Fitting the Gravity Model when Zero Trade Flows are Frequent: a Comparison of Estimation Techniques

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Abstract
Gravity model of trade has emerged as an important and popular model in explaining and predicting bilateral trade flows. While the theoretical justification is no longer in doubt, nonetheless, its empirical application has however generated several unresolved controversies in the literature. These specifically concerns estimation challenges which revolve around the validity of the log linear transformation of the gravity equation in the presence of heteroscedasticity, and the appropriate estimation techniques in the presence of zero trade observations. These two issues have generated several challenges concerning the appropriate choice of the estimation techniques. This necessitates a careful consideration of the appropriate estimation techniques since it is now clear that naive approaches to estimation may lead to biased and frequently misinterpreted results. This paper therefore evaluates the performance of alternative estimation techniques in the presence of zero trade observations, checks for the validation of their assumptions and their behaviour in cases of departure from their assumptions, particularly the departure from the heteroscedasticity assumption. We present a gravity model that accounts for multilateral resistant terms using Baier and Bergstrand Taylor-series approximation. Analysis was based on a dataset of Africa's fish exports to the European Union between 2007 and 2012, which contains about 60% zero trade observations. In essence, we find that choosing the best model depends on the dataset, the process generating the error term and advocate an encompassing toolkit approach of the methods so as to establish robustness. Given our dataset and the gravity equation specified, our results show that Multinomial Poisson Maximum Likelihood (MPML) estimator outperform all the other estimators. This points to the MPML as the most appropriate estimator for this particular dataset.

Keywords: Gravity equation, Zero trade flows, Estimation techniques, African trade data

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1.0 INTRODUCTION
Gravity model of trade has emerged as an important and popular model in explaining and predicting bilateral trade flows. The model has been used to analyze the economic impacts of trade, investment, migration; currency union, regional trade agreements, etc. Its general acceptance as the workhorse of international trade and its proven popularity are primarily due to its exceptional success in predicting bilateral trade flows and the theoretical foundations given to it by both the old, new and ‘new new’ trade theories. However, prior to its general acceptance, there have been several criticisms about its lack of strong theoretical application, but which was later justified by the notable work of Anderson, 1979; Bergstrand, 1989; Deardorff, 1998; Helman and Krugman, 1985; etc, all of whom gave theoretical justifications to the model.

While the theoretical justification is no longer in doubt, nonetheless, its empirical application has however generated several unresolved controversies. These specifically concern the appropriate estimation technique and specification of the gravity equation, the former of which has generated several debates in the literature. The first concern is the estimation challenges which revolve around the validity of the log linear transformation of the gravity equation in the presence of heteroscedasticity and zero trade observations. The challenges posed by the validity of the log linear gravity equation arise from the conventional practice in the literature which is to log linearize the multiplicative gravity equation. This is then estimated using ordinary least square (OLS) or by employing panel data techniques with the usual assumption of homoscedasticity across country pairs or countries (Gomez-Herrera, 2012). However, Santos Silva and Tenreyro (2006, 2011), pointed out that due to the logarithmic transformation of the equation, OLS estimator may be inconsistent in the presence of heteroscedasticity and non-linear estimators should be used.

There are also challenges presented by the appropriate choice of the estimation techniques in the presence of zero trade values observations which is very common in trade data, and particularly pervasive in disaggregated data. Usually, the common practice in the literature in dealing with these zero trade observations are by employing the truncation method where the zero trade observations are deleted completely form the trade matrix, or censoring method where the zeros are substituted by a small positive constant an arbitrary small value. However, Flowerdew and Aitkin, 1982; Eichengreen and Irwin, 1998; Linders and Groot, 2006 and Burger et al., 2009 posit that these methods are arbitrary, are without any strong theoretical or empirical justification and can distort the results significantly, leading to inconsistent estimates. In addition, Heckman (1979) posit that if the zeros are not random, deleting can lead to loss of information; adding an arbitrary constant to the zero observations is tantamount to deliberately introducing measurement error which can lead to selection bias.

More appropriate estimation techniques are increasingly employed to deal with the estimation challenges posed by the logarithm transformation and zero trade flows issues in the context of gravity trade literature. The models proposed by Tobit (1959), Heckman (1979) and Helpman, Melitz and Rubinstein (2008) have all been used to deal with the problem associated with zero valued trade flows. For instance, the Tobit model was employed by Rose (2004) and Baldwin and DiNino (2002) to deal with the problem of zero valued trade flows which resulted either because the actual trade flows are not observable or due to measurement errors from rounding. However, several studies notable among which are Linder and De Groot (2006) argued that the appropriateness of using the Tobit model to estimate zero valued trade flows in a gravity model depends on whether rounding up of trade flows is important or whether the desired trade could be negative. They posited that the desired trade cannot however be negative since the zeros do
not reflect unobservable trade flow, therefore, one cannot censor trade flow from below it. Likewise, sample selection models were developed by Heckman (1979) and Helpman et al., (2008) to deal with selection bias resulting from the non-random elimination of zeros from the trade matrix. The sample selection models have also been criticized on the ground that it is difficult to satisfy the exclusion restriction. In addition, Santos Sliver and Tenreyro (2009) and Flam and Nordström (2011) show that Helpman et al., (2008) model does not control for heteroscedasticity which is usually pervasive in most trade data, consequently casting doubts on the validity of inferences drawn from the model.

However, in an influential paper, Santos Siliva and Tenreyro (2006) suggest that non-linear estimators, precisely the poisson pseudo maximum likelihood (PPML) should be used to deal with the zero trade observations as it provides unbiased and consistent estimates that are robust to the presence of heteroscedasticity in the data and naturally take care of the zero observations of the dependent variable. Nonetheless, the influential work of Santos Siliva and Tenreyro (2006) has generated a lot of controversies in the literature and alternative estimation techniques have been proposed to accommodate zero trade values in the data (c.f. Burger et al., 2009; Martinez-Zarzaso (2013); Helpman et al., 2008; Martin and Pham, 2008; etc). These studies aim to identify the best performing estimator, comparing alternative estimation techniques, but obtained divergent outcomes. This has led to several debates in the literature about which of the different alternative estimators perform best. For instance, Santos Siliva and Tenreyro (2006) propose the usage of the PPML as against the usual OLS technique, with the justification that it is consistent in the presence of heteroscedasticity and deals naturally with the zero trade flows. However, in an earlier paper - Martínez-Zarzoso, Nowak-Lehmann, Vollmer¹ (2007) and also more recently, Martínez-Zarzaso (2013) found that although the PPML is less affected by heteroscedastic compared to other estimators, nevertheless, the PPML estimator proposed by Santos Silva and Tenreyro (2006) is not always the best estimator as its estimates are outperformed by both the OLS and FGLS estimates in out of sample forecast.

In response to this, Santos Siliva and Tenreyro (2008) posit that although the other estimators might outperform the PPML in some cases, however, the PPML should be a benchmark against which other alternative estimators be compared due to its identified advantages. Study by Burger et al., (2009) has also challenged that of Santos Siliva and Tenreyro (2006). They posit that PPML is vulnerable to the problem of overdispersion in the dependent variable and excessive zeros and propose the use of the Negative Binomial Pseudo Maximum Likelihood (NBPML) to correct for the overdispersion in the dependent variable. In addition, they also found PPML and NBPML to be inconsistent in the presence of excessive zero trade observations and propose the usage of the Zero-inflated models which are Zero-inflated Pseudo Maximum Likelihood technique (ZIPML) and Zero-inflated Binomial Pseudo Maximum Likelihood technique (NIBPML) as they are noted to be consistent in the presence of excessive zeros. Similar result has been found by Martínez-Zarzaso (2013) and Martin and Pham, (2008), with the latter claiming that the Heckman model is appropriate for dealing with this issue.

In their search for the most appropriate model, the above studies have explored the gravity model and estimated the effects of free trade agreement in their gravity model (Santos Siliva and Tenreyro; Burger, et al., 2009; Martínez-Zarzoso, 2013; etc). However, as a departure, our study models the trade effects of non-tariff barrier, specifically, standards in gravity model

¹ Martínez et al (2007) was published in a journal in 2013 as Martínez-Zarzaso (2013), and henceforth we will mainly refer to Martínez-Zarzaso (2013).
setting. This study is motivated by the methodological challenges which can be posed by standards as its imposition can bring about zero trade flows. While it is true that there are zeros that can be attributed to statistical zeros such as rounding up or a declaration threshold, however, many of these zeros may reflect inability to trade due to the lack of export profitability resulting from prohibitive fixed compliance costs of meeting food safety standards which necessary by African exporters to establish strong and continuous trading partnership with their trade partners.

Standards as a technical barrier to trade imposes additional trade costs on producers or exporters which can be enormous (Fisher and Serra, 2000) especially for producers from developing countries where imperfect market conditions exists (Wilson, 2004), thereby constituting an obstacle to trade. For instance, the higher cost of compliance may drive out less productive firms and discourage potential exporters from entering the exports market, which might results into zero trade flow, although this can at times serve to increase the volume of trade of the remaining exporters in the market (Bao and Chen, 2013). In addition, the imposition of standards can result in import rejection of sub-standard products, consequently leading to the presence of zero trade flows in the affected product’s trade flow matrix. This is particularly true for African countries which do not have the technical and financial capability and capacity to comply with importing countries standards which as a result, non-compliance to standards can also bring about decisions not to exports thereby aggravating the occurrence of zeros in the trade flow matrix. Thus, it would be interesting to show first, the extent to which standards can explain zero and positive trade flows in our model and second, the estimator that can give consistent estimates when the dependent variable takes on zeros frequently.

To this end, our objective is to compare the performance of alternative estimation techniques in the presence of zero trade observations using African dataset across different product lines and check for the validation of their assumptions and their behavior in cases of departure from their assumption, particularly the departure from the heteroscedasticity assumption. The focus of this study is methodological. As an empirical application, we investigate the impact of EU standards on Africa’s fish exports using trade data from 2007 to 2012 across a sample of EU 27 and 52 African countries. Our choice of agricultural food trade hinges on the premise that agricultural trade is often dominated by zero trade flows, in contrast to industrial trade flows (Haq, 2012).

Our study makes two important contributions to the existing methodological debate. First, most of the existing studies have investigated the performance of these estimators using developed and or developing countries dataset (Santos Siliva and Tenreyro, 2006; Martins and Pham, 2008, Staub and Winkelmann, 2012; Martinez-Zarzoso, 2013; etc). Our identified gap in this literature is that studies which have investigated the performance of the estimators using Africa’s dataset are rare. However, Martinez-Zarzaso (2007) deduced that zero trade usually occurs among small or poor countries of which Africa belongs. Given the peculiarity of Africa’s dataset in terms of missing data and or missing trade that usually characterize the above trade data problems which necessitates different estimators, we thus find it interesting to investigate the performance of alternative estimators given our particular dataset and add to the nascent of literature and debates on the best performing model.

\footnote{However, beyond the trade inhibiting effects of standards, its imposition can also have trade promoting effects. Standards reveal information about consumers’ tastes and production technologies across countries,( Blind, 2005). Thus, exporters are exporters are able to adopt their product much more easily to importers’ specifications (Moenius, 1999), thereby fostering trade.}
The second novelty of our research is that to the best of our knowledge, there exist no study within the standard-agricultural-trade literature which investigated the impact of standards on trade by comparing the performance of a large number of alternative estimators (e.g. see Fontagne, Mimouni and Pasteels, 2006; Disdier and Fontagne, 2010, Xiong and Beghin, 2010, 2013; Drogue and Demaria, 2012; Winchesta et al, 2012, Shepherd and Wilson, 2013; etc). Our analysis departs from existing studies which usually consider a limited number of estimation techniques (PMLs, Heckman and OLS). We consider a very much larger pool of estimators compared to past studies.

The rest of the paper is structured as follows. The next section reviews the theoretical foundations of the gravity model. Section 3 provides a short discussion of various gravity model estimation techniques and the challenges presented by them in the presence of heteroscedasticity and zero trade flows; and also reviews related empirical literature. Section 4 provides the methodology and describes the data, while section 5 discusses the results. The final section concludes.

