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Non-homothetic Preferences, Income Distribution, and the Burden of NTMs*

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Abstract

Trade-weighted coverage ratios are commonly used when estimating the effect of non-tariff measures on trade flows and other outcomes. Because they weight by import shares, for a given sector they can vary across countries even when actual policies are the same. While trade shares can depend on several factors, we link them to income distribution when preferences are non-homothetic. Further, the correlation between coverage ratios and income distribution measures can provide an indication of whether NTMs are more geared towards luxuries (consumed by primarily the wealthy) or necessities (which are consumed by all). Using data on coverage ratios during 2008-2014 in the European Union, our estimates suggest not only that the variation in coverage ratios are linked to income inequality, but that the relationship is consistent with NTMs primarily on luxuries. Finally, as other studies have shown that income distribution can itself have a direct impact on trade, our results suggest the potential for biased estimates when using NTM coverage ratios but not accounting for inequality.

JEL classification: F13, H57, F12

Keywords: Non-tariff measures; Coverage Ratio; Non-homothetic Preferences.

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1 Introduction

The link between trade and inequality has been of central importance in analyzing international trade since the seminal work of Stolper and Samuelson (1941). While early work on the topic was primarily theoretic, with improved data availability more recent contributions have examined it empirically, with examples using aggregate data including Bergh and Nilsson (2010) and those with micro data including Cosar, Guner and Tybout (2016).[1] Some studies such as Jaumotte, Lall, and Papageorgiou (2013) find that the inequality impact of trade is secondary when compared to factors such as technological change while others such as Lim and McNelis (2014) find that the impact is conditional on other factors. In any case, the evidence consistently points to a significant potential for increased trade to exacerbate inequality. More recent contributions, however, discuss the role in inequality itself in determining trade when preferences are non-homothetic. In particular, a growing literature has replaced homothetic preferences with Stone-Geary preferences. Examples include Bertoletti and Etro (forthcoming), Caron, Fally, Markusen (2014), Markusen (2013), and Bekkers, Francois, and Manchin (2012). In particular, this latter paper finds evidence in the data on prices of tradeables and inequality that is consistent with the hierarchical demand patterns predicted by the Stone-Geary approach to incorporating non-homothetic preferences in a trade model.[2] Within these models, the key is that the consumption of certain goods (luxuries) only begins when a given consumer reaches a minimum income level. The empirical work also finds that income distribution within a country can be a driving force in trade patterns (e.g. Tasarov (2012), Fieler (2011), Dalgin, Trindade, and Mitra (2008), and Hummels and Klenow (2005)).

This chapter contributes to this discussion by pointing out that when preferences are non-homothetic, income distribution can have an influence on the measurement of trade policies. We do so by presenting a simple trade model with modified Stone-Geary preferences in the

[1]Goldberg and Pavncik (2007) provide an overview of the literature, with Turnovsky and Rojas-Vallejos (2016) providing a recent theory contribution and an updated review.

[2]Choi, Hummels, and Xiang (2009) find a comparable result using income inequality measures.

presence of non-tariff measures (NTMs). In the empirical literature, where the researcher is often forced to work with aggregated rather than product level data, NTMs are commonly measured by coverage ratios.[3] These can be simple coverages, i.e. the share of products within a sector that face an NTM, or trade-weighted coverages where the measure factors in the share of imports within the sector made up of products facing an NTM.[4] The first is problematic because it misses the fact that some products are more important than others. The second is troublesome because trade values, and thus the trade shares, are determined by the NTMs, introducing endogeneity. Furthermore, as is the focus of our discussion, the trade shares can depend on other country characteristics driving the trade shares, including income inequality.

Because of this, trade-weighted coverage ratios will have variation driven, not by policy, but by country characteristics. As an example, consider Figures 1 and 2 which illustrates the country average coverage ratios for technical barriers to trade (TBTs) and sanitary and phytosanitary regulations (SPSs) across the EU. As can be seen, there is marked variation in each NTM measure despite the fact that the NTMs underlying them are the same across all these countries. While there can certainly be price variation across destinations due to, for example, heterogenous shipping costs, here, we demonstrate that such variation can also be driven by variations in income inequality in the presence of non-homothetic preferences. We then confirm this using data on TBTs and SPSs in the EU for 2008-2014.

In particular, our estimates suggest two things. First, given the predictions of our model, the estimates suggest that within the EU NTMs are tilted towards luxuries, i.e. those products purchased primarily by wealthier consumers, rather than necessities (products purchased by all). This is worth recognizing because understanding which consumers bear the burden of NTMs is important when considering the distribution of those costs across consumers of different income levels.[5] Second, given that the coverage ratio is correlated with inequality,

[3]Examples include Trefler (1993), Goldberg and Maggi (1999), Lee and Swagel (2000), Disdier, Fontagne, and Mimouni (2008), and Bao and Qiu (2010).

[4]See Deardorff and Stern (1997) for discussion of various NTM measurements.

[5]For example, if wealthier individuals are more able to carry the burden of NTMs leading to higher prices

something that itself affects trade volumes, our results suggest that failing to control for the direct impact of income inequality on trade has the potential to bias the estimated effects of NTMs.[6] Our estimates suggest that this may be a larger issue when using disaggregated data than in national-level import regressions.

In the next section, we introduce a stylized model of trade with non-homothetic preferences intended to illustrate the link between income inequality and the coverage ratio. In section 3, we introduce the data we use. Section 4 explores the linkage between income inequality and the coverage ratio. Section 5 concludes.

2 NTMs and the Coverage Ratio with Non-homothetic Preferences

In this section, we introduce a very simplified model of trade under non-homothetic preferences. The rationale for this is that it illustrates a link between income distribution and NTM coverage ratios which depends on whether NTMs fall on necessities, i.e. they impact all consumers, or on luxuries, meaning that they affect primarily high-income individuals.

To this end, consider a small open economy with N consumers, all of whom have identical preferences and all of whom face identical prices (which depend on, among other factors, whether or not a given product has an NTM). Each individual has an income $w_i > 0$ where aggregate income is $W = \sum_i w_i$. Preferences are across two goods, Y which is the numeraire with unit price and X which is a differentiated product sector. For simplicity, assume that

than are the poor, this may increase governmental willingness to introduce NTMs.

