a non-linear formulation is based on the work of Santos Silva and Tenreyro (2006). The authors find that linear OLS estimates of gravity models are subject to biases related to zero trade and fail to correct for pervasive heteroskedasticity. Certain non-linear estimators such as Poisson pseudo-maximum-likelihood (PPML)—their recommended estimator—correct for these issues.

There are numerous advantages to estimating the model at the sector or product level. Doing so permits greater precision in estimating product-specific trade costs, which may be particularly desirable for cases where NTMs or other costs vary significantly across products. As discussed by Yotov et al. (2016), extending the model to the sector can be done by pooling the sectors together or estimating them separately. Pooling together provides more information but can increase the

computational burden significantly. This is particularly true if the fixed effects or gravity covariates are made sector-specific by interacting each with a collection of sector dummies. While sector-specific estimates of the gravity covariates can provide interesting insight into differences in trade patterns across sectors, they will have limited direct impact on the importer or exporter fixed effect estimates and are not a primary concern with regards to the estimation of nondiscriminatory NTMs. Sector-specific importer and exporter fixed effects, however, can have a significant impact on the estimation of NTMs and are advisable. As an alternative to pooling the data, each sector can be estimated separately, which implicitly estimates sector-specific coefficients for all variables and fixed effects. Doing so is still consistent with structural gravity best practices as the theoretical model is separable. In the context of the current methodology, sector-specific analysis ought to improve the precision of trade costs estimates because there will be less averaging across products. However, given the flexibility of the model with regards to how it treats different sectors, I forgo including notation regarding sectors in most cases.

In equation (4), μ_{it} and ν_{jt} act as proxies for MRTs and therefore control for unobserved multilateral resistances that may not be fully accounted for in the measures of bilateral trade costs ($\mathbf{z}_{ijt}$). With respect to NTMs, these terms serve two important functions. First, they help in controlling for trade costs that are unobserved by the econometrician. Second, when intranational trade flows (X_{ii}) are not included in the gravity model, as has been typical in much of the past gravity literature, these terms capture nondiscriminatory international trade barriers.[2] NTMs have typically fallen into at least one if not both of these categories. Until recently, extensive NTM data has been lacking, often requiring that they be treated as unobserved factors. Additionally, gravity models that include intranational trade are relatively uncommon, implying that most structural gravity studies have implicitly used MRTs to capture the effects on nondiscriminatory NTMs. Nonetheless, in these cases, it is possible to make inferences about the barriers facing imports or exports in each country based on the estimated MRTs. With regard to the model in equation (4), the estimates $\hat{\mu}_{it}$ and $\hat{\nu}_{jt}$ will be used. Because NTMs are most often thought of as importer barriers, I will focus primarily on importer NTMs and ν_{jt} but the approach could equally be applied to export costs as well.

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[2]See Heid et al. (2017) for a more detailed description of how the incorporation of intranational trade permits the disentangling of nondiscriminatory international trade costs from importer/exporter fixed effects.

Fontagné et al. (2011) describe a methodology for inferring unobserved trade costs from a structural gravity model. The methodology, which is itself an extension of the earlier work of Park (2002), infers trade costs by comparing observed trade to the trade that would occur if there were no import costs. In the structural model given by equation (1), the ratio of observed to cost-free trade can be expressed as

$$\frac{X_{ijt}}{X_{ijt}^{free}} = \left(\tau_{ijt} \frac{P_{jt}^{free}}{P_{jt}} \right)^{1-\sigma}. \tag{5}$$

The relationship described in (5) assumes that under free trade, bilateral trade costs are zero ($\tau_{ijt}^{free} = 1$) and that output, expenditures, and outward multilateral resistances in each market are unaffected. Given this, the difference between observed and cost-free trade is determined by the differences in bilateral trade costs and inward MRTs.

Empirically, this relationship can be similarly derived from equation (4) in the following way:

$$\frac{X_{ijt}}{X_{ijt}^{free}} = \frac{\exp(\nu_{jt})}{\exp(\nu_{jt}^{free})}. \tag{6}$$

In this case, it is assumed that *bilateral* trade costs and the exporter fixed effects are unaffected by the removal of non-discriminatory trade costs. The assumption about unaffected bilateral trade costs follows from the fact that in an empirical model that does not feature domestic trade, nondiscriminatory trade costs are not captured by the bilateral trade cost proxies in z_{ijt} but rather by the fixed effects.

The theoretical model in equation (5) and the empirical representation in equation (6) can be combined in order to demonstrate the relationship between theoretical trade costs and inward MRTs and empirical importer fixed effects. Combining these equations, summing across exporters, and taking logs of both sides yields

$$(1-\sigma) \ln \left(\tau_{jt} \frac{P_{jt}^{free}}{P_{jt}} \right) = \nu_{jt} - \nu_{jt}^{free}. \tag{7}$$

Here, it is further assumed that trade costs are non-discriminatory ($t_{ijt} = t_{jt}$), which is reasonable given bilateral trade costs have been controlled for elsewhere in the estimation specification.[3]

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[3]Given the assumption that $t_{ijt} = t_{jt}$, neither side of equation (7) differs across each exporter. Thus, the summation results in each side being multiplied by the number of exporters, which simply cancels out.

Because cost-free trade is not observed, Fontagné et al. (2011) suggest using a benchmark country as a proxy for ν_{jt}^{free}. In particular, they select the country with the largest importer fixed effect estimate as the benchmark, arguing that the large fixed effect is reflective of low barriers to importing. Because expenditure in country j was controlled for explicitly in equation (4), the fixed effects capture only the inward multilateral resistances and not also the expenditure term from equation (1), thereby improving the connection between the fixed effect estimate and nondiscriminatory costs.[4] Notably, however, the use of a benchmark importer implies that all cost estimates are relative to the costs exhibited by the benchmark country.