2.0 THEORETICAL LITERATURE
The gravity equation was first used in the nineteenth century by Ravenstein (1885) and then by Zipf (1946) contrary to what a majority of trade economists believe. However, the formal usage of the model dated back to Tinbergen (1962) and Pöyhönen (1963). According to the early version of the model, bilateral exports between from country i to country j is explained by exporters and importers economic masses proxy by their income and the geographical distance between the country-pairs. In spite of the initial criticism that it is atheoretical, in the last decades, the gravity model has gained wide usage due to the rigorous theoretical foundation given to it and its empirical success in predicting bilateral trade flows of different commodities under different situations (Deardorff, 1984).

2.1 New Developments in the Theoretical Foundation
After more than two decades of an influx of models providing theoretical justification for the empirical success of the gravity equation, emphasis thereafter turned to ensuring that the empirical results of the gravity equation is well defined on theoretical grounds. One important contribution in this regard relates to the structural form of the equation and the implication of mis-specification or omitted variable bias. These relate to way trade costs and firm heterogeneous behavior is incorporated into the gravity equation.

Modeling Trade Costs – The Multilateral Trade Resistance
The multilateral trade resistance trade cost was discovered by Anderon and van Wincoop (2001, 2003) as the omitted variable in the gravity equation following the controversial study by McCallum (1995) who find that in 1988, US-Canadian border led to trade between Canadian provinces that are 22 (2200%) times more than trade between the US states and the Canadian provinces. This is termed the ‘border puzzle’ or a home bias. Motivated by the resulting border puzzle, Anderson and van Wincoop (2001, 2003) gave the gravity model a new theoretical underpinning by solving this border puzzle.

3Border puzzle is the tendency for a country to trade with and buy domestic products originating from domestic home country - a strong preference or bias for domestic goods. This phenomenon is termed border puzzle by McCallum (1995) and arises because countries borders are supposed to have a significant effect on the trade patterns between the countries especially if the countries are similar in terms of same language, culture and economic institutions as in the case of the US and Canada. However, the estimated patterns of trade indicates strong inter-provincial trade and less province-state (international trade) between Canada and the US, implying that national borders constraint trade among countries even though the countries are similar to one another (McCallum, 1995).
Extending Anderson 1979 theoretical derivation, they derive that economic distance between countries $i$ and $j$ is not only determined by a bilateral resistance term between these two countries as shown by previous derivations, but also by a weighted average of economic distance to all other trading partners of the given country. The latter is what they termed the multilateral resistance term and the theoretically appropriate average trade barrier. They posit that McCallum’s ratio of inter-provisional trade to province-state trade is very large because of omitted variables bias - the multilateral resistance term and the small size of the Canadian economy. They however got a smaller border effects than in McCallum (1995) after controlling for multilateral trade resistance in their gravity model.

Anderson and van Wincoop developed a monopolistic competition framework which is built on the Armington assumption in which each country specializes in the production of a single good, differentiated by region of origin and trade is therefore driven by consumers’ love for varieties such that all domestic and foreign goods are imported by the variety loving consumers. Optimizing consumers across countries have identical and homothetic utility function and this is captured by constant elasticity of substitution (CES) preference. Utility maximization subject to the budget constraint leads to a set of market clearing conditions for each good, a solution of which gives a micro-founded gravity equation specified as

$$V_{ij} = \frac{Y_i Y_j}{Y^w} \left( \frac{t_{ij}}{P_i P_j} \right)^{1-\sigma}$$  \hspace{1cm} (1)$$

Here, $V_{ij}$ is the volume of trade between countries $i$ and $j$, $Y_i$ and $Y_j$ are their respective income, $Y^w$ is global income, $t_{ij}$ denotes all bilateral trade resistance which are assumed to be symmetric such that $t_{ij} = t_{ji}$. These includes distance, binary variables indicating whether countries $i$ and $j$ have common border, colonial links, regional trade agreements, common currency arrangement etc. $\sigma$ is the elasticity of substitution between all goods which is assumed to be greater than one for there to be negative effect of $t_{ij}$ on trade, and $P_i$ and $P_j$ are respectively countries $i$ and $j$ consumer price indices. $P_i P_j$ is referred to as the multilateral trade resistance term by Anderson and van Wincoop since each of them is a function of all a country’s bilateral trade resistance and those of other countries. Thus, equation (1) relates bilateral trade flows to economic size and trade costs where the trade costs are decomposed into 3 components: $t_{ij}$- bilateral trade barriers between exporting country $i$ and importing countries $j$; $P_i$ - exporting country’s resistance to trade with all countries (inward multilateral resistance); and $P_j$ - importing country's resistance to trade with all countries (outward multilateral resistance). More specifically, the exporters and importers prices indices are defined as:

$$P_i = \left[ \sum_j (\delta_j p_j t_{ij})^{1-\sigma} \right]^{\gamma_{1(1-\sigma)}}$$ \hspace{1cm} and \hspace{1cm} $$P_j = \left[ \sum_i (\delta_i p_i t_{ij})^{1-\sigma} \right]^{\gamma_{1(1-\sigma)}}$$  \hspace{1cm} (2)$$

Where $\delta_j$ is the share of country $j$ in $i$’s consumption, $p_i$ and $p_j$ are the exporters and importers prices, and the summation sign comprises all of country $j$ prices including $p_i$ (in which in exceptional cases when there is no trade barrier, $t_{ij} = 1$. The corresponding explanation holds
for $P_j$. From equation (1), it is clear that any effect on the bilateral trade resistance term $t_{ij}$ in the numerator of equation 1) will also affect its denominator $P_i P_j$ too. This implies the impact of any particular trade friction depends on a ratio given as $t_{ij} / P_i P_j$. That is, trade impact is a function of all a country’s bilateral trade resistance relative to multilateral trade resistance (MTR).

To estimate the border effects, Anderson and van Wincoop (2003) derive a nonlinear estimation technique known as the Structurally Iterated Least Square Anderson and van Wincoop (2003) claim that the estimation procedure requires a customized nonlinear least square method because of the underlying nonlinearity of the endogenous multilateral (price) resistance term. Although their approach gives consistent and efficient estimates of the average border effects and the other gravity variables, one important disadvantage of the estimation technique is that it requires a customized nonlinear program to obtain the gravity model estimates (Fenstra, 2004). In addition, Baier and Bergstrand (2006) also noted that it is computationally cumbersome compared to ordinary least square (OLS) method, and it is subject to measurement error associated with internal distance indexes. Thus, other alternatives have been proposed and these are discussed below.

One common practice of proxying multilateral resistance terms (MRT) is using fixed effect for the importer and exporter in cross sessional data and using time varying importer and exporter fixed effect in panel data (Harrigan, 1996; Fenstra, 2004). This method is advantageous as it does not impose and strong structural assumption about the underlying model and its usage does not have anything to do with being consistent with theory (Head and Mayer, 2014). However, one major disadvantage of this approach is that the probability of running into computational problems when estimating panels with exceedingly large number of years or and industries as large number of dummies are generated as fixed effects. These large numbers of dummies can make estimation to be computational infeasible as a result of computational constraint imposed by a statistical package.

Head and Mayer (2000) and Eaton and Kortum (2002) proposed a solution which simplifies the computational problem by removing the importer term. This they did by normalizing bilateral trade flows by trade for a given year or industry so as to remove any traits of the importing country, but the exporter term still remains to be measured. Building on their approach, an alternative solution is Head and Reies Index in which Head and Reies (2001) proposed a simple index that cancels out the exporter terms.

Another alternative is the double demean approach which involves the double demeaning of the gravity dataset. There are two ways around this: demeaning in one dimension or demeaning in both dimensions. Demeaning in both directions involves one demeaning of the importer dimension and one demeaning of the exporter. This approach will only yield unbiased results if the trade matrix is completely full. The other approach is to demean in only one dimension with the usage of dummies in the other dimension. One advantage of this approach is that it does not require the dataset to be completely full, thus, one might still run into computational difficulties in large panel dataset.

One other alternative is the Bonus Vetus OLS (BV-OLS) approach proposed by Baier and Bergstrand (2009, 2010). This approach is a log linear first order Taylor series approximation of Anderson and van Wincoop (2003) system of price equations. Baier and Bergstrand developed two variant of approximating MRT: the GDP weighted version (Baier and
Bergstrand, 2009), and the simple averages version which is unweighted (Baier and Bergstrand, 2010). For each trade cost variable, the first order Taylor series is expanded and all the newly generated demeaned trade costs variables are then used in the regression. The major advantage of this approach is that it is computationally simple and it has been shown to produce estimates that are very close to Anderson and van Wincoop structurally iterated least square method (Baier and Bergstrand 2009, 2010; Egger and Nelson, 2011).

**Firm Heterogeneity and the Modeling of Zero**

Another major area of new contribution relates to methodological issue associated with the presence and behavior of heterogeneous firms operating in international markets which was spearheaded by Melitz (2003) and Bernard et al., (2003). Firm heterogeneity arises as not all existing firms in a country exports; only a minority of these firms participate in international market (Bernard et al, 2003). Furthermore, not all exporting firms export to all the countries in the rest of the world; they are only active in just a subset of countries and may choose not to sell specific products to specific markets (due to their inability to do so). The reason for this heterogeneity in firm behavior is because fixed costs are market specific and higher for international trade than for domestic markets. Thus, only the most productive firms are able to cover these costs, and firms’ inability to exports may be due to the high cost involved. Consequently, the bilateral trade flows matrix will not be full as many cells will have zero entries. This case is seen at the aggregated level of bilateral trade flows but more often in greater levels of product data disaggregation such as HS6 and HS8.

The prevalence of zero bilateral trade flows has important implication for modelling the gravity equation as the observed zeros might contain important information about the countries (such as why they are not trading) which should be exploited for efficient estimation (Helpman, Melitz and Rubinstein, 2008). Standard gravity equation usually neglect the issue of the prevalence of zero bilateral trade flows and predict theory consistent with only positive bilateral trade flows. However, Helpman, Melitz and Rubinstein (2008); Chaney, 2008; Melitz and Ottaviano, 2008; Chen and Novy 2011; etc) derived theoretical gravity equation which highlight the presences of zero trade records and gives theoretical interpretations for them. The ‘new new’ trade model of international trade with firm heterogeneity which was spear-headed by Metlitz (2003) is usually adopted in giving the gravity equation a theoretical basis.

Helpman et al. (2008) argue that “by disregarding countries that do not trade with each other, these studies give up important information contained in the data” (Helpman et al. 2008 p442), and that symmetric relationship imposed by the standard gravity model biases the estimates as it is inconsistent with the data. To correct for this bias, Helpman et al (2008) provides a theoretical gravity equation that explains/incorporates firm heterogeneity and positive asymmetric and was thus able to predict both positive and zero trade flows between country-pairs. Given firm level heterogeneity, they assume products are differentiated and firms are faced with both fixed costs and variable costs of exporting. Firms vary by productivity, such that only the more productive firms find it profitable to export; with the profitability of exports varying by destination. Since not all firms found it profitable, this gives rise to positive and zero trade flows across country-pairs. Furthermore, this difference in productivity gives rise to asymmetric positive trade flows in both directions for some pairs of countries. These positive asymmetric trade and zero bilateral trade flows then determine the extensive margin of trade flows (number of firms that exports). Moreover, given that firms in country ‘$j$’ are not productive enough to enable them profitably export to country $i$, this implies that will be zero trade flows from country $j$ to $i$ for some pairs of countries. This generates a model of firm
heterogeneity that predicts zero trade flow from countries $j$ to $i$ but positive exports from country $i$ to $j$ for some pairs of countries, and zero bilateral trade flows between countries in both direction.

In sum, more recent waves of contributions in the gravity equation is the development of an influx of theoretically consistent estimation techniques and those that would take care of the zero trade records. This necessitates a careful consideration of both theoretical underpinnings and the appropriate estimation techniques since it is now clear that naive approaches to estimation may lead to biased and frequently misinterpreted results.