[6]Examples of analyses using NTM coverage ratios are Trefler (1993), Goldberg and Maggi (1999), Lee and Swagel (2000), Disdier, Fontagne, and Mimouni (2008), and Bao and Qiu (2010). Note that this is not restricted to NTMs; trade-weighted tariff measures which are used by many of those suffer a similar problem. Further, this is simply one type of endogeniety of the coverage ratio; there is obviously the issue of how trade volumes and thus shares depend on the NTMs. This latter issue, however, is not relevant to our current discussion where we look, not on how trade depends on NTMs, but on how NTM measures depend on other variables.

all varieties of X are imported. Preferences are described by:

$$u_i(x_{1,i}, x_{2,i}, Y_i) = X^{\alpha} Y^{1-\alpha} = (x_{1,i} + \gamma)^{\alpha\beta} x_{2,i}{}^{\alpha(1-\beta)} Y_i^{1-\alpha} \tag{1}$$

with $\gamma_s > 0$ and $\alpha, \beta \in (0,1)$. In words, preferences are Cobb-Douglas across sectors, and, within the X industry, preferences across varieties are modified Stone-Geary preferences. We will refer to x_1 as a "luxury" good since, as is shown momentarily, consumption is positive only when minimum levels of consumption for the "necessities" x_2 and Y are reached.

Whether or not x_1 is consumed by consumer i depends on her income level. Specifically, demand for the two X varieties are:

$$x_{1,i}(p_1, p_2, w_i) = \begin{cases} \frac{\alpha\beta w_i}{p_1} - (1-\alpha\beta)\gamma & \text{if} w_i > p_1 \frac{(1-\alpha\beta)}{\alpha\beta}\gamma \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

and

$$x_{2,i}(p_1, p_2, w_i) = \begin{cases} \frac{\alpha(1-\beta) w_i}{p_2} + \frac{p_1}{p_2}\alpha(1-\beta)\gamma & \text{if} w_i > p_1 \frac{(1-\alpha\beta)}{\alpha\beta}\gamma \\ \frac{\alpha(1-\beta)}{(1-\alpha\beta)}\frac{w_i}{p_2} & \text{otherwise} \end{cases} \tag{3}$$

In words, the consumer purchases the luxury only when her income exceeds $p_1 \frac{(1-\alpha\beta)}{\alpha\beta}\gamma$. Let the set of consumers for whom w_i exceeds this level be denoted by Δ, a group we refer to as the "rich" with consumers not in this group referred to as "poor". Define $w_\Delta = W^{-1} \sum_{i \in \Delta} w_i$, i.e. the share of income held by the rich and n_Δ as the share of the population that is rich. Since demands for the commodities are linear in income within each group, aggregate demands for the two X varieties are:

$$x_1(p_1, p_2, W, N, \Delta) = \frac{\alpha\beta}{p_1} w_\Delta W - (1-\alpha\beta)\gamma n_\Delta N \tag{4}$$

and

$$x_2(p_1, p_2, W, N, \Delta) = (1 - \alpha\beta w_\Delta) \frac{\alpha(1-\beta)}{(1-\alpha\beta)} \frac{W}{p_2} + \frac{p_1}{p_2}\alpha(1-\beta)\gamma n_\Delta N. \tag{5}$$

From these, it is clear that aggregate demand, and therefore imports, are a function of the income distribution. For future use, the import share in X for the luxury x_1 is:

$$S_1\left(p_1, p_2, \frac{W}{N}, \Delta\right) = \frac{\alpha\beta w_\Delta \frac{W}{N} - p_1\left(1-\alpha\beta\right)\gamma n_\Delta}{\left(\frac{\alpha\beta(1-\alpha)}{(1-\alpha\beta)} w_\Delta + \frac{\alpha(1-\beta)}{(1-\alpha\beta)}\right)\frac{W}{N} - p_1\left(1-\alpha\right)\gamma n_\Delta}. \tag{6}$$

Thus the trade share depends on prices, per capita GDP ($\frac{W}{N}$), and the distribution of income across the two consumer types (Δ) .

2.1 The Coverage Ratio

The coverage ratio, C is calculated as the trade-weighted sum of indicator variables, NTM_i, that equal 1 when a variety faces an NTM, i.e. $C = S_1 NTM_1 + (1 - S_1) NTM_2$. Note that from this, holding policy constant but changing a variable z (such as per capita income), $\frac{dC}{dz} = (NTM_1 - NTM_2)\frac{dS_1}{dz}$. Thus, if the NTM is only on the luxury, i.e. $NTM_1 = 1$ and $NTM_2 = 0$, the impact of z on the coverage ratio will equal the impact of z on the luxury's share of imports. With this in mind, consider a rise in income inequality. This can be generated in three ways. First, suppose that the number of consumers in each group is constant, but income shifts from the poor to the rich, i.e. a rise in w_Δ.[7] When this happens, we see that:

$$\frac{dS_1\left(p_1, p_2, \frac{W}{N}, \Delta\right)}{dw_\Delta} = \frac{\alpha^2\beta\left(1-\beta\right)W^2}{\left(1-\alpha\beta\right)\left(\frac{\alpha\beta(1-\alpha)}{(1-\alpha\beta)} w_\Delta W + \frac{\alpha(1-\beta)}{(1-\alpha\beta)} W - p_1\left(1-\alpha\right)\gamma n_\Delta N\right)^2} > 0 \tag{7}$$

i.e. the luxury's share in imports rises. If there is an NTM on the luxury (necessity) only, then the coverage ratio rises (falls).[8] Similarly, we see that if we hold the income of the two groups constant but increase the percentage of the population qualifying as rich:

[7] Recall that shifts in income within groups do not affect aggregated demand, therefore we only examine shifts across groups.

[8] Note that if NTMs apply to both or neither, the coverage ratio is 1 or 0, regardless of the income distribution.

$$\frac{dS_1\left(p_1, p_2, \frac{W}{N}, \Delta\right)}{dn_\Delta} = \frac{-\alpha\left(1-\beta\right)W\gamma N}{\left(\frac{\alpha\beta(1-\alpha)}{(1-\alpha\beta)}w_\Delta W + \frac{\alpha(1-\beta)}{(1-\alpha\beta)}W - p_1\left(1-\alpha\right)\gamma n_\Delta N\right)^2} < 0. \tag{8}$$

The intuition is the following. Any poor individual purchases only the necessity with that amount depending on their individual income; all rich individuals on the other hand purchase an amount of the necessity that is independent of their income. Conversely, all poor buy an amount of the luxury that is independent of their income, i.e. 0; all rich use the income left over after buying the fixed amount of the necessity to purchase the luxury. Increasing the share of income held by the rich increases per-capita income of the rich and therefore the total amount of income remaining after the rich buy their necessities. Increasing the share of population that is rich lowers that group's per-capita income and has the opposite effect. Both of these predictions are consistent with the estimates of Dalgin, Trindade, and Mitra (2008), who delineate products into luxuries and necessities and find that, as importer inequality rises, imports shift towards luxuries. Note that an outcome of this prediction is that, if the NTM is only on the luxury (necessity), the coverage ratio falls (rises) as the share of the population that is rich increases (decreases).