Fontagné et al. (2011) make an additional assumption in equation (7) that the ratio of inward multilateral resistances is sufficiently close to 1 to be ignored. Thus, they propose a simplified version of equation (7) in which trade costs can be inferred as

$$\hat{\tau}_{jt} = 1 + \hat{T}_{jt} = \exp\left((\hat{\nu}_{jt} - \hat{\nu}_t^*)/(1 - \sigma)\right), \tag{8}$$

where $\hat{\ }$ denotes estimated values, $*$ denotes the benchmark estimate, and T_{jt} is the AVE of the trade cost. In the framework in which a single country's observed and free trade multilateral resistance terms were being compared rather than using a benchmark, this is a plausible assumption as trade costs would be the only significant difference in the fixed effects. However, in the empirical framework in which the fixed effect of a benchmark country is used, it is less appropriate. The importer fixed effect estimates generally reflect many important differences between country j and the benchmark country that go beyond nondiscriminatory trade costs, such as differences in preferences, wealth, productivity, and domestic trade. For this reason, it should be expected that Fontagné et al.'s aggregate AVE estimate reflects more than nondiscriminatory trade costs:

$$\hat{T}_{jt} = \tau_{jt}\widehat{\frac{P_t^*}{P_{jt}}} - 1. \tag{9}$$

Thus, additional care ought to be given to the interpretation of the estimated AVE. One such option is to try to disentangle the non-cost factors embodied in the inward MRTs from the trade

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[4]This alteration is also consistent with some past literature, which has estimated trade as a ratio of GDP. For example, Feenstra (2002) made similar assumptions and divided bilateral trade by both importer and exporter GDP using an elasticity of 1.

costs.

2.2 Decomposing Aggregate Trade Cost Estimates

Despite being a practical and appealing approach for estimating importer trade costs, Fontagné et al.'s (2011) methodology features some notable limitations given its simplifying assumption that the differences between the benchmark country and each other country represent only trade costs. As a consequence, the aggregate cost estimates ($\hat{T}_{ijt}$) cannot distinguish between actual trade costs and other factors that may impact importer fixed effects but are unrelated to costs. For example, one likely significant factor is domestic production. In a gravity model that does not include intranational trade flows, importer fixed effects will tend to be smaller in cases where countries produce more and import less as a result. In these cases, the method described above can incorrectly attribute the smaller fixed effect to higher trade barriers instead of lower demand for foreign products and overestimate trade costs. A second limitation is that the approach provides little insight into what factors are driving the estimated trade costs. From a trade policy perspective, for example, knowing that a country exhibits certain AVE import costs may not be particularly useful if it impossible to determine where those costs are coming from. Similarly, it provides little insight into how a change to a specific NTM would affect that aggregate estimate. For these reasons, I propose an additional stage of analysis that mitigates these limitations.

This second stage combines the aggregate trade cost estimates with additional data to econometrically identify the factors that comprise the aggregate trade costs. These factors should include NTMs or other policies of interest as well as non-cost factors that influence a country's proclivity to import. While there are many potential factors to consider, I will highlight three types: domestic production, import demand, and NTMs. Each factor is motivated by trade and gravity theory and is expected to have a significant influence over the estimated aggregate trade costs.

The first factor is a measure of domestic production. It serves the purpose of separating and removing influences of strong domestic supply from the cost estimates. In particular, it is meant to account for domestic trade patterns when that data is not available. I use each country's estimated exporter fixed effect as a measure of domestic production. In the Anderson and van Wincoop (2003) demand-side version of the model, the exporter fixed effects explicitly capture the value of output in the exporting country. In the Eaton and Kortum (2002) supply-side version of the gravity model,

exporter fixed effects are said to reflect many aspects of the countries' export competitiveness. Central to a country's competitiveness is the capacity and efficiency of producing the good. A country exhibiting export competitiveness in a particular sector is naturally less inclined to rely on foreign imports. If a gravity model does not include domestic shipments, a lack of foreign imports will manifest as a smaller importer fixed effect. The inclusion of each importer's exporter fixed effect in the second stage regression should help to separate this influence from that of trade costs.

The second factor is a measure of import demand, which aims to disentangle the additional effects of strong or weak demand for foreign imports from the effects of trade costs. While certain aspects of market size are exogenously controlled for through the treatment of GDP, other aspects may still be present and influence fixed effect estimates. To control for some additional demand factors, I include a measure of GDP per capita, which is intended to control for the relationship between consumer wealth and imports. Before the wide-spread adoption of gravity models that included country fixed effects, GDP per capita was a common bilateral trade determinant in gravity models and typically exhibited a positive relationship with trade (c.f. Rose (2004), Rauch (1999), and Anderson (1979)). In the estimating equation (4), this relationship is absorbed by the fixed effects and therefore affects the aggregate trade cost estimates. To mitigate its effect, GDP per capita is included in the second stage to remove that relationship between wealth, demand, and trade.

The third factor is measures of specific NTMs. These measures serve the purpose of tying trade cost estimates to actual policies in place. Recent efforts to expand our understanding of NTMs has generated some extensive datasets of NTM information that are well suited for this purpose. Some data, such as that provided by United Nations Conference on Trade and Development (UNCTAD) (2017) reflects the presence of specific measures affecting a wide range of products. Other candidate data are the numerous indices of trade policies that different organizations collect, such as the services trade restrictiveness indices published by Grosso et al. (2015) and Borchert et al. (2012). For example, early examples of this two stage approach can be found in the USITC's (2019) study of USMCA in which estimated AVE trade costs were regressed against the OECD STRI and the U.S. Chamber of Commerce's intellectual property rights index to identify the effcts of USMCA's data transfer and intellectual property provisions, respectively. Similarly, Herman et al. (2018) regressed estimated importer fixed effects for medical technology against measures of demand factors

for medical equipment, regulatory complexity, and approval delays. One benefit of the proposed framework is that it is particularly flexible with respect to the types of data that can be utilized and can therefore be adapted to suit the needs of a wide range of possible scenarios.