3.0 EMPIRICAL LITERATURE
The gravity model is very popular in explaining trade relations. First, this is due to the rigorous theoretical foundation given to it with the advent of trade theories especially the new trade theory. Second and more important, this is due to its empirical success in the analysis of foreign trade relations. However, in spite of the popularity it enjoys, there are still questions about the proper specification of the model as well as the proper econometric estimation technique(s) that would give consistent estimates when zeros are frequent in the dependent variable. This section therefore shed light on the various estimation techniques used to tackle this problem. Particular attention is focused on the problems or and advantages of each techniques in the presence of zero trade flows in the data, the occurrence of which is prominent as a result of disaggregated dataset in which over 50% of trade values are found to be zero. The section ends by reviewing the techniques employed in empirical studies of standard-trade literature. A summary of the critics and debate about the best performing variable is thereafter provided in Table A in the appendix.

3.1 Estimation Issues in Gravity Modelling – The Debate
Early empirical studies rely on cross sectional data to estimate the gravity model, thus the economic framework for the model was cross-sectional analysis, (c.f. Anderson, 1979; Bergstrand, 1985, 1989; McCallum, 1995; and Deardorff, 1998; etcetera). For such cross-sectional analysis, the ordinary least square (OLS) estimation technique or pooled OLS technique is normally employed. However, the traditional cross-sectional approach is affected by severe misspecification problems and thus previous estimates are likely to be unreliable (Carrerè, 2006). This is because the traditional cross sectional gravity model usually include time invariant variables (e.g. distance, common language, historical and cultural dummies, border effects), but the model suffers from misspecification problems as it fail to account for country specific time invariant unobservable effects. This unobservable country specific time invariant determinants of trade are therefore captured by the error term. However, these unobserved variables are likely to be correlated with observed regressors and since OLS technique is usually used, this renders the least square estimator to be inconsistent, which makes one its classical assumptions invalid. In addition, OLS does not control for heterogeneity among the individual countries, which has the potential of resulting into estimation bias as the estimated parameters may vary depending on the countries considered. Therefore, estimating cross sectional formulation without the inclusion of these country specific unobservable effects gives a bias estimate of the intended effects on trade. This renders the conclusions on cross sectional based trade estimates problematic (ibid).

However, over the last decade, there has been an increasing use of panel data in gravity modeling and the use of panel econometric methods (c.f. Egger, 2000; Rose and van Wincoop,
The panel specification is much more adequate as the extra time series data points gives more degree of freedom, results in more accurate estimates. A unique advantage of panel data is that the panel framework allows the modeling of the evolution of variables through time and space which helps in controlling for omitted variables in form of unobserved heterogeneity which if not accounted for can cause omitted variable bias (Baltagi, 2008). In addition, with panel data, the time invariant unobserved trade effects can easily be modeled by including country specific effects such as time dummies, and thus avoiding the consistency issue mentioned above.

With the availability of panel data, the two common techniques used in fitting the data are the fixed effects and random effect estimation techniques, where the choice between the two hinges on their a priori assumptions. The fixed effect assumes that the unobserved heterogeneity is correlated with the error term. In contrast, the random effect assumes that the unobserved heterogeneity is strictly exogenous i.e. it does not impose any correlation between the unobserved heterogeneity (individual effects) and the regressors. Under the null hypothesis of zero correlation, the random effect model is efficient; both models are consistent, but the random model is more consistent. If however the null hypothesis is rejected, the fixed effect is consistent and the random effect is neither consistent nor efficient. There are however, some drawbacks in the fixed effect model in the sense that all time invariant explanatory variables (are deem to be perfectly collinear with the fixed effects) would be dropped from the model. Consequently, fixed effect model eliminates some important theoretically relevant variables from the gravity equation which are distance, common language, common borders, and the effects of these variables cannot be established. In addition, studies have also applied the OLS technique to panel data. However, pooled OLS can only give precise estimators and test statistics with more power if the relationship between the dependent variable and the regressors remain constant over time.

Early gravity model estimation techniques used to estimate the equation by ordinary least squares, where the model is usually log linearized as a common practice. The validity of a log-linear gravity model hinges on the homoscedastic assumption, as the error term and the log must be statistically independent of the regressors. However, in recent times, Santos Silva and Tenreyro, (2006) have identified flaws with this practice. Their position is that due to the nature of trade data that are intrinsic to heteroscedasticity and pervasive zero trade observations, log linearizing the gravity equation and then applying OLS is problematic.

First, problems arise in logarithmic transformation due to heteroscedasticity which is usually present in trade data. As noted by Santos Silva and Tenreyro (2006) in their influential paper, the common practice of log linearizing the gravity equation and then estimating using OLS is inappropriate because, expected values of the log linearized error term will depend on the covariates of the regression and hence OLS will be inconsistent even if all observations of the dependent variables are strictly positive. This is because a logarithmic transformation of the gravity model changes the properties of the error term. In other words, OLS will produce consistent estimates as long as the error term \( E[\ln(\varepsilon_{ij}) \mid x_{ij}] = 0 \), which is the homoscedasticity assumption. However, logarithmic transformation generates estimates of \( E[\ln(\varepsilon_{ij})] \) and not \( \ln E(\varepsilon_{ij}) \), but \( E[\ln(\varepsilon_{ij})] \neq \ln E(\varepsilon_{ij}) \), where \( \ln E(\varepsilon_{ij} \mid x_{ij}) = 0; E[\ln(\varepsilon_{ij} \mid x_{ij})] \neq 0 \).
which is the well-known Jensen’s inequality\(^4\).

Consequently, due to Jansen’s inequality, the error term \((\varepsilon_{ij})\) is not equal to the log of the error term \((\ln \varepsilon_{ij})\) as the error terms in the log linear specification of the gravity equation are not statistically independent of the regressors but are rather heteroskedastic, leading to inconsistent estimates of the elasticity coefficients. Given this Jansen’s inequality, Santos Silva and Tenreyro (2006) argue that the log linear transformation of the gravity model is intrinsic to heteroskedasticity and applying OLS results into biased and inefficient estimates. They argue that even though economists have long known about Jensen’s inequality and that the concavity of the logarithm function could create a download bias when employing OLS, this important drawback has however been overlooked in bilateral trade studies. They confirm their argument as they found evidence of the presence of heteroskedasticity and inconsistency in the normal log-linear representation of the gravity model; which renders the estimates of elasticity obtained from least squares estimation technique to be both inefficient and inconsistent.

Second and probably more problematic is the presence of zero trade flows in the trade matrix and the appropriate estimation technique. While the Newtonian gravity theory from which the gravity model of trade was derived allows for very small gravitational force but not zero force, however, in trade, there are frequent occurrences of zero\(^5\) valued bilateral trade flows and the practice of estimating the log linear gravity model in the presence of such zero trade flows implies both theoretical and methodological problems; especially in cases where the presence of such zero values are excessive. In estimating the gravity model, the gravity model is log linearized and estimated using these linear regression techniques. However, given the predominance of zero trade records in the trade matrix, particularly at the more disaggregated level, where zero records can account for even more than 50% of trade flows, the logarithm transformation of the dependent variable is therefore problematic at least in cases in which the zeros contain relevant information. This is so because the logarithm of zero is indeterminate or not feasible.

However, the common practice in the literature employed to deal with the problem of zero records in the data are the truncation and censoring methods and thereafter applying linear estimation techniques. In the case of truncation method, the zero valued trade flows are dropped completely from the trade matrix, whereas, the censoring method involves substituting the zeros by a small positive arbitrary value. These methods are however arbitrary and are without any strong theoretical or empirical justification and can distort the results significantly, leading to inconsistent estimates (c.f. Flowerdew and Aitkin, 1982; Eichengreen and Irwin, 1998; Linders and Groot, 2006; Burger et al., 2009; Gomez-Herrera, 2013). In addition, Flowerdew and Aitkin\(^6\) (1982) show that the results are sensitive to (small) differences in the practice of estimating the log linear gravity model in the presence of such zero trade flows implies both theoretical and methodological problems; especially in cases where the presence of such zero values are excessive. In estimating the gravity model, the gravity model is log linearized and estimated using these linear regression techniques. However, given the predominance of zero trade records in the trade matrix, particularly at the more disaggregated level, where zero records can account for even more than 50% of trade flows, the logarithm transformation of the dependent variable is therefore problematic at least in cases in which the zeros contain relevant information. This is so because the logarithm of zero is indeterminate or not feasible.

\(^4\) Jensen’s inequality is named after Johan Jensen, the Danish mathematician who in 1906 discovered that: the secant line of all convex function (i.e., the means of the convex function) lies above graph of the function (i.e., the convex function of the weighted means) at every point. The reverse is true for a concave function. His inequality has appeared in many contexts and an example in this case is the arithmetic mean inequality. Thus, in simplified terms, his inequality states that the convex (or concave) transformation of a mean is less or equal to (greater or equal to) to the mean after a convex (concave) transformation. Thereafter, Economists have adopted his intuition to show that the logarithm transformation of an equation generates the expected value (mean) of the logarithmic transformation of the dependent variable \(E(\ln Y_i)\) and not the logarithm of the mean of the dependent variable \(\ln E(Y_i)\); and \(E(\ln Y_i) \neq \ln E(Y_i)\).

\(^5\)Frankel (1997) argued that these zero values arises as a result of lack of trade between countries, or from rounding errors when trade between countries does not reach a minimum value or can arise when they are rounded-down as zero, it can also results from measurement errors where observations are mistakenly recorded as zeros.

\(^6\)They vary the substituted constant between 0.01 and 1 and found that the regression coefficient decreases with the size of the chosen constant.
on the zero trade levels is left out of the model and this can generate biased results if the zero trade flows are not randomly distributed; while Heckman (1979) and Helpman et. al., (2008) posit that omitting these zero trade observations can result into sample selection bias. The loss of information is said to reduce efficiency and omission of data produces biased estimates (Xiong and Beghin, 2011; Gomez-Herrera, 2012). In addition, Xiong and Beghin (2011) noted that deleting the zero trade observations prevents the possibility of exploring the extensive margin of trade – the creation of new bilateral trade relations, which implies that estimates are conditioned on trade that already took place – the intensive margin of trade. They concur that ignoring zeros limits the economic interpretation of the model as nothing can be said on the implication for new trade.

Likewise, Linder and Groot kicked against truncating and censoring and argued that zero trade observations may provide important information for understanding the bilateral trade patterns and therefore should not be eliminated a-priori. Disregarding the zero trade flows can bias the results if they do not randomly occur. This is because zero trade flows provide information about the probability to engage in bilateral trade. Thus, if distance, low levels of GDP, the lack of historical or cultural links, etcetera makes trade to be non-profitable, thereby reducing trade or bringing about no trade, then eliminating zero flows from the analysis is tantamount to sample selection bias and applying OLS will lead to underestimating of the gravity equation coefficients (downward bias).

Therefore, in recent years, attention has been on the appropriateness of the estimation technique especially those relating to the problems of zero trade costs and logarithmic transformation of the gravity equation, and the constant emphasis on the inappropriateness of linear estimators in taking care of these two problems. Consequently, more appropriate estimation techniques are being increasingly employed to deal with these two issues in the context of gravity trade literature. The Tobit and Probit models, truncated regression, Poisson and modified Poisson models, Nonlinear Least Square (NLS), Feasible Generalized Least Square (FGLS) and the Helpman, Melitz and Rubinstein (2008) approach have all been used to deal with the problem associated with log normal formulation and the excessive zero valued trade flows.

Early studies have relied on the Tobit model to deal with the zero trade problems. For instance, the Tobit model has been employed by Rose (2004) and Andersen and Marcoiller (2002) to deal with the problem of zero valued trade flows that resulted either because the actual trade flows are not observable or due to measurement errors from rounding. The Tobit estimator is applied to fit the data when outcome/data are only observable over some range. It is applied in cases of measurement errors (e.g rounding up) or when actual outcomes cannot seem to reflect the desired outcomes. The Tobit censoring method involves rounding (censoring) part of the observation to zero or rounding up the zero trade flows below some positive value.