In the data, we do not know precisely how income and population are distributed across the two groups. However when there are two groups, the Gini coefficient, which is observed, is $G = w_\Delta - n_\Delta$. As such, if the NTM is on the luxury good, an increase in the Gini coefficient (from either a rise in w_Δ or a fall in n_Δ) should increase the coverage ratio. If the NTM is on the necessity, the coverage ratio falls as the Gini coefficient rises. Alternatively, we have access to income shares by quantiles. Since quantiles hold the share of consumers in a given group constant (i.e. n_Δ does not change), then an increase in the share of income held by the top quantile would be equivalent to an increase in w_Δ, with predictions for trade shares and the coverage ratio the same as a rise in the Gini coefficient.

In addition to income distribution, an increase in average income would increase the trade share of the luxury:

$$\frac{dS_1\left(p_1,p_2,\frac{W}{N},\Delta\right)}{d\frac{W}{N}}=\frac{\alpha\left(1-\beta\right)p_1\gamma n_\Delta}{\left(\frac{\alpha\beta(1-\alpha)}{(1-\alpha\beta)}w_\Delta\frac{W}{N}+\frac{\alpha(1-\beta)}{(1-\alpha\beta)}\frac{W}{N}-p_1\left(1-\alpha\right)\gamma n_\Delta\right)^2}>0. \tag{9}$$

Thus, as per capita GDP rises (i.e. GDP rises and/or population falls) the coverage ratio rises (falls) if the NTM is only on the luxury (necessity).

As a final note, recognize that where

$$M\left(p_1,p_2,W,N,\Delta\right)=\frac{\alpha\left(1-\beta\right)+\left(1-\alpha\right)\alpha\beta w_\Delta}{\left(1-\alpha\beta\right)}W-p_1\left(1-\alpha\right)\gamma n_\Delta N \tag{10}$$

is the value of X imports, that:

$$\frac{dM\left(p_1,p_2,W,N,\Delta\right)}{dw_\Delta}=\frac{\left(1-\alpha\right)\alpha\beta}{\left(1-\alpha\beta\right)}W>0 \tag{11}$$

and

$$\frac{dM\left(p_1,p_2,\Delta\right)}{dn_\Delta}=-p_1\left(1-\alpha\right)\gamma N<0 \tag{12}$$

i.e. the value of imports is increasing in the Gini coefficient. Dalgin, Trindade, and Mitra (2008) estimate the effect of importer income inequality on total imports, finding that the effect varies according to the importer and exporter income level. In particular, as the importer becomes richer (increasing relative demand for luxuries) and the exporter becomes richer (increasing the production of luxuries), total imports increase as inequality rises. That said, as their data works on a bilateral basis and here we do not distinguish across origin of the imported products, there is not a clear mapping between their results and our theory.

As the coverage ratio is correlated to with the Gini coefficient, this suggests that failure to control directly for the Gini coefficient will bias the estimated impact of the NTM on trade values upwards if the NTM is on the luxury only or downwards if it is only on the necessity. Since Dalgin, Trindade, and Mitra (2008) find that the impact of inequality on trade is sizable, there is a potential for such biases to be economically meaningful.

3 Empirical Specification and Data

In the above stylized model, we show that the relationship between income distribution and coverage ratios depends on whether the NTMs are on luxuries (where rises in per capita income and/or the Gini coefficient increases the coverage ratio), necessities (where the opposite occurs), or neither/both (where the coverage ratio is 0 or 1 accordingly). We take this prediction to data on the coverage ratio across European Union countries from 2008-2014 where, since policies are the same, variation in the coverage ratio for a given sector s across countries c in year t is driven only by variation in the trade shares of products within the sector.[9]

We use trade-weighted coverage ratios for two different types of NTMs: TBTs and SPSs. Both are obtained from data compiled by Ghodsi, Reiter, and Stehrer (2015).[10] These measures are on the unit interval. The initial data is a dummy variable equal to 1 if there is an NTM of the relevant type on a 6-digit product. Note that this information indicates whether or not there is *any* SPS/TBT on this product which applies to all imports, i.e. we do not consider exporter-specific NTMs. These are then aggregated up to coverage ratios for 4-digit sectors in our baseline results (with 2 digit sectors and national coverage ratios being used in alternative specifications). Note that when all 6-digit products are covered (or not) by an NTM, the coverage ratio is 1 (or 0) regardless of the trade shares. Even when this is not the case, the coverage ratio can be 1 or 0 because, within the 4-digit sector, only products with/without NTMs are imported. Our trade data used for aggregating come from the BACI dataset which is based on the COMPTRADE data.[11]

In the data, 84 of the 1194 4-digit sectors we use have no variation in the TBT coverage ratios across countries. Of these, 14 (16% of this group) fall in HS sector 26 (ores, slag, and

[9]Note that our data is an unbalanced panel across sector-countries. In particular, there is a dropoff in observations after 2012, with roughly 19% of observations coming from each of the prior years. If we omit the 2013-2014 observations, results are essentially unchanged.

[10]See Ghodsi, Gruebler, and Stehrer (2016a) and Ghodsi, Gruebler, and Stehrer (2016b) for examples working with such data.

[11]The can be found at `http://www.cepii.fr/`.

ash) with no other discernable pattern. In comparison 647 have no variation in SPS coverage across countries (with 8 of the 84 sectors without variation in TBTs also without variation in SPSs). Here, there is no clear pattern across sectors with the largest percentage (6%) in HS sector 84 (nuclear reactors, boilers, machinery, and mechanical appliances). Setting sectors without variation aside, in Table 1, we list the ten 4-digit sectors with the largest standard deviation for the TBT and SPS coverage ratios, i.e. those with the most variation across EU countries (relative to the average size of the coverage ratio).[12] Looking at these, certain products such as paper products for TBTs and minerals for SPSs do not immediately come across as consumer products at all and read more as intermediate inputs (and as such may not be good candidates for applying our theory). Others, such as "base metals clad with silver", "perfumes", and "candles" are arguably more in line with items consumed directly; further, one could make a case that such products are luxuries rather than necessities.[13] In any case, the theory does not make predictions about which products do or do not have NTMs applied to them, but that there is a relation between the coverage ratio and income distribution, with the direction of the correlation dependent on the nature of the sector.