The general version of the second stage model takes the following form:

$$\hat{T}_{jt} = \beta + \boldsymbol{\gamma} \boldsymbol{D}_{jt} + \boldsymbol{\delta} \boldsymbol{N}_{jt} + \xi_{jt}. \tag{10}$$

As before, $\hat{T}_{jt}$ denotes the estimated aggregate AVE trade costs from equation (8). β represents either a constant or, if appropriate given the specification, a collection of fixed effects such as sector fixed effects if the observations are pooled across sectors. $\boldsymbol{D}_{jt}$ denotes the control(s) for importer domestic production, demand, or other non-cost factors. $\boldsymbol{N}_{jt}$ represents the measure(s) of nondiscriminatory trade costs affecting imports such as NTMs. Finally, ξ_{jt} is an error term that captures additional unobserved factors underlying the aggregate trade cost estimates. The components in equation (10) reflect those in equation (9). The nondiscriminatory cost measures $\boldsymbol{N}_{jt}$ represent trade costs τ_{jt}, the non-cost measures $\boldsymbol{D}_{jt}$ represents the inward MRTs P_{jt}, and the benchmark inward multilateral resistances P_t^* are captured in the fixed effects or constant β.

Estimates from equation (10) can be used to both decompose the aggregate trade costs into some of their constituent parts and identify the marginal cost of a change to the policy variables. The coefficient estimates reflect the average marginal impacts of the explanatory measures so that the product of the coefficient and the observed measures provides their total AVE cost impact. Further, the domestic production term allows for the removal of the some of the non-trade-cost noise embodied in the aggregate estimate, thereby improving the precision of the remaining aggregate cost estimate. This type of information can be instrumental in determining the likely impact of new trade policies and provides a tariff rate equivalent cost that can be introduced into other models such as commonly used computable general equilibrium or partial equilibrium frameworks.

3 Empirical Demonstration

In this section, I demonstrate the methodology described in section 2 using a typical panel gravity dataset and data on NTMs. The produced estimates provide useful insight into several ideas

presented above. First, there is strong evidence that non-cost factors significantly affect estimated aggregate trade costs. Across all specifications, exporter fixed effects and GDP per capita consistently and significantly raise the total cost estimates. Second, the two NTMs included in the analysis—SPS measures and TBTs—represent statistically significant components of the total costs. Finally, the factors included in the analysis capture only a small share of the total estimated costs, indicating that there are still important trade cost and non-trade cost components that are not being accounted for in the model.

3.1 Data

The data used for analysis is compiled from three sources. Trade data was sourced from the January 2020 revision of the BACI dataset produced by Gaulier and Zignago (2010).[5] The data provides bilateral trade values—including zeros—for more than 200 hundred countries at the 6-digit HS level. For the present analysis, the data was aggregated to the 2-digit HS level in order to reduce the number of sectors under consideration. The trade data was combined with standard gravity variables sourced from the Dynamic Gravity dataset developed by Gurevich and Herman (2018).[6] The gravity variables include distance, contiguity, common language, colonial ties, and preferential trade agreements (PTA).

NTM data for the second stage analysis was taken from UNCTAD's TRAINS database (UNCTAD, 2017).[7] The TRAINS database classifies NTMs into 16 categories or "chapters" depending on the type of measure. For example, these categories include SPS measures, TBTs, pre-shipment inspections, export subsidies, price controls, quantity controls, rules of origin, and numerous others. The classification follows a tree structure in which each chapter is subdivided into multiple sections and subsections to better distinguish different types of measures. For example, the SPS chapter features seven sections such as conformity assessments and measures governing the treatment of pests and diseases, which are themselves further subdivided into subsections like different types of treatments. For additional information on the TRAINS classification system, see UNCTAD (2019). Using this classification scheme, UNCTAD and its partners have been recording NTMs at

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[5]Available for download fat http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=37.

[6]Available for download at https://www.usitc.gov/data/gravity/dataset.htm.

[7]Available for download at https://trains.unctad.org/ or as a panel dataset at https://trains.unctad.org/forms/Analysis.aspx.

the country level for nearly 100 countries and the E.U. over the last several years. While the data collection remains an active effort, the resources compiled so far present a valuable tool for the analysis of NTMs.

For the present analysis, I focus on two of the most prominent and frequently studied categories of NTMs: SPS measures (chapter A), and TBTs (chapter B). To match with the 2-digit HS sectors in the gravity data, the NTM data was aggregated from the 6-digit level. The aggregation constructs an average number of each of the two types of NTMs across all 6-digit HS codes contained in each 2-digit code. Additionally, the NTM data is listed at the subsection level. For the sake of reducing the number of individual NTM types used in the second stage, the subsection measures were aggregated up to the chapter level. This process produced two measures reflecting the average number of individual SPS and TBT measures across the products in each 2-digit HS category. In the model, these aggregate measures are meant to capture the average trade cost impact of additional NTMs within each category. It should be noted that although the NTM data is not necessarily recorded on an annual basis, it does provide an indication of when a measure went into force and, if applicable, went out of force. Thus, it is possible to create a panel dataset but users should be aware that it does not represent an ideal time series.

In total, the dataset used in the empirical demonstration covered 96 sectors and an average of 97 countries per sector for the years 2012, 2015, and 2018. The years chosen provide a short panel spanning 7 years and represent the years in which the collection of NTM data was most extensive. For each sector, a selection of countries was chosen based on the minimum number needed to explain 99 percent of trade. This sub-selection of countries served several purposes: it reduced the computational burden of the gravity estimations, it omitted countries with little trade and a high number of zeros that provide limited information to the model and can often inhibit convergence, and it reduced the likelihood of extreme outliers in terms of the estimated fixed effects. This last purpose in particular is important because the AVE cost estimates are based on relative importer fixed effects. Small trading countries with atypical trade patterns can sometimes have large perverse effects on the relative trade cost estimates for reasons that are typically unrelated to NTMs of interest and are therefore best left out of the analysis.