Nevertheless, (Linder and Groot, 2006) have debated on the appropriateness of using the Tobit model to fit zero valued trade flows in a gravity model will depend on whether the desired trade could be negative or whether rounding up of trade flows is important. Their argument is that in the gravity model, the zero trade flows cannot be censored at zero as the desired trade cannot be negative in the gravity equation; this can only occur if the GDP of one or country pair is equal to zero which is unlikely in real life. They further argue that censoring at a positive value is not also appropriate. The intuition is that the UN COMTRADE database reports trade values, even for very small values (up to $1), indicating that rounding to zeros is not an important cause of zero observation as most zeros are caused by economic
reasons such as lack of profitability. This implies that zero trade flows is likely to occur from binary decision making about the profitability of engaging in trade, and not from rounding up (censoring), thus the model might not be appropriate for taking care of zero trade flows. In addition, Frankel (1977) and Rose (2000) noted that the Tobit estimator involves an artificial censoring of positive albeit small trade values, however, the trade flow is subject to measurement errors, and they may have a high influence on the regression results.

Furthermore, Martin and Pham (2008) show that although both truncated OLS and censored Tobit model lead to bias results but the censored method generally produced much worse results in comparison to the truncated method, and suggested that Eaton and Tamura (1994) threshold Tobit model gives the lowest bias and outperform all other estimators in a simulation exercise. However, in contrast, in a simulation exercise, Santos Silva and Tenreyro (2011) found the Tobit model of Eaton and Tamura (1994) to have large bias, which increases with sample size, which also confirm its inconsistency as an estimator. Nevertheless, Head and Mayer (2013) recently propose the use of an alternative Tobit procedure that avoids the problem of selecting a value for small trade flows without any criteria. In particular, based on Eaton and Kortum (2001) they propose to replace the zeros by the minimum level of trade for a given $i$ from all destination $j$, which we denote as $y_{ij}$. To estimate the model, all the observed zeros in $y_{ij}$ (the dependent variable) are replaced with $y_{ij}$ and the new bottom-coded $\ln y_{ij}$ is the dependent variable in a Tobit model that allows for a user-specified lower limit of $\ln y_{ij}$. The EK Tobit, as this method is referred to by them, has two advantages. First, it does not require any exclusion restrictions and second, it is easily estimated using Stata’s intreg command.

Attention has also been shifted to the use of the Poisson and the modified Poisson specifications of the gravity model. Santos Silva and Tenreyro (2006; 2011) used the Poisson Psuedo Maximum Likelihood (PPML) method to deal with the zero valued trade flow and the logarithm transformation. According to them, in the presence of zero valued observations and also due to the logarithm transformation of the gravity equation, OLS (both truncated and censored OLS) are inconsistent and have very large bias which do not vanish as the sample size increase which confirm that they are inconsistent (Santos Silva and Tenreyro 2011). However, the PPML estimates the gravity equation in levels instead of taking its logarithms and this is said to avoid the problem posed by using OLS under logarithm transformation. According to them, this model is appropriate: first, the Poisson model takes account of observed heterogeneity. Second, the fixed effects PPML estimation technique gives a natural way to deal with zero valued trade flows because of its multiplicative form. Third, the method also avoids the under-prediction of large trade volumes and flows by generating estimates of trade flows and not the log of the trade flows. In their 2006 influential paper, they find the PPML estimator, which need not be does not need to be log-linearized, to be the best performing estimator that naturally deal with zero trade flows, consistent and gives the lowest bias among the other estimators. They therefore suggest it as the new workhorse for the estimation of the typical constant elasticity models, such as the gravity model.

However, their influential paper has however generated some controversies in the literature (c.f. Martinez-Zarzoso et al., 2007; Martin and Pham 2008; Burger et al., 2009; etcetera). For instance, Burger et al. (2009) identified some important limitations of the PPML model. They noted that the model is vulnerable to the problem of overdispersion in the dependent variable
and excess zero flows. They posit that the model only takes account of observed heterogeneity and not unobserved ones and this is an important limitation of the PPML model. While an important condition of the PPML is the assumption of equi-dispersion (the conditional variance is equal to the conditional mean) in the dependent variable, however, due to the presence of unobserved heterogeneity which are not accounted for in the model, there is an over-dispersion in the trade flows (dependent variable). The over-dispersion is said to generate consistent but inefficient estimates of trade flow (Burger, et al. 2009; Turkson, 2010).

Contrary to Burger et al. (2009) who noted that the model is vulnerable to the problem of over-dispersion in the dependent variable and excess zero flows, which generate consistent but inefficient trade estimates, Santos Sliver and Tenreyro (2011), find that PPML is consistent and generally well-behaved even in the presence of overdispersion in the dependent variable (i.e. when the conditional variance is not equal to the conditional mean) and that the predominance of large proportion of zeros does not affect its performance. In addition, Soren and Bruegger (2012) find that the PPML performs quite well under over-dispersion, and show that the PPML is well-behaved under bimodal distributed trade data. More recently Head and Mayer (2014) claim that a Multinomial Psuedo Maximum Likelihood (MPML) approach perform better in simulations than the PPML. Assuming that it is reasonable to assume that market shares, \(Y_{ij}/Y_j\), are an appropriate dependent variable for the gravity model, then, the Multinomial PML is the solution advanced by Eaton et al. (2012) for the case of finite numbers of firms. The Multinomial PML can be estimated by applying the ‘poisson’ command to the market share variable \(Y_{ij}/Y_j\), along with exporter and importers fixed effects (Head and Mayer, 2014).

Nonetheless, attempts have also been made to correct for the over-dispersion in the dependent variable and the vulnerability of the PPML to excessive zero flows using other estimation techniques apart from the PPML. These are the Negative Binomial Pseudo Maximum Likelihood (NBPML) and the Zero-inflated models which are Zero-inflated Pseudo Maximum Likelihood technique (ZIPML) and Zero-inflated Binomial Pseudo Maximum Likelihood technique (NIBPML) (Burger et al. 2009). They posit that the NBPML corrects for the overdispersion the estimator incorporates unobserved heterogeneity into the conditional mean and thus, takes care of unobserved heterogeneity. However, an important drawback of the NBPML and PPML relates to the excessive number of zero in the observation which means that the number of zero flows is greater than what the models predicts; where excessive zeros is said to be derived from the ‘non-Poissoness’ of the model (Johnson and Kotz, 1969). Thus, Burger et al. (2009) posit that even though the Poisson model and the NBPML model can technically handle with zero flows, both models are however not well suited to handle cases where the number of observed zero valued trade flows is greater than the number of zeros predicted by the model.

They posit that the zero inflated models (ZIPPML and ZINBPML) perform better as correct for excess zeros and overdispersion in the dependent variable. They also noted that zero-inflated models has an added advantage as they theoretically well suited in modeling the origin of zero counts because the models account for two different types of zero trade flows, which are countries that have never trade (the non-poisson group), implying a data that strictly have zero counts; and countries that presently do not trade but potentially could, i.e. those that have a non-zero probability of having non-zero counts (the poisson group). Thus, these models make

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7Burger et al. (2009) identified that one important cause of non-Poissoness is when some zeros in the observation are produced by a different process compared to the remaining observations (including some other zeros).

8The zero inflated models consider two different groups within the population: the poisson group and the non-poisson group. The non-poisson group are countries which have strict zero probability of trading but do not trade at all. The non-poisson zeros might be caused by lack of trade due to bans or other trade embargoes or simply the lack of resources. The poisson group consist of those countries with non-zero probability to
allowances for the possibility to separate the probability to trade from trade volume as it provides additional information on the causes of the probability of the different kinds of zero valued flows. Given these, Turkson (2011) argued that the choice of the model to use will depend on whether the sample has excessive zero trade flow or not. However, Burger et al. (2009) posit that the Poisson model and the NBPM model are not well suited to handle cases where the number of observed zero valued trade flows is greater than the number of zeros predicted by the model.

Head and Mayer (2014) also finds that the PPML and Gamma PML remain consistent even under over-disperion and advised that finding that the variance exceeds the mean does not justify the usage of the NBPM. This is because estimates obtained by NBPM method vary according to the dependent variable’s units of measurement (Boulhol and Bosquet, 2012). For instance, they show that measuring trade in thousands of dollars instead of billions of dollars leads to large changes in the magnitude of the estimates and also reverses the signs obtained on some of the explanatory variables.

Contrary to Burger et al. (2009), Staub and Winkelmann (2012) also find that the PPML is consistent even when zeros are excessive. They also show that both ZIPPML and ZINBPML are inconsistent if the underlying assumptions of the distribution of model are violated, i.e. if the models are misspecified. They instead recommend the use of zero inflated Poisson Quasi Likelihood (PQL) estimator which was shown to be consistent in the presence of excessive zeros and it is unaffected by unobserved heterogeneity and found to robust to mis-specification as it consistently estimate the regression coefficients irrespective of the true distribution of the counts while ZIPPML and ZINBPPML demonstrate considerable bias in medium sample. They also noted that the PQL can be less efficient compared to zero inflated estimators if the zero inflated model is correctly specified.

Similar to Burger et al., (2009), Martinez-Zarzoso (2013) also find out that the PPML estimator proposed by Santos Silva and Tenreyro (2006) is not always the best estimator as its estimates are outperformed by both the OLS and FGLS estimates in out of sample forecast. In addition, the PPML assumption regarding the pattern of heteroscedasticity is rejected by the data in most cases. However Santos Silva and Tenreyro (2008) responded by justifying the use of PPML as the best estimator in the context of gravity model, but also acknowledged that PPML estimator can be outperformed by other estimators in some cases.

Furthermore, Martinez-Zarzoso (2013) also finds the PPML to be outperformed by both the OLS and FGLS estimates in out of sample forecast and deduced that it is not always the best estimator. She finds that PPML assumption regarding the pattern of heteroscedasticity is rejected by the data in most cases. She opined that even in the presence of unknown form of heteroscedasticity, FGLS can still be applied as FGLS is an efficient estimator within the class of least squared estimator, but the variance of the disturbances should then be re-estimated to correct for heteroscedasticity errors. They pointed out that FGLS is well suited to estimating parameters in the presence of heteroscedasticity, so, the comparison of the best performing estimator should be between FGLS and the class of generalized linear models (GLM) such as the Non-linear least square (NLS), Gamma Poisson Maximum Likelihood (GPML), and PPML. However Santos Silva and Tenreyro (2008) in their response, provided justification for
the PPML estimator in the context of log linear gravity model, and acknowledged the fact that in some specific situations, the PPML estimator can be outperformed by other estimators.

Martinez-Zarzoso (2013) compares the performance of different estimators via a Monte Carlo simulation exercise and find that although PPML to be less affected by heteroscedasticity compared to FGLS, NLS and GPML, nonetheless, its performance is found to be similar both in terms of bias and standard errors to the performance of the FGLS estimator, particularly for small sample size; with the lowest bias and standard errors found in the GPML in the simulations which has non-zero values in the dependent variable. Further empirical analysis using three different real datasets\(^{11}\) reveal that the choice of the performance of the model is sensitive to the sample size; for small sample size, FGLS could be perfect way to deal with the heteroscedasticity problem, while the PPML will be appropriate when the sample size is large and there is measurement error in the dependent variable. However, for large sample size, PPML bias is found to decrease in large sample size while FGLS bias is found to remain almost constant. In addition, the PPML standard error falls considerably but it still remains twice the FGLS standard errors. Conclusively, Martinez-Zarzoso (2013) find that the choice of the best estimator is dependent on the specific dataset, and there is no generally best estimator for these three datasets; thus the appropriate estimator for any application is data specific which could be determined using a number of model selection tests.

Martin and Pham (2008) has also challenge Santos Sliver and Tenreyro (2006) findings and posit that although the PPML estimator is less subject to bias resulting from heteroscedasticity problem, however, it is not robust to the joint problems of zero trade flows and heteroscedasticity. Based on this, they conclude that the estimator could be appropriate for other multiplicative models\(^{12}\) which have relatively few zero observations. They proposed that the Eaton and Tamura (1994) threshold Tobit model perform better than the PPML and other estimators considered as it recorded the smallest bias in a simulation exercise.