With that in mind, following on from the theory, the baseline specification is:

$$ln(CR_{c,s,t}) = \beta_c + \beta_s + \beta_t + \beta_1 ln(\text{GDP per capita}_{c,t}) + \beta_2 Inequality_{c,t} + \varepsilon_{c,s,t} \tag{13}$$

i.e. we regress the coverage ratio (for TBTs or SPSs) on log of per capita income and a measure of income inequality. We use two measures of inequality: the log of the Gini coefficient (*Gini*) and the log of the share of income held by the richest quintile (*Quintile*). If the NTM in question falls primarily on luxuries, we expect positive coefficients for β_1 and β_2. We alter this specification in two ways. First, rather than using logged GDP per capita, we instead use logged GDP and logged population separately. Although the theory indicates that only per capita income matters, this alternative specification relaxes the assumption

[12]We use the standard deviation here as the small average for some sectors created large coefficients of variation although the coverage ratios all fell within a fairly narrow band.

[13]Others, such as "hydraulic brake fluids" seem much more like a necessity.

that the coefficients are equal yet opposite. Second, although the theory predicts that country size is unimportant for trade *shares* and thus the coverage ratio, we consider a specification using both logged GDP and logged GDP per capita to examine this further. Our non-NTM data are all obtained from the World Development Indicators (World Bank, 2016).[14]

Table 2 indicates the average 4-digit coverage ratio for each NTM, the coefficient of variation in this, and the averages for our two inequality measures for each of the countries in our sample.[15] As can be seen, there is significant variation in average coverage ratios both across countries and across 4-digit sectors within a country. For TBTs, Denmark has the highest average coverage ratio across 4-digit sectors (.4208) and Croatia has the lowest (.0497). Since the average of this across countries is .35, this indicates significant differences across nations. Turning to SPSs, Croatia again has the lowest average whereas Slovenia now has the highest at .29, 50% higher than the average across countries. Note that Croatia has a much lower average NTM coverage than the other countries for both measures; we therefore test the robustness of our results to its exclusion below. Likewise, we find differences in inequality across countries. In terms of the Gini, the average across nations is 32.3, ranging from a high of 46.65 for Slovenia to a low of 26.08 in Slovakia. *Quintile* shows a similar variation, with a high of 52.2 in Slovenia to a low of 35.58 in Slovakia (and an average across countries of 40.2). Finally, it is worth recognizing that there are differences across countries in terms of how much the coverage ratios vary across products within a country.

Table 3 reports the summary statistics for the sample. In our estimations, errors are clustered at the country-year level (excepting when using country wide coverage ratios; there we cluster only at the country level).

[14]These data are at `http://http://databank.worldbank.org/`.

[15]The averages in this table are those used to construct Figures 1 and 2.

4 Results

In Table 4 we present our baseline results using the 4-digit coverage ratios. Columns (1)-(4) use TBT coverages whereas (5)-(8) use SPS coverages. Even numbered columns utilize per-capita GDP; odd numbered ones split it into GDP and population. Finally, columns (1), (2), (5), and (6) use *Gini* as the measure of inequality with the remainder using *Quintile* instead. Next to each variable name, in parenthesis, is the predicted coefficient sign presuming that the NTMs are on the luxuries. As discussed above, this suggests that a rise in inequality (equations (7) and (8)) would increase the coverage ratio. Similarly, an increase in per capita income would increase the coverage ratio (equation (9)); this would also occur from a rise in GDP or a fall in population.

As can be seen, our results are broadly in line with our predictions when the NTM is on the luxury good. Beginning with the inequality measures, in all but one case we find that more inequality is correlated with a higher coverage ratio. Further, these coefficients are economically meaningful, with column (1) suggesting a 1% rise in the Gini coefficient would be associated with a coverage ratio .1 higher, an increase of 27.5% relative to the sample mean. The results are even larger for the *Quintile* measure of inequality where the estimated effect would be nearly twice as large. As inequality has been shown by others to have a meaningful predictive power for trade levels, this suggests that including TBT coverage ratios but not inequality has the potential to bias the estimated effect of TBTs (with the direction of the bias depending on whether inequality increases or decreases imports, something which Dalgin, Trindade, and Mitra (2008) show is a complicated relationship). Compared to TBTs, the estimated change in the SPS coverage ratio is smaller, roughly half the size when using the Gini coefficient and one-third as large when using *Quintile*. That said, because the average SPS coverage ratio is smaller (.190 as compared to .356 for TBTs), the percentage change relative to the mean is only slightly smaller, estimated at 22.1%.

Turning to the income measures, although in each case the estimated coefficient has a sign in line with NTMs on luxuries, the coefficients are less precisely estimated. When using GDP per capita, we only find significance for this variable when using *Quintile* as the inequality measure. When relaxing the assumption that the GDP and population coefficients are proportional but opposite, we find a significant population coefficient in each case, where again it points towards NTMs on luxuries. The GDP coefficient, however, is only significant once (where as predicted it is positive). One noticeable difference between the GDP and population coefficients is their point estimates; the estimated coefficients for GDP are about 10% as large as those for population (in absolute value). In unreported results, since Table 2 indicated that Croatia has very low coverage ratios relative to the other countries, we omitted this nation and repeated our estimation. When doing so, we found comparable results to the full sample estimates, and, if anything, slightly higher point estimates.[16]

In Tables 5 and 6, we repeat this exercise but use coverage ratios at the 2-digit and country-wide levels. Our expectation is that when sectors are more aggregated this increases the likelihood of NTMs applying to both necessities and luxuries within the increasingly broad category. This could potentially weaken the links between income distribution and changes in the coverage shares in our estimates. Starting with the 2-digit results, we find that the coefficient signs on inequality again point towards NTMs on the luxuries. Now, however, we find far less significance than in the 4-digit results. In part, this is to be expected given the fall in the number of observations when we aggregate. Alternatively, as just mentioned, this may result from 4-digit sectors where the NTMs are relatively clearly on luxuries or necessities, but when aggregated to a 2-digit sector, this broader classification is less clearly delineated. Turning to the other variables, we find that when using SPS NTMs, the coefficients are also in line with NTMs on the luxury. In addition, we find somewhat more significance for GDP and per capita GDP than we did in the 4-digit results. In contrast, when using TBTs, although the population coefficients point towards NTMs on the luxuries, the GDP and GDP per capita coefficients suggest the opposite. Beyond these differences, when using the 2-digit data the point estimates for all the coefficients fall in size. When using

[16]These are available on request.

the country-level data in Table 6, we again see a decline in significance and the magnitude of the point estimates. That said, our inequality measures are still significant when using the SPS coverages where they continue to point towards NTMs on the luxuries. Taken together, the results of 5 and 6 show two things. First, even at higher levels of product aggregation, we find evidence suggesting that NTMs are geared towards luxuries (although the results are less robust). Second, since the link between the coverage ratio and inequality grows smaller as the level of aggregation rises, the potential for bias when using NTM coverage ratios but not inequality may be more severe when using disaggregated data than, say, total trade levels.