3.2 Empirical Results

Gravity models were estimated using a PPML estimator for each of the 2-digit HS sectors. Figure 1 presents the estimated coefficients with 95 percent confidence intervals for each sector. The estimates are generally consistent with most past gravity research (see Head and Mayer (2014) for a meta-analysis of gravity estimates.) Variation in the estimates across sectors is to be expected as products all face different costs to trading. Distance coefficients are consistently negative and clustered around -1, representing typical distance elasticities. The remaining variables are all generally positive, implying that each is significantly trade promoting in most cases.

Figure 1: Gravity estimates and 95 percent confidence intervals for each sector
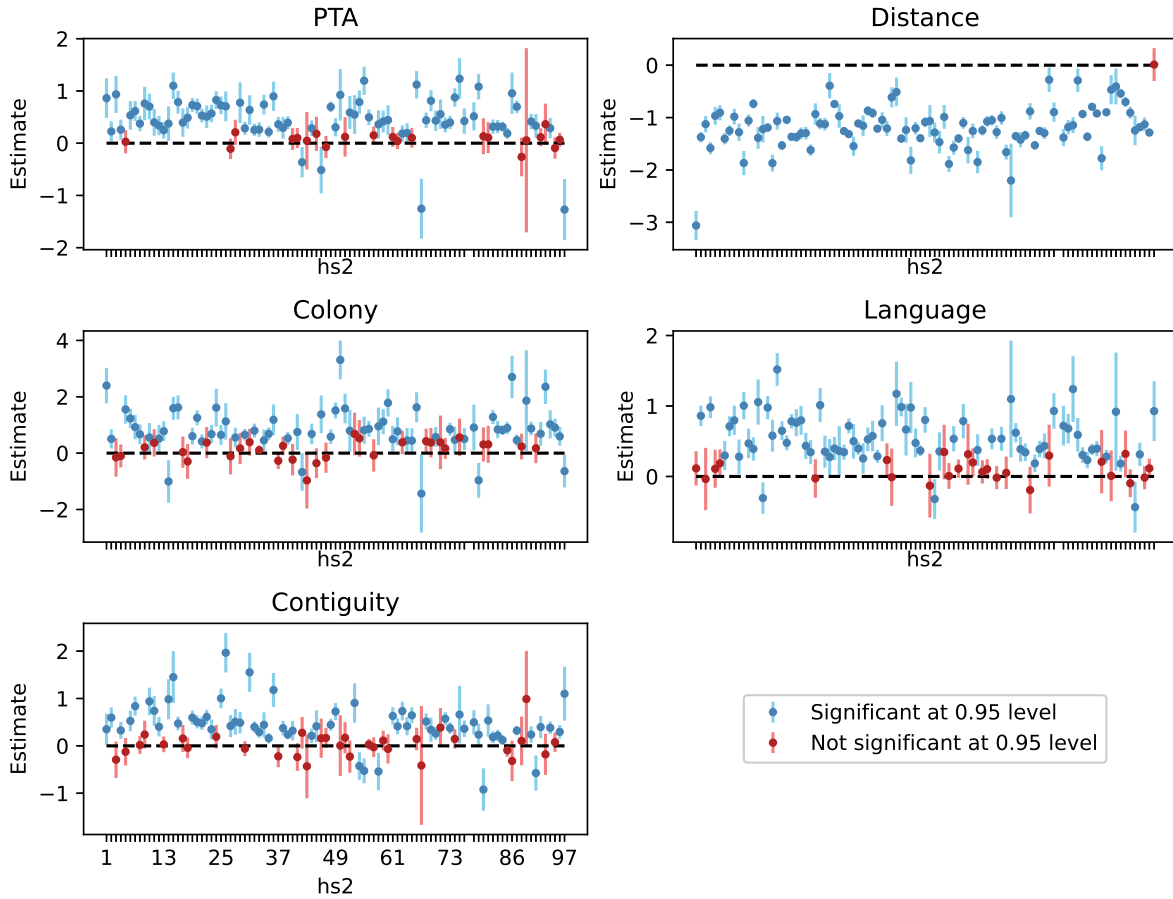
The fixed effect estimates from each of the 96 gravity models were used to construct AVE trade costs according to equation (8). The distributions of estimated aggregate trade costs for each sector are presented in figure 2. These estimates are based on a common elasticity of substitution (σ) of

5, which is representative of those present in the literature (Yotov et al., 2016; Felbermayr et al., 2014).[8] The shaded boxes in the plot depict the twenty-fifth to seventy-fifth percentile across all countries in the sector with a mark at the median estimate. Throughout much of this discussion, extreme outlying AVE values are omitted. In some cases, estimated fixed effects can be extremely large or small, which is generally indicative of highly atypical trading patterns. In these cases, NTM trade costs are unlikely to explain the magnitudes of the estimates yet these outliers have a significant influence on the second stage regressions. To avoid this undue influence, AVE values exceeding the ninety-fifth percentile are omitted from the main analysis. However, an additional analysis that includes these outliers is presented later in this section as a robustness exercise. The whiskers in figure 2 depict the general range of estimates, excluding the extreme outliers. Across all sectors, the mean cost estimate is 136 percent with a standard deviation of 94 percentage points. While many sectors have similar distributions, there is also a lot of heterogeneity across sectors, suggesting that nondiscriminatory trade costs are highly sector-dependant. Finally, recall that theses estimates are relative to the benchmark country and not a truly cost-free baseline, so the estimates may underestimate true aggregate costs in some cases.

The aggregate costs were then regressed against the NTM data, GDP per capita data, and estimated exporter fixed effects according to equation (10). Sector-level fixed effects representing the 96 2-digit HS sectors were included in the specifications to act as additional controls for sector-specific aspects of trade. The main second stage estimates are presented in table 1.