The Monte Carlo simulation done by Santos Silva and Tenreyro (2006), has also generated some debates. Although the authors find that the PPML is able to deal with zero trade flows, interestingly, their simulation done in order to determine the best performing model were without any zeros, except where the dependent variable was contaminated with measurement errors. This has made some studies to question the performance of the PPML in cases where there are excessive zeros in the dependent variable (c.f. Martinez et. al., 2007; Martinez-Zarzoso, 2013; Martin and Pham, 2008). Martin and Pham (2008) therefore used a data generation process\(^{13}\) different from that used by Santos Sliver and Tenreyro (2006), which include a high proportion of zero values and show PPML to be highly vulnerable to bias in the presence of high percentage of zero values in the dependent variable. Similar result has been found by Martinez-Zarzoso (2013). However these results have been challenged by Santos Silva and Tenreyro (2011).

In response to these studies, Santos Silva and Tenreyro (2011), argued that both of the simulations done by Martinez-Zarzoso et al., (2007); Martin and Pham (2008) and Martinez-Zarzoso (2013) reveal no information on the performance of the PPML model of constant

\(^{11}\)The 3 dataset consist of about 13%, 15%, 25% of zero trade values.

\(^{12}\)For instance the Cobb-Douglas production function, the consumer-demand systems and the Stochastic impact by regression on population, affluence and technology, which is a popular model used in environmental economics.

\(^{13}\)Santos Silva and Tenreyro (2006) used a data generating process that generates no zero values but only positive values. Martin and Pham adopted similar design to Santos Silva and Tenreyro (2006) Monte Carlo simulation but however modified it by including a threshold trade level that must be exceeded before positive trade levels are observed. Where the chosen threshold generates zero trade frequencies, which is similar to those observed in studies using aggregate trade flows.
elasticity model as the data used in their simulation exercises are not generated by a constant elasticity model. Santos Silva and Tenreyro (2011), however, further investigate the performance of the PPML estimator when the dependent variable has large percentage of zeros and when the data generating process is given by a constant elasticity model (both of which are typical in trade data used in gravity modeling). Similar to their 2006 findings, they also find the PPML estimator to be consistent and generally well-behaved in the presence of high proportion of zeros, and to be more robust to departures from the heteroscedasticity assumption (overdispersion); as its performance is not affected even with the overdispersion in the dependent variable and the presence of excessive zero values.

It is worth to notice however that the simulation results presented by Head and Mayer (2013) support the findings of Martinez-Zarzoso (2013) and indicate that the selection of the most appropriate estimation has to be made in accordance with the process generating the error term. They propose that other methods should be used along with the PPML “rather than selecting the Poisson PML as the single ‘workhorse’ estimator of the gravity equation” (Head and Mayer, 2013, p44). According to their simulations, under a Poisson-like error (the Poisson assumption of variance proportional to the mean), a Multinomial PML is preferred, whereas under the log-normal error (the normality assumption), the EK Tobit is the preferred estimator.

Among the class of the generalized linear models, the Gamma Pseudo Maximum Likelihood (GPML) technique has also been used in taking care of the zero trade values and associated problem of the logarithm transformation (c.f. Manny and Mullay, 2001). Similar to the log linear model, the GMPL is said to be a more efficient estimator under the assumption that the conditional variance is a function of higher powers of the conditional mean, as it gives more weights to the conditional mean. Santos and Silva and Tenreyro (2011) found that the GPML is consistent and well behaved under Monte Carlo simulation in the presence of excessive zero values whose data generation process follows the constant elasticity model. However, it is found to have a larger bias than the PPML suggesting that the GPML the best performing estimator (c.f. Santos Silver and Tenreyro, 2011). In addition, Martinez- Zarzoso (2013) noted that the GPML may also suffer from substantial loss of precision particularly if the variance function is mis-specified or if the log-scale residuals have high kurtosis.

Another class of the generalized linear model is the nonlinear least square (NLS) technique, which has also been used in the trade literature (c.f. Frankel and Wei, 1993) or used in comparison with other non-linear estimators (e.g. Santos Silva and Tenreyro 2006; Gomez-Herrera, 2012; Martinez-Zarzoso, 2013). Santos Silva and Tenreyro (2006) however show that although both GPML and NLS can be take care of these two problems, the PPML is still the preferred estimator as the NLS technique assign more weight to noisier observations, which reduces the efficiency of the estimator. This is because while PPML gives the same weights to all observations, and assumes that the conditional variance is proportional to the conditional mean, however, GPLM and NLS give more weights to observations with large mean. This is because the curvature of the conditional mean is more pronounced here, which are also generally observations with large variance, implying nosier observations. In addition, ibid noted that the estimator can also be very inefficient because it generally ignores the heteroscedasticity in the data.

Another approach that is not considered in the simulation comparison by Head and Mayer (2014) is Heckman (1979) sample selection model\textsuperscript{14} and it has also been frequently used in the

\textsuperscript{14} Heckman model is also referred to as sample selection or Tobit II model. The model makes a selection of trading and non-trading country
literature. Noting that the standard practice of excluding zero bilateral trade observations can potentially give rise to sample selection bias, especially if the eliminated zeros are not randomly done, and estimating non-randomly selected sample is a specification error and can potentially bias the results. Heckman, therefore, developed a model that corrects for this sample selection bias which is a two-step statistical approach in which the model is estimated under the normality assumption. The first step of the Heckman model involves estimating an equation (Probit regression) for the probability of exporting at the firm level based on the decisions of the firms and then using it in estimating the volume of trade. Heckman (1979) correction model allows one to correct for selection bias in non-randomly selected samples and has also been frequently used in the gravity model trade literature to correct for problems relation to zero valued trade flows (c.f. Linder and Groot, 2006; Munasib and Roy, 2011). Linder and Groot, (2006) noted that sample selection model uses the information provided by the zero valued trade observations; thus, providing information on the underlying decision process regarding the zero trade flows, while arbitrary truncating and censoring are ad-hoc crude methods and they do not give accurate results compared to the sample selection model. They argued that unlike truncated OLS, without sound theoretical background, the samples election model is theoretically sound and offers an econometrically elegant solution to estimate gravity equation that includes zero trade flows.

However, in a methodological paper, Helpman, Melitz and Rubinstein (2008) (thereafter HMR), noted that the estimation of bilateral trade flows using the gravity equation is not only subjected to sample selection bias (if the non-zero exports do not occur randomly), but that estimates may also be vulnerable to omitted variable bias if the number of exporting firms within an industry (extensive margin of trade) is not accounted for. The idea is that due to trade costs, firms differ in productivity (firm heterogeneity) and only firms with productivity level beyond a threshold end up exporting.

HMR therefore extended Heckman (1979) procedure by controlling for both sample selection bias and firm heterogeneity bias and approached the zero issue by also developing a two-steps estimation procedure which exploits the non-random presence of zero trade flows in the aggregate bilateral trade data. The aim of the HMR two-step procedure is to correct both the sample selection bias resulting from eliminating zero trade flows when estimating the logarithmic form of the gravity equation and the bias caused by unobserved firm heterogeneity which result from omitted variable, which also measures the effect of the number of exporting firms (extensive margin). The first step involves estimating an equation (Probit regression) for the probability of exporting at the firm level based on the decisions of the firms and then using it in estimating the effects on the extensive margin of trade (the decision to export from country $i$ to $j$). The second step is a gravity equation estimated in its logarithm form and involves using the predicted probabilities obtained in the first step to estimate the effects on the intensive margin of trade (the number of exporting firms from country $i$ to $j$).

Helpman et al., (2008) posit that the excluded variable must not be correlated with the error term of the second stage equation but must be correlated with trade volume (the dependent variable). In addition, the excluded variable must be influence trade through fixed trade cost and not through variable trade cost because the latter impact on the extent of trade volume, and as such, is not uncorrelated with the second stage equation. However, Burger et al., (2009) noted that one important drawback of the Heckman (1979) and Helpman et al. (2008) models is that it is difficult to satisfy the exclusion restriction as the instrumental variable is most often
difficult to find. Examples of exclusion variables used in the literature are common religion and common language variables (Helpman et al., 2008); governance indicators of regulatory quality (Shepotylo, 2009); historical frequency of positive trade between country pairs (Linder and de Groot, 2006; Haq et al., 2010 and Bouet et al., 2008). However, both Linder and de Groot (2006) and Haq et al., (2010) include the excluded variable in both equations and impose the normality of the error term in the two equations – an identification condition implying a zero covariance between both equations.

Notwithstanding the aforementioned advantages of the HMR model, some limitations have been identified regarding its application. Both the Heckman (1979) and the HMR trade flow equations are usually transformed to the logarithmic form before estimated and might cause biased coefficient (Haworth and Vincent, 1979; Santos Silva and Tenreyro. 2006). In addition, Santos Silva and Tenreyro (2009) and Flam and Nordström (2011) also show that HMR model does not control for heteroscedasticity which is usually pervasive in most trade data, but this can be done using available procedures. For instance, Santos Silva and Tenreyro (2009) show that the assumption of homoscedasticity error term for all country pairs by the HMR’s results in serious misspecifications as HMR does not control for heteroscedasticity, consequently casting doubts on the validity of inferences drawn from the model. They also pointed out that in contrast to models which can be made robust to the presence of heteroscedasticity, the consistency of the HMR model is only possible under the ‘unrealistic’ homoscedasticity assumption, which they identified as the most important drawback of the model as it is too strong to make it applicable or practicable to trade data in which heteroscedasticity is pervasive. They therefore posit that the presence of heteroscedasticity in the data preclude the estimation of any model that purports to identify the effects of the covariates in the intensive and extensive margins, at least with the current econometric technology (Santos Silva and Tenreyro, 2009).

In sum, as noted in the review, each technique has its pros and cons and the ‘workhorse’ or best performing model for the estimation of the gravity equation still remains unclear as the consensus on a commonly accepted solution has not yet been reached. Therefore, given the pros and cons of each estimator, the determination of the best performing estimator (given our set of data application) remains an empirical issue.

3.2. Related Literature

With the increasing role of food safety standards in as a non-tariff trade barrier, several studies have empirically investigated the impact of these standards and or regulations on international trade, and more specifically on agricultural-food trade using both aggregated and disaggregated data. In most cases, gravity models are typically used in evaluating the empirical role that standards exert on trade flows. As previously identified, the estimated gravity model within the standard-trade literature might show scope for improvement especially in two areas: the econometric estimation technique and the proper specification of the model, especially given the peculiarities of the countries studied.

Early studies on food standard-trade have estimated the standard log linear gravity model using OLS both with the occurrence and non-occurrence of zero trade flows. For instance, study by Otsuki et al. (2001a) (which is perhaps the most cited literature) which investigate the impact of a proposed 1998 EU stricter aflatoxin standard on African exports of groundnut products, have applied OLS estimation techniques and took care of zero trade flows data by adding one

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15The Helpman et al., (2008) model hinges heavily on both the homoscedasticity and normality assumptions to be consistent.
to them. The study found food safety standards to have a statistically significant negative impact. A significant negative trade impact was also found by Otsuki et al. (2001b) in their investigation of aflatoxin standards on world trade using OLS. This method is nonetheless said to suffer from deliberate measurement error (Winchester, et al., 2012). However, since the publication of these papers, there have been two main developments in the gravity modelling. The first is Anderson and van Wincoop (2003) theoretical paper which show that trade costs should be measured as multilateral trade costs in addition to the usual bilateral trade cost employed. The second and most important development is the issue of zero trade records and the proper estimation technique to tackle it and the problem posed by the logarithmic transformation of the gravity model (Santos Sliver and Tenreyro, 2006).