In the theory, the trade shares and therefore the coverage ratio, were independent of country size.[17] As such, in the baseline estimates, we used either per capita GDP or its decomposition into GDP and population as controls. In Table 7, we use the 4-digit data in an extended specification where we control for inequality, per capita GDP, and GDP, i.e controlling for the distribution of income, average income, and total income.[18] When compared to the corresponding columns in Table 4, the only change we find is that the point estimates for per capita GDP increase by an order of magnitude. In addition, we find that, holding the average income and inequality constant, larger countries have lower coverage ratios with this estimate significant in the SPS regressions. Although we do not have a prior for this coefficient, this suggests that even when controlling for country size, the other coefficients are suggestive of NTMs on luxuries.

In Tables 8 and 9 we repeat our Table 4 specification but split our 4-digit data into manufacturing and non-manufacturing samples respectively.[19] Beginning with the manufacturing results in Table 8, for TBTs we find results comparable to the whole sample estimates in

[17]Note that we are discussing trade shares, not values such as in Dalgin, Trindade, and Mitra (2008) or prices as was done in Bekkers, Francois, and Manchin (2012). In those specifications, theory indicated a role for market size. Were we to estimate import values (as in equation (11)), we would need to do so as well.

[18]In unreported results, we also did so for the 2-digit and country-level data. when doing so, we found results comparable to Table 7 but, as in the baseline, significance and point estimates decline as aggregation increases.

[19]Specifically, manufacturing includes 4-digit sectors in 2-digit codes 25 and higher.

Table 4, i.e. TBTs on luxuries. For SPSs, on the other hand, although the sign pattern is consistent with SPSs on luxuries, we find no significant estimates. One possible reason for this is the relative infrequence of SPSs on manufactured goods; the average TBT coverage ratio for manufactures is .329 while the average SPS coverage ratio is only .114. Non-manufactures, on the other hand, exhibit significant coefficients only for SPSs as reported in Table 9. Here, as in the full sample results, the estimates are consistent with SPSs on luxuries and the significance of the coefficients is quite strong. TBTs, on the other hand display no significance and the sign pattern suggests TBTs on necessary non-manufactures. It is worth noting that for non-manufactures, NTM coverages are higher than in manufactures, with an average coverage ratio of .454 for TBTs and .463 for SPSs. In Table 10 we instead use our extended specification using both GDP and GDP per capita. When doing so, we find significant coefficients for manufacturing TBTs and non-manufacturing SPSs where the estimates suggest the NTMs are tilted towards luxuries.

Finally, one feature of the coverage ratio data is that there are a sizable share of observations where the coverage ratio is either zero or one. A zero occurs when there are no NTMs on imported 6-digit products or are simply no NTMs (and thus the coverage ratio is independent of trade shares). Similarly, a coverage ratio of one means that NTMs apply to all imported products or all of them face NTMs. For TBTs, 17% of the sample has a zero coverage and 26% has a coverage of 1. For SPSs, the coverage ratio equals zero 61% of the time (again, recall the relative infrequency of SPSs compared to TBTs) and 1 15% of the time. With this in mind, we reestimate our baseline results two final times, using a Tobit estimator in Table 11 and a Poisson estimator in Table 12.[20] As those tables show, the results tell the same story as the original estimates: NTMs seem to be applied mostly to luxuries.

[20] Results using Poisson Pseudo Maximum Likelihood (PPML) are available on request. These yield similar results.

5 Conclusion

With declining tariffs, the impact of NTMs has risen in importance when discussing trade policy. As the literature on NTMs continues to grow, it is important for researchers to be aware of how these measure are constructed. Here, we discuss one feature of this – the impact of trade shares on NTM coverage ratios. In particular, we show how even among a group of countries where NTMs are the same, coverage ratios can vary considerably. Here, we link this variation to income distribution, a trade determinant receiving a resurgence in attention. When import demand is driven by Stone-Geary preferences where some goods are luxuries consumed only by the rich and others necessities consumed by all, we show that the correlation between the coverage ratio and income distribution measures can suggest whether NTMs are on average applied to luxuries or necessities. Using data on the EU for 2008-2014, we find that the estimates point towards NTMs on luxuries. Since this would imply that the NTM burden would fall relatively on the wealthy, recognizing this may be of use in debating the impact, merits, and political economy of NTM liberalization.

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Figure 1: Average TBT Coverage Ratio