Column (1) of table 1 presents the effects of additional SPS and TBT measures while controlling for sector-level effects. Both estimates are positive, implying that each type of NTM raises estimated aggregate costs. An additional SPS or TBT measure would increase import costs by 0.38 and 0.47 percentage points, respectively.

Column (2) adds the two non-cost controls: GDP per capita (GDPPC) and exporter fixed effects (F.E.). Both factors are significantly positive. The GDPPC estimate indicates that wealth tends to inflate the cost estimates. Similarly, the exporter fixed effect exhibits a significant positive relationship as well, suggesting that competitive exporters tend to have higher estimated trade costs. This is consistent with the idea that exporters of a product are less reliant on foreign

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[8]A higher elasticity of substitution would produce smaller cost estimates while a lower elasticity would produce larger costs.

Figure 2: Distribution of estimated aggregate AVE trade costs in each sector (percent)
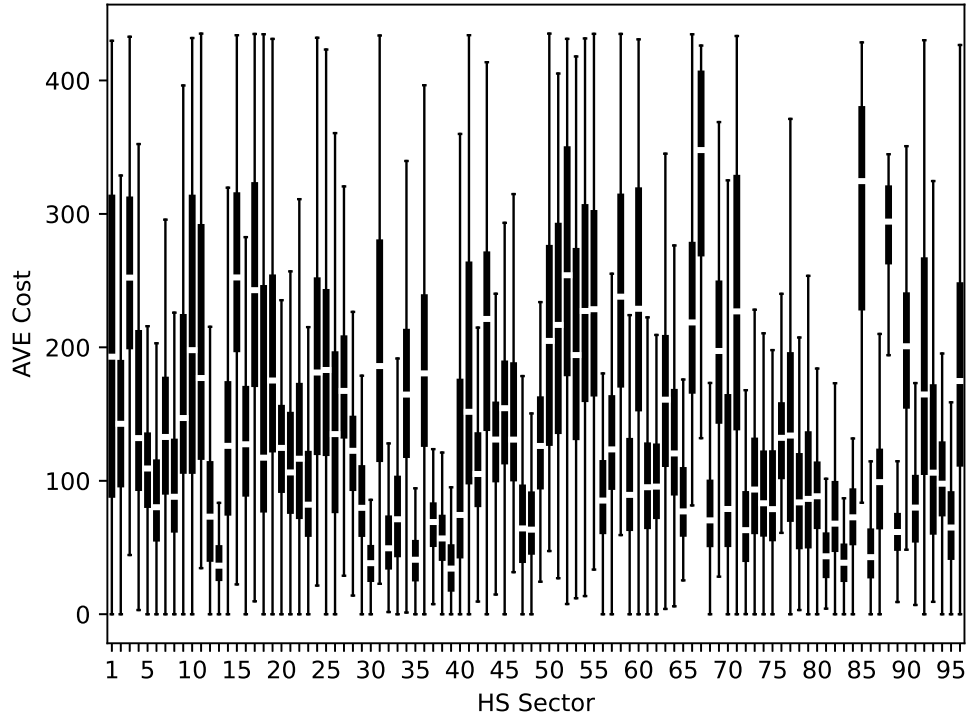
imports and therefore have smaller importer fixed effects and higher inward multilateral resistance. The addition of these terms also reduces the effects of both SPS and TBT measures. This suggests that the specification in column (1) is subject to some omitted variable bias and underscores the importance of controlling for more types of factors in the second stage. Finally, while these non-cost factors increase the adjusted R^2 value of the regression by about 9 percent (3.8 percentage points), there is still a considerable amount of unexplained variation in the aggregate cost estimates. This suggests that there are still many cost and non-cost factors that are not accounted for.

When analyzing measures such as SPS and TBTs, there is some concern that there are strong correlations between the measures. Countries and sectors with many SPS regulations may also tend to be the ones with many TBTs. To test for this type of overlap, columns (3) and (4) include each NTM measure independently. One their own, both estimates are larger in magnitude than in the column (2) specifications while the GDPPC and exporter F.E. estimates are largely unchanged, suggesting that there is some overlap in the information contained in each NTM measure.

Finally, it should be expected that the effects of NTMs differ across sectors. In practice, one should consider estimating heterogeneous effects across sectors to capture these differences when

Table 1: Second stage regression results for AVE trade cost factors

	(1)	(2)	(3)	(4)	(5)
SPS	0.380***	0.309***	0.355***		
	(0.031)	(0.029)	(0.026)		
TBT	0.467***	0.167***		0.461***	
	(0.049)	(0.048)		(0.043)	
GDPPC		5.990***	6.171***	6.148***	6.198***
		(0.543)	(0.541)	(0.543)	(0.544)
Exporter F.E.		4.896***	4.935***	5.000***	4.884***
		(0.244)	(0.243)	(0.245)	(0.243)
SPS x Agr.					0.219***
					(0.041)
TBT x Agr.					0.590***
					(0.107)
SPS x (Not Agr.)					-0.046
					(0.061)
TBT x (Not Agr.)					0.012
					(0.047)
Adjusted R^2	0.426	0.464	0.464	0.460	0.465
Observations	18609	18417	18417	18417	18417

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. Sector fixed effects included but not reported.

possible. While a granular analysis of the sector-level effects of SPS and TBT measures is beyond the scope of this paper, column (5) presents a demonstration of how this could be done. In the column (5) specification, each NTM variable is split into two. The new variables interact the measures with an agriculture sector indicator that takes the value of one if the sector is an agriculture or food sector (HS chapters 01–24) and zero otherwise. This generates estimates specific to agriculture and food and separate estimates for all other sectors. Agriculture and food was chosen as the division due the to the fact that SPS measure almost exclusively apply to these products.[9] TBT measures are also prominent on agriculture and food products but are common across other sectors such as manufacturing as well.