Various estimation techniques that incorporate zero trade record in the empirical analysis were therefore adopted. For instance, studies by Frahan and Vancautereen (2006), Fontagne, Mimouni and Pasterels (2006); went beyond the OLS technique and instead used the censored Tobit model with random effects in order to deal with the zero trade flows. The former find a positive trade effects of standard on agricultural food products while the later study found negative trade effects in agricultural products and positive trade effects in manufacturing and processed agricultural sectors. However, the Heckman model were employed by Chevassus-Lozza et al. (2008), Jayasinghe et al. (2009), Vigani et al. (2010), Disdier and Marette (2010) to tackle the selection bias resulting from eliminating the non-random occurring zero trade flows from the trade matrix. These studies find negative impact of standards on trade except for Vigani et al. (2010) which find a mixed effect. Other studies have taken advantages of the availability of panel data and employed either the random or fixed effect model or both (c.f. Disdier et al., 2008; Jonguanish, 2009; Melo et al., 2012; etc) where the model is log linearized, with the zero trade flows truncated or deliberately deleted.

Nonetheless, following Santos Sliver and Tenreyro (2006), studies by Disdier and Fontagne, (2010), Wilson and Bray (2010), Gerras et al. (2011), Shepherd and Wilson (2013), have applied the PPML to investigate the impact of standards on trade flows and to deal specifically with the presence of zero trade flows observations. While the first two studies found a negative impact on trade using PPML, the last two however found mixed effects depending on the standards considered.

There are also a few studies which compare different estimation techniques in the presence of zero trade flows (c.f. Drogue and DeMaria, 2010; Xiong and Beghin, 2011) to determine the best performing estimator. However, these studies compare only few of the estimators and chose the best performing model within these limited models considered. Drogue and DeMaria (2011) considered between 3 estimation methods (OLS, PPML and ZINB) but relied on the ZINB model as providing the best fit and parsimonious specification among the models. Estimating their gravity equation with country-pairs and time fixed effects, they find negative impact of dissimilarity in standards on trade and vice versa. Similarly, included country-pairs and time fixed effects, Xiong and Beghin (2011) compared between 5 estimation techniques to investigate the impact of standards on the extensive and intensive margins of trade across 3 groundnuts products. Based on some diagnostic tests, their preferred models are ZINB and Heckman models in order of preference. They find similar results for both the Helpman and ZINB estimation techniques. For these two models they find no significant impact of standards on shelled groundnut and groundnut oil exports but positive impact on edible groundnuts exports. Similarly, Drogue and Demaria (2010) also obtained similar when different estimators (Hurdle, Heckman, and ZIP) were considered, indicating that the results are insensitive to the estimation used.
An important limitation of both studies lie in the invariability of their measure of standards, which makes the identification of the impact difficult. Drogue and DeMaria (2010) measure of standard is the dis(similarity) between the maximum residual limits (MRL) of pesticides in force in country $i$ and $j$ in force between 2000 and 2009 and it is time invariant as they are reported to be the same over this period. Xiong and Beghin (2011), however used MRL on aflatoxin B1 imposed by each importer in each year. This measure is not bilateral in nature as it is the same measure faced by all trading partners without regards to the origin ($i$). However, Head and Mayer (2014) noted that variables that affect imports (exports) without regards to the country of origin can no longer be identified in a gravity equation setting estimated with exporter and importer fixed effects.

However, our approach of measuring standards will be devour of this identified limitation as our measurement is constructed to ensure variability over time and between country $i$ and $j$, as would be shown in the proceeding session. In addition, our study departs from previous studies which only consider a few estimation techniques, our analysis is wider in scope and more encompassing as we will include a wide coverage of estimation techniques and not a subset of techniques as is common practice in the literature, in order to objectively identify the best performing technique. As zero trade usually occur among small or poor countries (Martinez-Zarzoso, 2013), therefore, our focus will be on African countries, majority of which are predominantly poor and the small country assumption is also applicable to them, thus making our dataset to be more appropriate in the test of the most appropriate estimation technique(s).

4.0. METHODOLOGY
In line with the various estimation techniques previously discussed, the volume of bilateral trade flow between countries $i$ and $j$ in year $t$ can be represented in either the multiplicative or logarithmic forms. For the sake of comparison and completeness, we adopt the Anderson and van Wincoop (2003) equation as our preferred theoretical model in which the MRT was first developed. We however used Baier and Bergstrand (2010) approach to model the multilateral trade resistance which if omitted can bias the estimated gravity coefficients (c.f. Baldwin and Taglioni, 2006; Fenstra 2006, etc). Baier and Bergstrand (2009, 2010) first order log linear Taylor series approximation of Anderson and van Wincoop’s nonlinear systems of price equation which also give rise to theoretically motivated MRT.

4.1 Model Specification and Estimation Techniques
We begin with the following multiplicative gravity equation:

$$y_{ijt} = \beta_0 GDP_i^{\beta_1} GDP_j^{\beta_2} S_{ij}^{\beta_3} Dist_{ij}^{\beta_4} Lang_{ij}^{\beta_5} Col_{ij}^{\beta_6} Llock_{ij}^{\beta_7} RTA_{ij}^{\beta_8} \varepsilon_{ijt}$$

Taking the natural logarithm of both sides of equation (1), yields the transformed log linear gravity model:

$$\ln y_{ijt} = \beta_0 + \beta_1 \ln GDP_i + \beta_2 \ln GDP_j + \beta_3 S_{ij} + \beta_4 \ln Dist_{ij} + \beta_5 Lang_{ij}$$
$$+ \beta_6 Col_{ij} + \beta_7 \ln Llock_{ij} + \beta_8 RTA_{ij} + \varepsilon_{ijt}$$

Where $\ln$ denotes the natural logarithms of the variables; $i$ and $j$ are exporter and importer

---

16 As a solution, they proposed that the trade impact can be identified by dropping one or more of the country dummies, or by creating new dyadic bilateral variables which have straightforward interpretation. See Head and Mayer (2013) for other factors that cannot also be identified, and possible solutions to this.
subscripts respectively while \( t \) denotes time period; \( y_{ijt} \) is exports value from country \( i \) to country \( j \) in time \( t \) in current US $; \( GDP_{it} \) and \( GDP_{jt} \) are respectively is the gross domestic products of countries \( i \) and \( j \) in time \( t \) in current PPP US $. \( S_j \) denotes European Union food safety standards on fish products, which can be otherwise called a non-tariff barrier and it is the main variable of interest in this study. \( Dist_{ij} \) is the geographical distance between the major cities of countries \( i \) and \( j \). \( Border_{ij} \), \( Lang_{ij} \), \( Col_{ij} \), \( Llock_{ij} \), \( RTA_{ij} \) respectively are dummies that take the value of 1 when countries \( i \) and \( j \) share a border, speak the same official language; when countries \( i \) had been colonized by country \( j \) in the past; when at least one of the country-pair is a landlocked countries; when trading countries belong to similar trade agreement; zero otherwise and \( \varepsilon_{ijt} \) is the disturbance term.

\( \beta_1 \) and \( \beta_2 \) are proxies for the supply and demand capacities of these exporter and importing countries respectively. Thus, apriori, we expect \( \beta_1 \) to be positive as high level of income and population in the exporting country denotes a high level of production ceteris paribus, which increases the exports goods; the coefficients on \( \beta_2 \) is also expected to be positive as high income level in importing countries stimulates higher imports. The distance coefficient is however expected to be negative as it is a proxy of all trade cost. The coefficients on Lang, Col, and RTA are all expected to be positive, and that on Llock to be negative.

To account for the influence of MTR, we apply a first order Taylor expansion to the trade costs variables and then used the newly transformed variables in the regression. Simple averages weights \((1/N)\) are used in their construction as shown in BB (2010) in contrast to the GDP weighted MRT in Baier and Bergstrand (2009). With symmetric but non-zero trade costs, the first order Taylor series approximation of the gravity model for panel data in log form is given as:

\[
\ln y_{ijt} = \ln GDP_{it} + \ln GDP_{jt} - (\sigma - 1) \ln t_{ijt} + (\sigma - 1) \left[ \frac{1}{N} \sum_{t=1}^{N} \ln t_{ijt} - \frac{1}{2} \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \ln t_{ijt} \right] + (\sigma - 1) \left[ \frac{1}{N} \sum_{j=1}^{N} \ln t_{ijt} - \frac{1}{2} \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \ln t_{ijt} \right]
\]

In equation (5), \( t_{ijt} \) refers to any of the bilateral trade cost variables associated the coefficients of B3 to B8 in equation (4). In our case, these are food safety standards, distance, common language, colony landlocked and RTA. The first term on the right hand side is the simple average of gross trade cost costs facing exporter \( i \) across all importer \( j \). The second term on the right hand side denotes the simple average of all trade costs faced by importer \( j \) across all exporters \( m \).

Following Egger and Nelson (2011), (using distance variable as an example), each bilateral trade cost variables are transformed using the following approximation:

\[
\ln Dist_{MRTij} = \ln Dist_{ij} - \frac{1}{N} \sum_{j=1}^{N} \ln Dist_{ij} - \frac{1}{2} \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \ln Dist_{ij}
\]

(5)

The transformed variable \( \ln dist_{ijMRT} \) is defined as exporter and importer time fixed effects, and
Similar definition holds for the other trade costs (Egger and Nelson, 2011). Inserting equation (4) into (3) and using the definition given by (5) gives the transformed log linear model which fully accounts for the influence of MRT as given below:

\[
\ln y_{ijt} = \beta_0 + \beta_1 \ln GDP_i + \beta_2 \ln GDP_j - (\sigma - 1)\beta_3 S_{ijMRT} - (\sigma - 1)\beta_4 \ln Dist_{ijMRT} - (\sigma - 1)\beta_5 Lang_{ijMRT} - (\sigma - 1)\beta_6 Col_{ijMRT} - (\sigma - 1)\beta_7 Lock_{ijMRT} - (\sigma - 1)\beta_8 RTA - RTA_{ijMRT} + \varepsilon_{ijt}
\]

We estimated equation (6) is using Truncated OLS and other estimators such as fixed effect and random effect estimators, Tobit. Although the Heckman and Helpman are also used to deal with zeros, however we did not consider them here. They are designed to estimate an entirely different set of parameters in contrast to the other approaches which give estimates that combine both the intensive and extensive margins of trade (Head and Mayer, 2014). This is because the major aim of these models is to estimate/remove the effect of the extensive margin of trade in order to estimate the intensive margin trade effects.

Furthermore, we also estimated equation (6) with the dependent variable in levels and share using two alternative generalized least square (GLS) method - MPML and PPML respectively with Baier and Bergstrand approximation in all models to control for multilateral trade resistance.

### 4.1.1 Log-Linear Models

**Truncated OLS regression model**

The OLS estimation of equation (2) is estimated using truncated OLS regression where all zero records are deleted. Here, the model assumes the error term to be linearly and independently distributed with zero mean and constant variance \( \varepsilon \sim N(0, \sigma^2) \).

**Panel Fixed effects model**

An alternative way to estimate equation (2) is to control for unobserved heterogeneity using panel data estimators such as the fixed effects technique. Thus, we also estimated equation 2 using the fixed effect panel model which assumes that the explanatory variables and the unobserved heterogeneity (captured by country specific unobservable effects – the exporter, importer and time fixed effects) are correlated and that the explanatory variables are independent of the residual error term.

**Panel Random effects model**

Alternatively, equation (2) can be estimated using the GLS estimator which on the contrary assumes that the explanatory variables are independent of the unobserved heterogeneity and the error term (Baltagi, 2008). The choice between the fixed and random effects models is then decided by the Hausmann test. Acceptance of the null hypothesis of zero correlation implies that the random effect model is efficient; both models are consistent. If however the null hypothesis is rejected, the fixed effect is consistent and the random effect is neither consistent nor efficient.

**Feasible Generalised Least Square Estimator (FGLS)**

FGLS corrects for heteroskedastic error structure across panels and the presence of autocorrelation with panels as well as cross sectional correlations. FGLS is an efficient estimator within the class of least squared estimator, and it is well suited to estimating
parameters in the presence of heteroscedasticity.