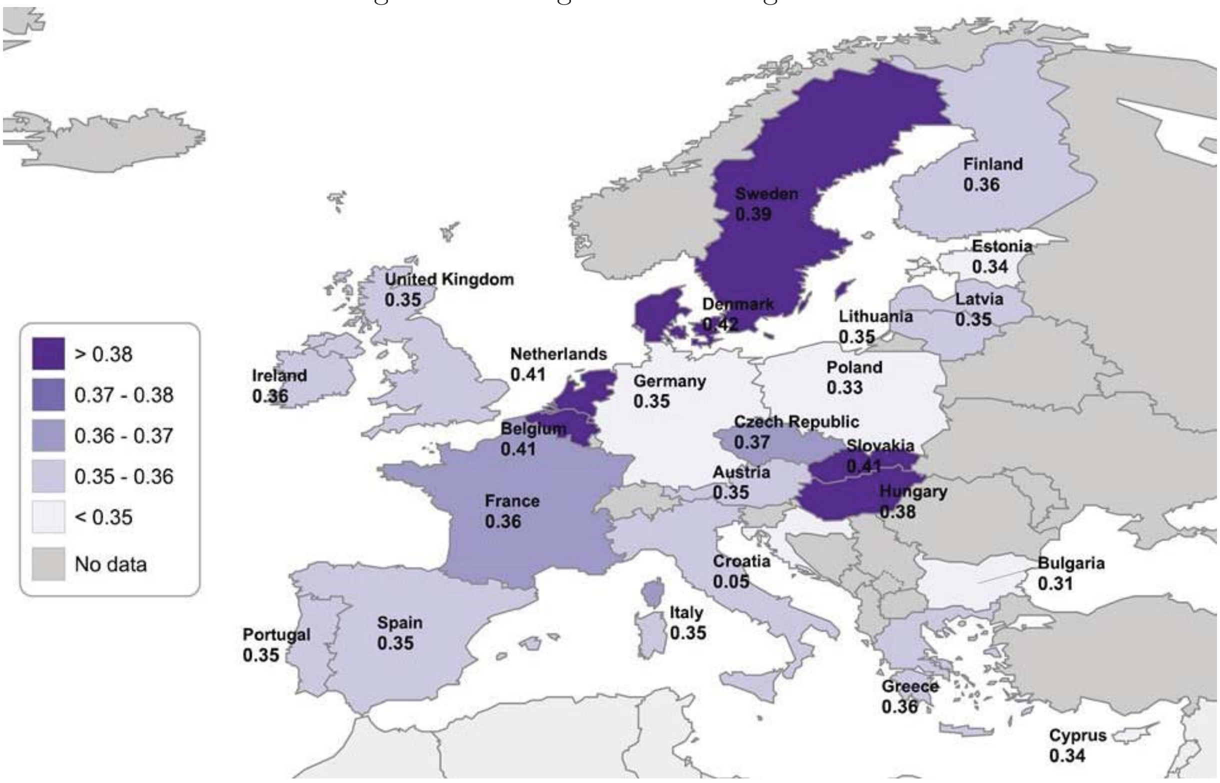

Figure 2: Average SPS Coverage Ratio

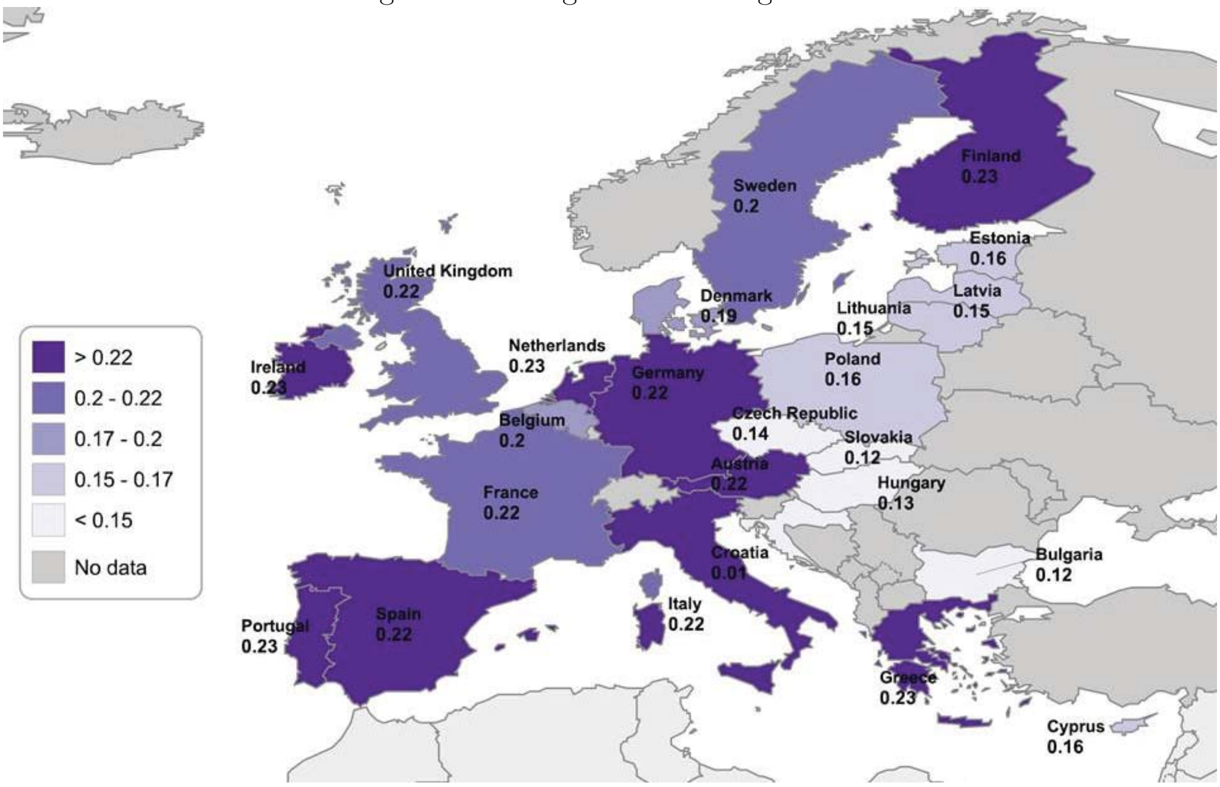

Table 1: Top 15 Sectors Ranked by Cross-Country Variance in Coverage Ratio

TBT	HS Sector Code	Average	Std. Dev
Balloons and dirigibles	8801	0.487	0.502
Parachutes	8804	0.487	0.502
Tugs and pusher craft	8904	0.4722	0.5016
Fishing vessels	8902	0.4615	0.5013
Vessels and other floating structures	8908	0.4554	0.5005
Containers for compressed or liquefied gas	7311	0.4508	0.4996
Aluminium containers for compressed or liquefied gas	7613	0.4508	0.4996
Base metals clad with silver	7107	0.6667	0.488
Coins	7118	0.6667	0.488
Refractory cements	3816	0.3647	0.4842
Tar distilled from coal	2706	0.6449	0.4808
Newsprint, in rolls or sheets	4801	0.3478	0.4784
Tissue, towel, napkin stock or similar	4803	0.3478	0.4784
Composite paper and paperboard	4807	0.3478	0.4784

SPS	HS Sector Code	Average	Std. Dev
Sulphur of all kinds	2503	0.5574	0.4987
Chalk	2509	0.5574	0.4987
Siliceous fossil meals	2512	0.5574	0.4987
Slate	2514	0.5574	0.4987
Limestone flux	2521	0.5641	0.498
Casks, barrels, vats, tubs	4416	0.5667	0.4976
Wood tar	3807	0.5785	0.4959
Asbestos	2524	0.5761	0.494
Phosphides	2853	0.5906	0.4937
Hydraulic brake fluids	3819	0.5906	0.4937
Reagents	3822	0.5906	0.4937
Colour lakes	3205	0.5984	0.4922
Organic compounds	2942	0.5984	0.4922
Perfumes and toilet waters	3303	0.5984	0.4922
Candles, tapers and the like	3406	0.5984	0.4922

Notes: Average and Standard Deviation are calculated by 4-digit sector across countries.