The results in column (5) indicate that the effects differ across types of sectors significantly. SPS and TBT measures both significantly increase aggregate trade costs in agriculture and food sectors. The effect of SPS measures is slightly smaller than in previous specifications while the

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[9]There are a few additional sectors containing products derived from animals and other organisms that are subject to some SPS measures.

effect of TBTs is larger. There is no significant relationship between either category of NTMs and non-agricultural sectors. This result for SPS measures is unsurprising given their limited presence in non-agricultural sectors. That TBTs are also insignificant is more surprising given other sectors such as manufacturing are often subject to TBT measures such as safety or environmental requirements. One likely explanation is that the grouping of all non-agriculture sectors is too broad and may be underestimating the effects in some sectors due to pooling them with others, which is exacerbated by the fact that TBT-intensive agriculture sectors are excluded from that pool. While there is still much to understand about the specifics of these findings, they do demonstrate the importance of taking sectoral heterogeneity into account.

In addition to the estimates presented in table 1, I conducted several additional analyses examining the robustness of the results to several potentially influential modeling decisions. The first analysis re-estimated the same five specifications but did not exclude the outlying cost estimate observations. A full presentation of these estimates can be found in table 2 in the appendix. The inclusion of outliers has some minor impacts on the estimates. The most notable difference is that the effects of TBTs in several of the specifications change significantly. Under specifications (2) and (5), in which both NTMs and the non-cost controls are included, TBTs have a negative—and in the case of (5), significant—effect on the cost estimates. Given that the values of the two NTM estimates are similar in specifications (3) and (4), it is possible that the inclusion of outliers increases the overlap of these terms. Alternatively, it is also possible that the omitted estimates tended to belong to countries and sectors with few TBTs, which would push the estimates down. The remainder of the results are largely unchanged. Compared to table 1, most estimates differ only in magnitude, which should be expected given the addition of more, especially large observations to the sample. The results of this test provide additional support for excluding outlier variables. In the few cases in which estimates differ significantly, the changes are likely due to disproportionate influence from extreme values rather than new economic insight.

The second robustness test considers the effects of not including sectoral-fixed effects. A full presentation of these results can be found in table 3 in the appendix. As in the previous case, many of the results are largely unchanged by replacing the sector fixed effects with a single constant. The primary differences are that some of the TBT estimates are negative again and the SPS measure on non-agriculture sectors is negative. These results are likely indicative of the importance of

controlling for sectoral heterogeneity. In particular, the strong negative effect of SPS measures in non-agriculture sectors is suspect given how uncommon they are within that group of sectors, which would suggest that the regression is failing to control for important factors. The other estimates are consistent with those in table 10 and differ only slightly in magnitude.

3.3   The Costs of Specific NTMs

Using the estimates from the second stage, it is possible to decompose the estimated aggregate trade costs into their constituent parts. In this section I demonstrate this decomposition using the estimates from specification (5) in table 1. In particular, I look at the two agriculture and food specific NTM measures, which are both statistically significant and account for greater sectoral heterogeneity than the NTM estimates in other specifications. To produce the decomposition, I first calculate the AVE trade cost associated with each NTM component by multiplying the observed NTM data with the estimated marginal impact from the second stage regression. This provides a total component-specific trade cost for each country, sector, and year combination. To calculate the contribution of the component-specific cost to the total, I divide the component cost by the aggregate cost and multiply by 100 to generate a percentage share.

The estimated trade costs in agriculture and food sectors for SPS measures are presented in figure 3. The left plot depicts the distribution of estimated AVE SPS costs across countries in each of the 24 sectors. As with figure 2, the filled boxes reflect the twenty-fifth to seventy-fifth percentiles of the estimates. The whiskers denote the range of estimates, though extreme outliers are again excluded. Across all of the sectors, the mean and median costs of SPS measures are 7.3 and 3.8 percent, respectively, with a standard deviation of 8.6 percentage points. The sectors with the highest average SPS costs are fish and other sea creatures (HS chapter 3) and preparations of meat and seafood (HS chapter 16), with have mean costs of 14.6 and 11.8 percent, respectively. The least impacted sectors are tobacco (HS chapter 24) and vegetables either used for plaiting or not elsewhere included (HS Chapter 14), which have average SPS costs of 0.5 and 3.0 percent, respectively. In both cases, these relative impacts are a direct result of the number of SPS measures in place on those products throughout the world.

The right panel in figure 3 presents the distribution of the share of SPS costs in the estimated aggregate costs. On average, SPS measures represent 9.0 percent of the aggregate costs of each