Eaton and Kortum (EK) Tobit Model
A Tobit model is also estimated to deal with the zero trade problems that resulted from actual zero trade between country-pairs; a level of trade below some threshold; or a choice by the exporter to report only data aggregated over several sources. There is the usage of Eaton and Tamura (1994) threshold Tobit model known as ‘ET Tobit’\(^{17}\) to accommodate zero trade flows, where the dependent variable is in form of \(\ln(a+Y_{ij})\). Here, instead of setting \(a = 1\), it is treated as a parameter to be estimated. The method defines a strictly positive latent variable \(y^*_{ijt}\) and a threshold \(a\) in such a way that \(y^*_{ijt} = Y_{ijt} - a\) is observed when \(y^*_{ijt} > a\); and \(y_{ijt}\) is observed when \(y^*_{ijt} \leq a\). However, the estimated \(\hat{a}\) is said to lack compelling structural interpretations and the method is said not to be a ‘canned’ program. As commonly practice in the literature, we also replaced all the zeros in the dependent variable by a small positive value (such as 0.001 or 1) before taking the log. Head and Mayer (2014) however advised against using the ET Tobit method because the result varies depending on the unit of measurement used.

The model which is expressed in terms of the latent variable is specified as follows.

Given that \(y_{ijt} = x_{ijt}\beta + \varepsilon_{ijt}\) then,

\[
\begin{align*}
y_{ijt} &= 0 \quad \text{if} \quad y^*_{ijt} \leq 0 \quad \text{or} \\
y_{ijt} &= y^*_{ijt} \quad \text{if} \quad y^*_{ijt} > 0
\end{align*}
\]

However, Head and Mayer (2014) recently propose the use of an alternative Tobit procedure that avoids the problem of selecting a value for zero trade flows without any criteria. In particular, following Eaton and Kortum (2001) Tobit method also used in Head and Mayer (2013), we employ the Eaton and Kortum Tobit model used by them in tackling missing trade flows. For each exporter \(i\), the bilateral zero trade flow \(y_{ij}\) is replaced by the minimum trade flow value \(y_{ij}^*\) taken over all destination country \(j\) appearing in the data. The new dependent variable now becomes \(\ln(y_{ij}^*)\) which is then plugged into equation 2 and then estimated as a Tobit model, along with importer, exporter and time effects using the maximum likelihood estimator. The EK Tobit, as this method is referred to by Head and Mayer, has the two advantages: First it does not require exclusion restrictions; second, it has a sound structural interpretation and; third, it can easily be estimated in Stata with the \textit{intreg} command (Head and Mayer, 2014).

4.1.2 Multiplicative Models’ Estimators – The Generalized linear models (GLM)
The generalized linear models estimate the constant elasticity gravity model in its multiplicative form as:

\[
y_{ijt} = \exp(x_{ijt}\beta)\varepsilon_{ijt}
\]

Where \(E(\varepsilon_i | x) = 1; x_{ijt}\) are the explanatory variables of the gravity equation earlier defined in equation (6) above; \(\beta\) is the parameters and \(\varepsilon_{ijt}\) is the composite error term which contains the importer and exporter fixed effects, time effects and the remainder of the error term.

\(^{17}\) However, the method is said be subject the trade flow to measurement errors, and they may have a high influence on the regression results, Rose (2000) and without any criteria.
**The Poisson Pseudo Maximum Likelihood (PPML) Estimator**

The PPML estimates \( \beta \) by solving the following first-order conditions:

\[
\sum_{i=1}^{n} \left[ y_{ijt} - \exp(x_{ijt}\beta) \right] x_{ijt} = 0 \tag{10}
\]

Equation (10) is the PPML estimator, which is consistent\(^{18}\) under the estimator's equidispersion\(^{19}\) assumption that the conditional mean \( E[y_{ijt} \mid x] \) given as \( \exp(x_{ijt}\beta) \) is equal to the conditional variance \( V[y_{ijt} \mid x] \) - this is implied by equation (11) which imposes restrictions on the conditional moments of the dependent variable.

\[
E[y_{ijt} \mid x] = \exp(x_{ijt}\beta) \propto V[y_{ijt} \mid x] \tag{11}
\]

However, the equi-dispersion assumption is unlikely to hold (Santos Sliver and Tenreyro, 2006; Martinez-Zarzoso, 2013) as the estimator does not fully account for the presence of heteroscedasticity in the model. In other words, the estimator does not fully take account of the presence of unobserved heterogeneity caused by the unobserved trade costs, thus making the conditional variance to be greater than the conditional mean\(^{20}\). Thus, inferences are based on the Eicker-White robust covariance matrix estimator (Eicker, 1963; White, 1980).

**Multinomial Poisson Maximum Likelihood (MPML) Estimator**

The Multinomial Poisson model is alternatively employed to deal appropriately with the occurrence of zero or missing trade (c.f. Eaton et al, 2012; Head and Mayer, 2014). Assuming that market shares are appropriate dependent variable in our gravity equation, then for a finite number of firms, the dependent variable then takes the form:

\[
\pi_{ij} = \frac{y_{ij}}{y_j} \tag{12}
\]

Where \( \pi_{ij} \) represents country \( i \) market share in \( j \); \( x_{ij} \) is the exports of fish to country \( j \) from country \( i \); \( x_j \) is world exports of fish to country \( j \). Incorporating equation (12) into (10) gives the Multinomial PML estimator with the same poisson restriction given as equation (11). The MPML is then given as:

\[
\sum_{i=1}^{n} \left[ \pi_{ijt} - \exp(x_{ijt}\beta) \right] x_{ijt} = 0 \tag{13}
\]

Since the sum of \( \pi_{ij} \) sums up to one across all destinations \( i \) (for any \( j \)), the gravity variables can thus be estimated using the multinomial pseudo maximum likelihood estimator.

---

\(^{18}\) To obtain consistent estimates, while the trade flow variable is assumed to follow a Poisson distribution, however, the data need not follow a Poisson distribution, and the independent variable needs not be an integer (Gourieroux, Monfort, and Trognon, 1984).

\(^{19}\) PPML gives the same weights to all observations, such that all the observations have the same information on the parameters because the additional information about the curvature of the mean which comes from observations with large mean is offset by their large variance (Santos Silva and Tenreyro, 2006).

\(^{20}\) Although the PPML specification hinges on the assumption of equi-dispersion of the dependent variable, however, SST 2006 show that the PPML is still well-behaved and consistent even with departure from this assumption.
(Gourieroux, Monfort and Trognon, 1984) without violating Jensen’s inequality. This is the estimation technique advanced by Eaton et al., (2012) for the case of a finite number of buyers and sellers and also used by Head and Mayer (2014) in their study. One advantage of the MPPML is that it is closer to the PPML approach as the estimator also tackles the zero problems. Furthermore, as proved by Sebastian Sotelo in his unpublished notes, the model is easily estimated in Stata by applying the poisson command to the market share variable $y_{ij} / y_j$ along with country and time fixed effects (see Head and Mayer, 2013). Eaton et al, 2012 in a footnote highlights the properties of this model as distinct from the log linear and PPML models. Their distinction is in terms of the penalties (weights) they give to deviations in large and small trade flows. The log linear approach treats proportional deviations as equally likely across large and small trade flows; while PPML assigns a greater penalty to proportional deviations in large trade flows than in small trade flows. However, MPML normalizes bilateral trade flows by the importers’ total trade absorption, (it gives less importance to large levels of trade and shares prevents the dependent variable from obtaining values over one), thereby eliminates different penalties for proportional deviations in the large and small trade flows.

4.2. Empirical Strategy

Equation (6) is the general log-linear model which we estimated using Truncated OLS, panel fixed and random effects model, FGLS and EK Tobit. Equations (10) and (13) are the multiplicative GLM model estimated using Poisson PML and Multinomial PML respectively. Our approach is to investigate how zero values in the dependent variable affect the performance of our estimators. The preferred estimator depends on the assumptions about how the conditional variance of the dependent variable relates to its expected value.

In particular, first, we are interested in investigating if the structure and assumption about the structure of the error term of each estimator holds in the presence of zero trade flows. We are interested in ascertaining whether the patterns of heteroscedasticity assumed by the various estimators are acceptable. Second, we are interested in determining the efficient estimator which is able to accommodate a dependent variable in which zeros are frequent. We investigate the performance in of zero trade flows containing about 63% zero trade observations. Following Santos Silva and Tenreyro (2006) and Martinez-Zarzoso (2013), we proceed by assessing and comparing the performances of the selected estimators. Comparison of the performances of the various estimation techniques would be based on the MaMu test also known as Park test, the Ramsey Reset test, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

A Park-type test (Park, 1966) is used to check for the adequacy of the log linear model versus the GLM models as well as to determine the pattern of heteroscedasticity assumed by the estimators (are accepted). In addition, the Ramsey Reset test (Ramsey, 1969) is also used to check for the adequacy and misspecification of all the estimators. Performances among the estimators are checked using AIC and BIC.

4.3. Data Description

Our dataset covers bilateral trade on fish exports between the 27 European Union countries and 40 African countries between 2007 and 2012 and this gives a balanced panel dataset of 6,480 observations on bilateral exports flows (27 x 40 x 6) out of which about 63% constitute zero trade flows. A list of countries included in the analysis is available in Table A1 in the appendix. The choice of our period of analysis is hinge on two factors. First, analysis from 2007 enables us to include all the existing 27 EU countries who have adopted the harmonised EU standards. Second, this period is an important period in which many food safety standards
were harmonised among the EU members. Third, the period also captures the period of the global financial crisis, which it is posited that the EU region tightened its non-tariff barriers, restrict market access in response to the financial crisis (Bussière, Pérez-Barreiro, Straub and Taglioni, 2010). In particular, it was speculated that standards becomes more protectionist in nature during this period, thus justifying our focus on this time period.

Bilateral exports data are extracted from the United Nations COMTRADE at the SITC Revision 1 product code. There are however some unique features of our data which is worth mentioning. About 63% of the bilateral trade flows between these trading countries are zeros. While some of these zeros may be due to statistical zeros such as rounding up or incompleteness of COMTRADE, but majority of the zeros are more likely to be a result of African exporters’ inability to trade due to some prohibitive fixed cost they have to bear in establishing trade partnership with the EU countries. One of these prohibitive fixed costs is compliance costs of meeting the restrictive food safety standards set by the EU by most exporters. Thus, it is important to know the extent to which standards can explain both positive and zeros trade, and also determine the appropriate estimation technique that allows for consistent estimates in the presence of our dependent variable with a high frequency of zeros.

Data on distance, language, colony were collected from the CEPII database, GDP data comes from the World Bank, while data used to construct the regional agreement dummy comes from the World Trade Organisation. Data on food safety standards on fish was obtained from Perinorm database which differentiates between national standards defined as those developed and adopted by all EU Member state, and international standards which we define as those developed by the Codex Alimentarius Commission. Standards are classified and reported according to the International Classification for Standards (ICS) system of classification. However, this system of reporting differs from how trade items are reported.

To construct our database we therefore collate all EU standards in force over the period of 2007 to 2012 by matching the standards in each year against the appropriate Standard International Trade Classification (SITC) for fish products. A standard is said to be in force in a particular year if it was published in that year or published prior to the year considered but it is still exists or has not been withdrawn. Amendments to existing standards are treated as additional standards and all draft standards are excluded from our dataset (see also Shepherd and Wilson, 2013). Likewise standards which denotes ‘terminology’ or vocabulary’ of a products are deem not to be substantive and are also excluded. The summary statistics of all the variables are provided in Table A2 in the appendix.