Table 2: Coverage Rates Across and Within Countries

		TBT		SPS			
Country	Obs.	Average	Coeff. Variation	Average	Coeff. Variation	Gini	Quintile
Austria	4,675	0.3517	0.9527	0.2247	1.4778	30.45	38.61
Belgium	5,349	0.4116	0.8283	0.1961	1.629	29	37.38
Bulgaria	3,833	0.3142	1.0664	0.1181	2.227	33.57	41.01
Cyprus	3,708	0.3401	1.0021	0.1617	1.8642	31.71	40.6
Czech Republic	4,290	0.3659	0.8958	0.1402	2.0176	26.29	36.5
Germany	3,766	0.345	0.9744	0.2233	1.4872	31.29	39.6
Denmark	5,635	0.4208	0.8036	0.1874	1.6827	28.89	36.28
Spain	4,709	0.3522	0.9541	0.2238	1.4851	34.8	41.19
Estonia	3,710	0.3363	1.0027	0.157	1.9055	32	40.09
Finland	4,656	0.3589	0.9383	0.2261	1.4812	27.85	37.24
France	3,848	0.3637	0.9235	0.2188	1.51	33.08	41.22
UK	4,780	0.3541	0.9481	0.2199	1.504	34.37	41.71
Greece	4,662	0.3552	0.948	0.2278	1.4744	34.22	41.16
Croatia	2,335	0.0497	3.3668	0.0057	8.3339	33.71	42.25
Hungary	4,624	0.3821	0.89	0.1315	2.0924	27.53	36.44
Ireland	4,682	0.3578	0.9489	0.2286	1.4785	30.91	39.28
Italy	4,704	0.3519	0.9544	0.2228	1.4875	33.74	40.73
Lithuania	3,810	0.3525	0.9664	0.1534	1.917	35.77	42.86
Latvia	3,756	0.3544	0.9643	0.1513	1.9259	37.41	43.6
Netherlands	5,461	0.4144	0.8159	0.2267	1.44	29.93	38.34
Poland	5,463	0.331	0.9901	0.156	1.8816	33.72	41.75
Portugal	4,675	0.3533	0.9519	0.2253	1.48	36.63	44.12
Slovenia	4,430	0.2818	1.2156	0.29	1.2524	46.65	52.2
Slovakia	5,079	0.4089	0.8199	0.1151	2.2827	26.08	35.58
Sweden	5,364	0.3864	0.8733	0.1974	1.6303	27.13	36.07

Notes: Average is the average of the coverage ratio across 4-digit sectors within the country. Coeff. Variation is the coefficient of variation in the coverage ratio across 4-digit sectors within the country. Gini and Quintile are the non-logged averages of a given country over the sample period.

Table 3: Summary Statistics

	Obs.	Mean	Std. Deviation	Minimum	Maximum
TBT Coverage Ratio	112004	0.3560937	0.3387033	0	1
SPS Coverage Ratio	112004	0.1897906	0.316561	0	1
GDP	112004	26.46304	1.308321	24.03815	28.86857
GDP per capita	112004	10.30581	0.4080621	8.905566	10.77051
Population	112004	16.16675	1.128554	13.8897	18.22357
Gini Coefficient	112004	3.455952	0.1221655	3.258865	3.842673
Quintile	112004	3.68207	0.0758006	3.55134	3.955082

Notes: GDP, GDP per capita, Population, Gini Coefficient and Quintile are all measured as natural logs.

Table 4: Baseline Results: 4-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	0.0231		0.0185		0.0229*		0.0194	
	(0.0300)		(0.0289)		(0.0131)		(0.0126)	
Population (-)	-0.257**		-0.281**		-0.228***		-0.234***	
	(0.116)		(0.114)		(0.0532)		(0.0548)	
GDP per capita (+)		0.0184		0.0143		0.0274*		0.0231*
		(0.0341)		(0.0328)		(0.0146)		(0.0139)
Gini (+)	0.0981**	0.0949**			0.0419**	0.0417**		
	(0.0445)	(0.0435)			(0.0171)	(0.0197)		
Quintile (+)			0.174**	0.155**			0.0536**	0.0405
			(0.0670)	(0.0652)			(0.0260)	(0.0287)
Observations	112,004	112,004	112,004	112,004	112,004	112,004	112,004	112,004
Adjusted R-squared	0.801	0.801	0.801	0.801	0.808	0.808	0.808	0.808

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 5: Baseline Results: 2-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	-0.00513*		-0.00520**		0.00443**		0.00391*	
	(0.00260)		(0.00256)		(0.00211)		(0.00202)	
Population (-)	-0.0179**		-0.0194**		-0.0339***		-0.0343***	
	(0.00826)		(0.00821)		(0.00792)		(0.00802)	
GDP per capita (+)		-0.00471*		-0.00480*		0.00466*		0.00403*
		(0.00281)		(0.00274)		(0.00237)		(0.00225)
Gini (-)	0.00433	0.00409			0.00531*	0.00513		
	(0.00311)	(0.00337)			(0.00318)	(0.00331)		
Quintile (-)			0.00941*	0.00757			0.00581	0.00378
			(0.00495)	(0.00535)			(0.00472)	(0.00499)
Observations	8,604	8,604	8,604	8,604	8,604	8,604	8,604	8,604
Adjusted R-squared	0.897	0.897	0.897	0.897	0.780	0.780	0.780	0.780

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 2-digit sector dummies.

Table 6: Baseline Results: Country Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	-3.57e-05		-4.44e-05		-3.64e-06		-6.52e-06	
	(5.47e-05)		(4.86e-05)		(1.36e-05)		(1.29e-05)	
Population (-)	-0.000171		-0.000197		-2.74e-05		-3.06e-05	
	(0.000196)		(0.000186)		(4.42e-05)		(4.44e-05)	
GDP per capita (+)		-5.28e-05		-6.31e-05		-7.51e-06		-1.06e-05
		(6.13e-05)		(5.53e-05)		(1.48e-05)		(1.42e-05)
Gini (+)	0.000140	0.000124			3.29e-05**	2.98e-05**		
	(9.12e-05)	(0.000104)			(1.22e-05)	(1.22e-05)		
Quintile (+)			0.000211	0.000173			4.42e-05**	3.78e-05**
			(0.000140)	(0.000158)			(1.69e-05)	(1.80e-05)
Constant	0.00330	0.000250	0.00366	0.000150	0.000457	1.43e-05	0.000535	1.14e-05
	(0.00327)	(0.000947)	(0.00318)	(0.00106)	(0.000704)	(0.000176)	(0.000700)	(0.000182)
Observations	101	101	101	101	101	101	101	101
Adjusted R-squared	0.896	0.892	0.897	0.892	0.971	0.971	0.971	0.971

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country in parentheses. All specifications include country and year dummies.