Figure 3: Estimated AVE trade costs of SPS measures on agriculture and food sectors and their contribution to the total cost estimates (percent)
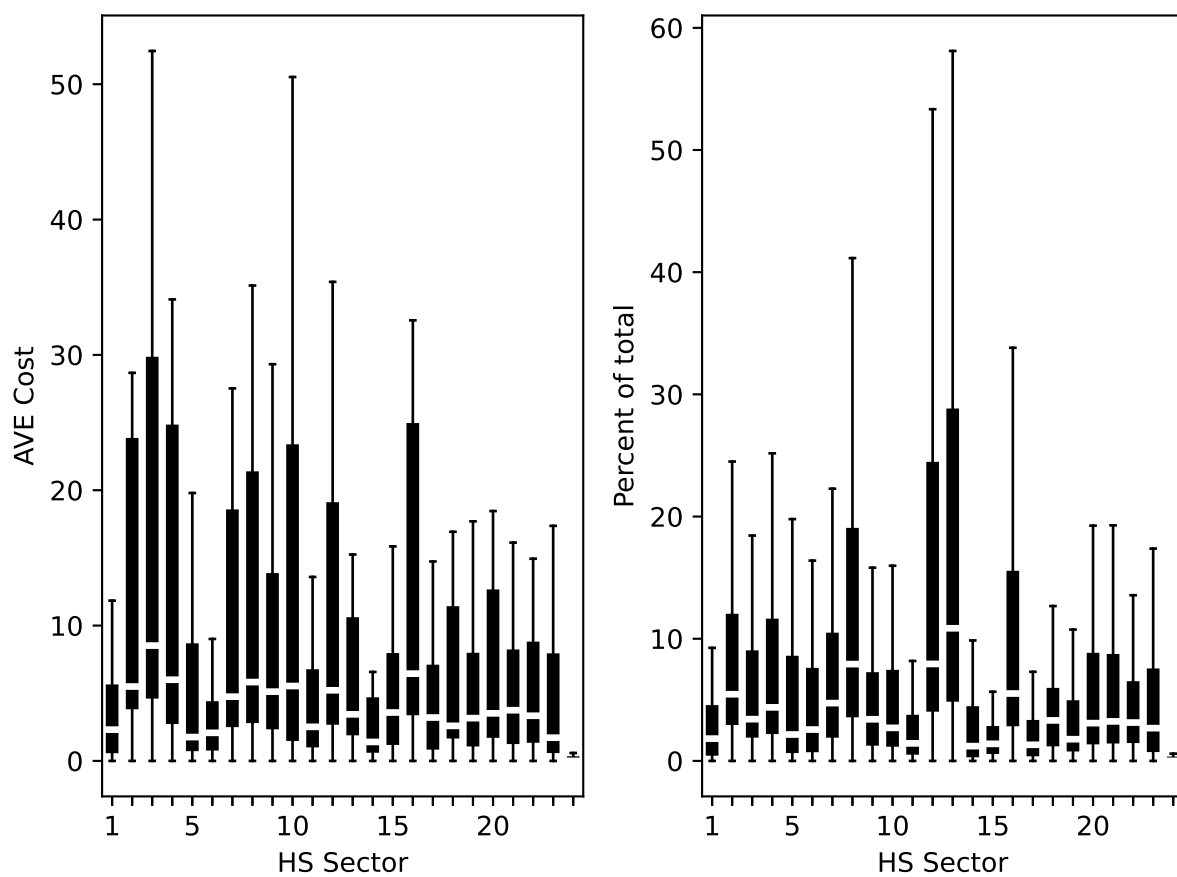
country in each sector. The median share is even lower at 3.1 percent of the total.[10] This suggests that in general, SPS measures are a significant but small share of the total costs that agriculture and food products are subject to. Notably, lac, gums, and resins (HS chapter 13) generally have a much higher share of costs attributed to SPS than the other sectors.

The effects of TBTs on agriculture and food sectors are presented in figure 4. The left panel depicts the distribution of TBT costs across countries for each sector. The mean and median AVE effects are 5.9 and 2.7 percent respectively, with a standard deviation of 8.5 percentage points. The sectors with the largest effects are again fish and sea creatures (HS sector 3) and meat and seafood preparations (HS chapter 16), which have average TBT costs of 12.1 and 10.2, respectively. The sectors with the smallest TBT costs are vegetable plaiting materials (HS chapter 14) and live animals (HS chapter 1), which have average TBT costs of 1.1 and 1.9 percent, respectively.

The right panel in figure 4 depicts the distribution of TBT costs as a share of the aggregate cost estimates. The mean and median shares across all sectors are 6.8 and 2.0 percent, respectively. As with SPS, TBTs generally account for a higher share of the costs experienced by lac, gums, and resins (HS chapter 13) than other sectors.

These decomposed costs estimates demonstrate two key components of the methodology. First, they demonstrate that it is possible to get highly granular estimates of the trade costs attributed to specific NTMs at the country and sector level using a conventional gravity model and freely available data on the NTM policies in place in each market. Second, the results also demonstrate the importance of estimating specific costs and not relying on aggregate estimates. Aggregate estimates reflect many types of trade costs as well as non-cost factors. For the agriculture and food sectors discussed here, SPS and TBT measures account for less than 5 percent of estimated aggregate costs in most cases. For this reason, analyses studying the impacts of NTMs should take care to ensure that their estimates truly reflect the policies in which they are interested. As demonstrated, this is particularly true when differences in imports are used to infer the effects of NTMs or other trade policies.

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[10]The large differences between the mean and median shares can be attributed to the fact that some countries and sectors have many SPS measures, implying a high SPS cost, but very low aggregate costs. This results in some shares greatly exceeding 100 percent, which raises many of the averages considerably.