Table 7: Extended Results: 4-digit Level

	(1) TBT	(2) TBT	(3) SPS	(4) SPS
GDP (?)	-0.0877	-0.113	-0.140**	-0.148***
	(0.134)	(0.132)	(0.0554)	(0.0563)
GDP per capita (+)	0.101	0.121	0.159***	0.163***
	(0.140)	(0.139)	(0.0583)	(0.0598)
Gini (+)	0.0958**		0.0432**	
	(0.0435)		(0.0178)	
Quintile (+)		0.165**		0.0532**
		(0.0650)		(0.0268)
Observations	112,004	112,004	112,004	112,004
Adjusted R-squared	0.801	0.801	0.808	0.808

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 8: Manufacturing Results: 4-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	0.0355		0.0291		0.00262		0.00190	
	(0.0393)		(0.0377)		(0.00564)		(0.00548)	
Population (-)	-0.405**		-0.434***		-0.0122		-0.0136	
	(0.156)		(0.153)		(0.0164)		(0.0169)	
GDP per capita (+)		0.0305		0.0242		0.00276		0.00207
		(0.0458)		(0.0441)		(0.00576)		(0.00562)
Gini (+)	0.134**	0.130**			0.00972	0.00974		
	(0.0586)	(0.0585)			(0.00610)	(0.00618)		
Quintile (+)			0.230**	0.203**			0.0135	0.0129
			(0.0889)	(0.0885)			(0.00988)	(0.00986)
Observations	87,641	87,641	87,641	87,641	87,641	87,641	87,641	87,641
Adjusted R-squared	0.770	0.770	0.770	0.770	0.718	0.718	0.718	0.718

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 9: Non-Manufacturing Results: 4-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	-0.0106		-0.0104		0.0908**		0.0793*	
	(0.00849)		(0.00848)		(0.0451)		(0.0438)	
Population (-)	0.0420		0.0449		-0.818***		-0.849***	
	(0.0275)		(0.0277)		(0.189)		(0.193)	
GDP per capita (+)		-0.0112		-0.0110		0.108**		0.0956**
		(0.00875)		(0.00872)		(0.0494)		(0.0469)
Gini (+)	-0.00732	-0.00722			0.146**	0.141**		
	(0.0137)	(0.0137)			(0.0636)	(0.0675)		
Quintile (+)			-0.0156	-0.0131			0.211**	0.152
			(0.0217)	(0.0209)			(0.0937)	(0.0972)
Observations	24,363	24,363	24,363	24,363	24,363	24,363	24,363	24,363
Adjusted R-squared	0.923	0.923	0.923	0.923	0.882	0.881	0.882	0.881

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 10: Manufacturing and Non-Manufacturing Extended Results: 4-digit Level

	Manufacturing				Non-Manufacturing			
	(1)	(2)	(3)	(4)	(5)	(2)	(3)	(4)
	TBT	TBT	SPS	SPS	TBT	TBT	SPS	SPS
GDP (?)	-0.157	-0.188	-0.00608	-0.00792	0.0197	0.0227	-0.489**	-0.524**
	(0.188)	(0.185)	(0.0116)	(0.0118)	(0.0224)	(0.0229)	(0.203)	(0.206)
GDP per capita (+)	0.178	0.202	0.00847	0.00956	-0.0296	-0.0322	0.563***	0.586***
	(0.197)	(0.195)	(0.0138)	(0.0142)	(0.0234)	(0.0238)	(0.211)	(0.216)
Gini (+)	0.131**		0.00979		-0.00756		0.150**	
	(0.0578)		(0.00618)		(0.0138)		(0.0646)	
Quintile (+)		0.218**		0.0135		-0.0155		0.207**
		(0.0867)		(0.00999)		(0.0219)		(0.0947)
Observations	87,641	87,641	87,641	87,641	24,363	24,363	24,363	24,363
Adjusted R-squared	0.770	0.770	0.718	0.718	0.923	0.923	0.881	0.881

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 11: Tobit Estimation: 4-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	0.0389		0.0293		0.0915**		0.0734*	
	(0.0469)		(0.0451)		(0.0463)		(0.0434)	
Population (-)	-0.521***		-0.547***		-0.902***		-0.903***	
	(0.181)		(0.181)		(0.206)		(0.210)	
GDP per capita (+)		0.038		0.0284		0.114**		0.0940*
		(0.0546)		(0.0524)		(0.0531)		(0.0489)
Gini (+)	0.177**	0.171****			0.177**	0.174**		
	(0.0704)	(0.0721)			(0.0692)	(0.0835)		
Quintile (+)			0.283***	0.251**			0.200*	0.162
			(0.109)	(0.110)			(0.102)	(0.118)
Constant	7.163***	-0.495	7.396***	-0.726	11.83***	-1.309*	12.22***	-1.089
	(2.621)	0.7081	(2.589)	(0.747)	(2.697)	(0.792)	(2.731)	(0.846)
Sigma	0.202***	0.202***	0.202***	0.202***	0.259***	0.260***	0.259***	0.260***
	(0.00821)	0.0082	(0.00821)	(0.00821)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
Observations	112,004		112,004	112,004	112,004	112,004	112,004	112,004
Pseudo R-squared	0.9119	0.9117	0.9120	0.9119	0.8370	0.8367	0.8369	0.8367

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

Table 12: Poisson Estimation: 4-digit Level

	(1) TBT	(2) TBT	(3) TBT	(4) TBT	(5) SPS	(6) SPS	(7) SPS	(8) SPS
GDP (+)	0.0534		0.0333		0.186**		0.145*	
	(0.0914)		(0.0874)		(0.0903)		(0.0825)	
Population (-)	-0.992***		-1.020***		-1.781***		-1.780***	
	(0.344)		(0.345)		(0.418)		(0.421)	
GDP per capita (+)		0.0547		0.0341		0.215**		0.168*
		(0.106)		(0.101)		(0.102)		(0.0923)
Gini (+)	0.318**	0.311**			0.327**	0.332**		
	(0.138)	(0.143)			(0.131)	(0.159)		
Quintile (+)			0.464**	0.416*			0.346*	0.296
			(0.218)	(0.221)			(0.190)	(0.220)
Constant	12.59**	-2.357*	12.96***	-2.594*	21.62***	-4.139***	22.52***	-3.588**
	(4.927)	(1.387)	(4.944)	(1.472)	(5.518)	(1.537)	(5.524)	(1.599)
Observations	112,004	112,004	112,004	112,004	112,004	112,004	112,004	112,004

Notes: ***, **, and * on coefficients denote significance at the 1%, 5%, and 10% levels respectively. Robust standard errors clustered by country-year in parentheses. All specifications include country, year, and 4-digit sector dummies.

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