Figure 4: Estimated AVE trade costs of TBTs on agriculture and food sectors and their contribution to the total cost estimates (percent)
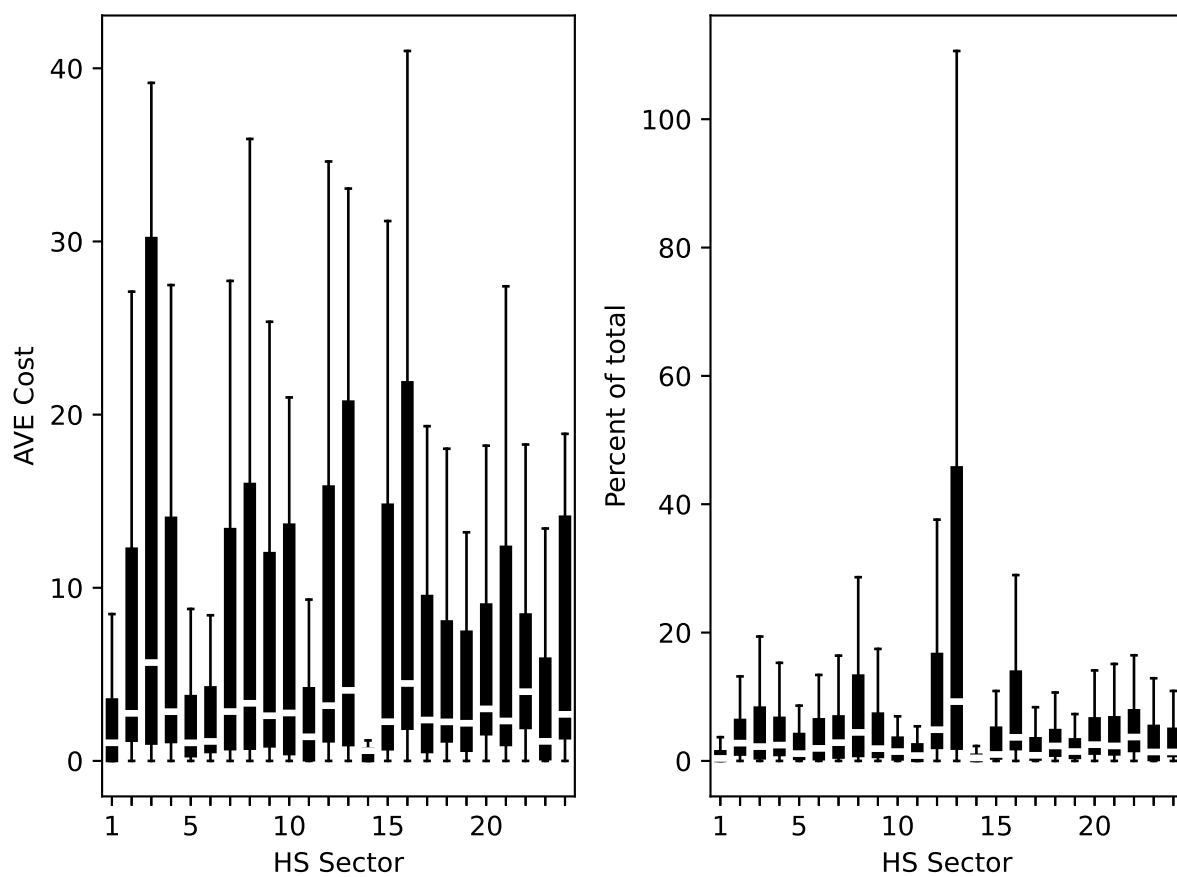
4 Conclusion

Understanding the costs of nondiscriminatory NTMs is an increasingly important part of international trade and policy analysis. Most current methods for estimating these costs exhibit significant and often prohibitive challenges or limitations in terms of the data required, the broad scope of the produced estimates, or the statistical techniques used. In this paper, I propose a novel approach that mitigates these issues and provides a means by which to estimate the effects of specific nondiscriminatory NTMs using widely available public data and standard econometric methods. My approach is an extension of an oft used method proposed by Fontagné et al. (2011). I suggest using a second stage of analysis to decompose the aggregate trade cost estimates generated by their methodology into costs of specific NTMs and to separate out the effects of non-cost factors that erroneously contribute to the aggregate estimates. This extension helps to mitigate some of the notable limitations of Fontagné et al.'s original methodology.

I demonstrate the approach using publicly available trade and NTM data and show that the second stage analysis does offer significant improvements. First, I find that non-cost factors do significantly contribute to estimated aggregate trade costs. This implies that the broad estimates of nondiscriminatory trade costs produced by the model erroneously reflect more than just trade costs. Second, I demonstrate that the individual contribution of specific types of NTMs can be identified from the broad measure. In particular, I find that nondiscriminatory SPS measures increase trade costs in agriculture and food sectors by 7.3 percentage points on average. TBTs increase agriculture and food costs by trade costs by about 5.9 percentage points on average. Finally, these factors explain only a small share of the estimated trade costs, implying that there are numerous other additional factors affecting imports and contributing to estimated trade costs that are unaccounted for in the model.

While the purpose of this paper is to demonstrate a methodology, it also raises some intriguing questions about the nature of certain NTMs. Most notably, the analysis is conducted at the level of nearly 100 different sectors, each exhibiting very different relationships with NTMs. The main estimates of interest are generated by pooling across sectors broadly, which likely under- or overestimates them in certain cases. Future work could refine these findings by independently examining certain factors within specific sectors. For example, studying the impacts of TBTs on

individual sectors should provide better insight than averaging their effect over all non-agriculture and food sectors.

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A Additional Tables

Table 2: Second stage regression results including outlier AVE cost estimates

	1	2	3	4	5
SPS	0.539***	0.442***	0.439***		
	(0.050)	(0.048)	(0.041)		
TBT	0.337***	-0.013		0.415***	
	(0.069)	(0.069)		(0.058)	
GDPPC		4.510***	4.496***	4.760***	4.635***
		(0.818)	(0.814)	(0.818)	(0.831)
SPS x Agr.					0.386***
					(0.071)
TBT x Agr.					0.306*
					(0.168)
Exporter F.E.		7.481***	7.478***	7.631***	7.473***
		(0.392)	(0.390)	(0.393)	(0.392)
SPS x (Not Agr.)					0.015
					(0.079)
TBT x (Not Agr.)					-0.130**
					(0.065)
Adjusted R^2	0.601	0.622	0.622	0.620	0.622
Observations	19618	19420	19420	19420	19420

*** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors in parentheses. HS2 sector fixed effects included but not reported.

Table 3: Second stage regression results without sector fixed effects

	1	2	3	4	5
SPS	0.601***	0.623***	0.558***		
	(0.030)	(0.029)	(0.026)		
TBT	-0.042	-0.306***		0.376***	
	(0.062)	(0.062)		(0.063)	
GDPPC		3.463***	3.083***	3.347***	3.955***
		(0.599)	(0.596)	(0.604)	(0.599)
Exporter F.E.		4.116***	4.017***	3.995***	4.096***
		(0.221)	(0.220)	(0.223)	(0.220)
SPS x Agr.					0.423***
					(0.046)
TBT x Agr.					0.525***
					(0.131)
SPS x (Not Agr.)					-0.317***
					(0.068)
TBT x (Not Agr.)					-0.540***
					(0.063)
Constant	129.392***	99.083***	100.997***	101.881***	96.175***
	(0.808)	(5.639)	(5.640)	(5.679)	(5.631)
Adjusted R^2	0.028	0.056	0.055	0.031	0.064
Observations	18609	18417	18417	18417	18417

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