4.3.1. Stringency of Standards
Although standards represent legitimate concern for human, plant and animal life and safety, however, it can also have protectionist intent, hence creating unnecessary obstacles to trade. Previous studies have viewed protectionism in different ways: Study by Disdier, Fontagne and Mimouni (2008) view protectionism to exist when a SPS standards is enforced by only a few countries; while Disdier and van Tongern (2010) view protectionism to be responsible for some variation in the incidences of non-tariff measures across agricultural food products. However, World Trade Organisation defined protectionism as a precautionary policy which is without scientific evidence. Thus, in the presence of established scientific evidence, the

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21 SITC Revision 1 codes 0444 is used as the product categories for fish, crustacean.
22 Perinorm is a subscription-only database covering standards on 22 countries including those set by international bodies such as CODEX, ISO and CEN.
identification of protectionism intent is more cumbersome (Li and Beghin, 2013). Study by Li and Beghin, (2013) however define protectionist standards as those that exceed their internationally science-based ones (i.e. Codex). Our analysis departs from Li and Beghin whose protective measure is limited to only one standard – pesticide standards.

4.3.2. Constructing Protectionism Indices of Standards

To avoid using standard as a protectionist tool, the WTO obliged its members to employ internationally scientific based standards such as the Codex Alimentarious standards whenever it is possible. We define protectionism as the fraction of a country’s standards that is more stringent than the standards internationally recognized by the WTO. Thus, our measure of protectionism is constructed by measuring the differences in EU standard against an international benchmark. We employ Codex standards as the ‘non-protectionist’ scientifically based benchmark. Following Li and Beghin (2013), we developed a simple criterion of protectionism: EU standards that exceed those set by Codex are taken to be protectionist, while those that are laxer than Codex’s is defined to be anti-protectionist. Our trade weighted product level protectionism index for fish standard is given as:

\[
P_{ij} = \frac{\text{Codex}_{std} - \text{EU}_{std}}{100} w_{ij}
\] (14)

Where \( P_{ij} \) measures the extent of protectionism of EU fish standard imposed by a given importer on country \( i \) exports at time \( t; \) \( \text{EU}_{std} \) denotes the EU fish standards at time \( t; \) \( \text{Codex}_{std} \) is the international codex standard in fish at time \( t. \) \( w_{ij} \) is the weight of the import value of fish (the product affected by standards) in world imports in fish. More specifically, \( w_{ij} \) is given as

\[
w_{ij} = \frac{IM_{ij}}{IM_{t}}
\] (15)

\( IM_{ij} \) is the share of bilateral fish import values from country \( j \) to \( i \) in a given year, and \( IM_{t} \) is world fish imports in the corresponding year. \( w_{ij} \), also known as the import coverage ratio is a popular way of calculating trade weighted standard measure in the literature (see Disdier, Fontagne and Mimouni (2008), de Frahan and Vancauteren, 2006; Bao and Qui, 2010; etc). While the first part of the measure \( (\text{Codex}_{std} - \text{EU}_{std}) \) covers the stringency of the standard, the second part \( (w_{ij}) \) is similar to the coverage ratio and captures the extent of trade covered by standard. More specifically, the coverage ratio of standard in any country \( i \) in a particular year is the share of bilateral import values from country \( j \) to \( i \) in the affected product in a given year in total world exports in the affected product that year. Thus our measure of standards introduces variability across importers, exporters and time.

Equation (15) results into indices that are lower and upper bounded, negative values indicate protectionism while positive values are indicative of anti-protection, and zero values implies neutrality of standards between EU and Codex. The higher the deviation of EU standards from international codex, the more negative the index becomes and vice versa. The lower the index is (i.e. the more negative it is), the higher its stringency, and the more costly it becomes to

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23 However, the WTO also allows it members to use precautionary principle by setting their own appropriate level of protection different from international one, in as long as their national standards are non-discriminatory, have scientific backings and least trade restrictive (WTO SPS agreement).

24 Ideally, for a given country weights should reflect the dead-weight loss of the product aggregated over all products. Unfortunately, data dead-weight loss are not readily available, thus, we instead substitute import value.
5.0 RESULTS AND DISCUSSION

Table 1 presents the results of the theoretically justified gravity model for both the linear estimators and the generalised linear models. The log-linear model were estimated using Truncated OLS, panel fixed and random effects models, FGLS ET and EK Tobit model, while the GLM model were estimated using Poisson PML and Multinomial PML. The dependent variable for the log linear models is the logarithm of exports and for the Poisson and Multinomial Poisson models, the dependent variables are respectively exports and export share in levels. As a first step, we tested for the presence heteroskedasticity and autocorrelation in our data. Thus, we estimated both the fixed and random effects models with the “xtregar” command in Stata. In addition, in the FGLS model, choose the options that corrects for both panel heteroscedasticity and autocorrelation of order one within panel. All other models were estimated using clustered robust standard errors.

Table 1: Results from the Various Estimators

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<th>FGLS lexport</th>
<th>Fixed lexport</th>
<th>Random Lexport</th>
<th>ET Tobit lexport</th>
<th>EK Tobit Lexport</th>
<th>PPML Export</th>
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<td></td>
<td>(b/se)</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
<td>b/se</td>
</tr>
<tr>
<td>Log of Exporter GDP</td>
<td>0.528***</td>
<td>0.634***</td>
<td>-0.075</td>
<td>0.498***</td>
<td>1.027***</td>
<td>1.501***</td>
<td>0.139</td>
<td>0.469***</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.035)</td>
<td>(0.210)</td>
<td>(0.080)</td>
<td>(0.131)</td>
<td>(0.179)</td>
<td>(0.161)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Log of Importer GDP</td>
<td>0.734***</td>
<td>0.669***</td>
<td>0.136</td>
<td>0.792***</td>
<td>1.745***</td>
<td>2.440***</td>
<td>0.143</td>
<td>0.189**</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.037)</td>
<td>(0.178)</td>
<td>(0.083)</td>
<td>(0.138)</td>
<td>(0.176)</td>
<td>(0.367)</td>
<td>(0.080)</td>
</tr>
<tr>
<td>Fish Standard</td>
<td>-0.007</td>
<td>-0.001</td>
<td>0.002</td>
<td>0.004</td>
<td>0.005*</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log of Distance</td>
<td>-0.813</td>
<td>-1.098***</td>
<td>-0.811</td>
<td>-1.526</td>
<td>-1.782</td>
<td>-1.111</td>
<td>-0.235</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.000)</td>
<td>(0.384)</td>
<td>(0.871)</td>
<td>(1.874)</td>
<td>(2.545)</td>
<td>(1.176)</td>
<td>(0.552)</td>
<td></td>
</tr>
<tr>
<td>Com Language</td>
<td>-0.277</td>
<td>-0.578**</td>
<td>-0.442</td>
<td>-0.888</td>
<td>1.758</td>
<td>-1.541</td>
<td>-0.426</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.745)</td>
<td>(0.232)</td>
<td>(0.608)</td>
<td>(1.071)</td>
<td>(1.583)</td>
<td>(0.931)</td>
<td>(0.670)</td>
<td></td>
</tr>
<tr>
<td>Colony</td>
<td>0.497</td>
<td>0.846***</td>
<td>1.307</td>
<td>3.082**</td>
<td>3.703**</td>
<td>2.454**</td>
<td>2.285**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.854)</td>
<td>(0.269)</td>
<td>(0.761)</td>
<td>(1.346)</td>
<td>(1.855)</td>
<td>(0.990)</td>
<td>(0.914)</td>
<td></td>
</tr>
<tr>
<td>Landlocked</td>
<td>-6.437***</td>
<td>-5.331***</td>
<td>-3.129</td>
<td>-1.982</td>
<td>-1.489</td>
<td>-10.023***</td>
<td>-2.516**</td>
<td>-2.516**</td>
</tr>
<tr>
<td></td>
<td>(1.756)</td>
<td>(0.520)</td>
<td>(1.001)</td>
<td>(1.208)</td>
<td>(1.906)</td>
<td>(2.558)</td>
<td>(0.881)</td>
<td></td>
</tr>
<tr>
<td>RTA</td>
<td>0.535</td>
<td>0.433***</td>
<td>-0.021</td>
<td>0.268</td>
<td>0.339</td>
<td>0.393</td>
<td>0.009</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.503)</td>
<td>(0.142)</td>
<td>(0.396)</td>
<td>(0.283)</td>
<td>(0.431)</td>
<td>(0.687)</td>
<td>(0.276)</td>
<td>(0.354)</td>
</tr>
<tr>
<td></td>
<td>(2.938)</td>
<td>(1.004)</td>
<td>(0.536)</td>
<td>(2.188)</td>
<td>(3.493)</td>
<td>(4.325)</td>
<td>(7.432)</td>
<td>(2.061)</td>
</tr>
<tr>
<td>Observations</td>
<td>2188</td>
<td>2345</td>
<td>1870</td>
<td>2412</td>
<td>6480</td>
<td>6480</td>
<td>6480</td>
<td>6480</td>
</tr>
<tr>
<td>AIC</td>
<td>10551.544</td>
<td>5433.016</td>
<td>12595.81</td>
<td>16010.19</td>
<td>2098e+06</td>
<td>2709.765</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>10608.451</td>
<td>5460.685</td>
<td>16073.35</td>
<td>16084.73</td>
<td>2098e+06</td>
<td>2777.530</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ramsey Test</td>
<td>0.646</td>
<td>0.152</td>
<td>0.2819</td>
<td>0.014</td>
<td>0.012</td>
<td>0.033</td>
<td>0.222</td>
<td>0.137</td>
</tr>
</tbody>
</table>

Note: the dependent variable is the logarithm of exports for all models except for the Poisson and Multinomial Poisson models whose dependent variables are respectively exports and export share in levels. All models control for multilateral trade resistance using Baier and Bergstrand (2009) approximation. Clustered robust standard errors are in bracket and * p<0.10; ** p<0.05; *** p<0.01

For all models, the coefficients on the income elasticity of exporters' GDP are far below the theoretical value of 1. Exception to this is the EK Tobit model whose coefficient is about 1.5. However, there have been justifications for the coefficients on exporter and importers' elasticity of income to fall below or above one in the literature (c.f. Rahman, 2009). Furthermore, the coefficients are insignificant when the gravity equation is estimated by PPML.
and fixed effect models. However, most of the coefficients on importers' income elasticity are closer to the theoretical value of 1. All the coefficients are also statistically significant except for the PPML and fixed effect models. In addition, concerning fish standards, all models are indicative of insignificant negative effect of EU fish standard on African export at least at the 5% conventional significance level. This is indicative of the fact that EU fish standards in relation to the ones imposed by Codex Alimentarius are not protectionist in nature.

Regarding the other costs variables, the results show geographical distance as having negative effects on exports for all the models which is in line with our a priori expectation, but all models are statistically insignificant with the exception of FGLS model which produce a significant trade effect. With respect to the common language variable, all the models with the exception of the EK Tobit model which predict negative effect of sharing a common language on exports negating our a priori expectation of a positive trade effect. However, they are all insignificant except the FGLS model at 5% level. Furthermore, in conformity with our a priori expectation, all estimates model predicts negative and statistically significant effects of being landlocked on exports, except the EK Tobit which produced insignificant effect. Contrary to our expectations, regional trade agreements between country-pairs does not have any effect on trade for all models except for the FGLS models where it has a positive and large significant effect on fish exports.

In general, from Table 1, the differences in the techniques is mostly seen in the magnitude of the standard errors and coefficient predicted and in seldom cases, in the signs of the parameters of the gravity variables. However, the main difference between them lies in the standard error - the measure of precision. Table 2 summarizes the top two consecutive estimators with the lowest standard errors and the estimator with the highest standard error. We could see that FGLS and MPML in most cases exhibit the least standard errors depending on the variable considered, indicating that their estimates are more accurate. However EK Tobit and PPML models mostly exhibit the highest standard errors.

Table 2: Estimators with the Lowest/Highest Standard Errors

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Lowest</th>
<th>(2) Lowest</th>
<th>(3) Highest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log of Exporter GDP</td>
<td>FGLS</td>
<td>MPML</td>
<td>Random Effect</td>
</tr>
<tr>
<td>Log of Importer GDP</td>
<td>FGLS</td>
<td>MPML</td>
<td>PPML</td>
</tr>
<tr>
<td>Fish Standard</td>
<td>PPML</td>
<td>MPML</td>
<td>Trun OLS</td>
</tr>
<tr>
<td>Log of Distance</td>
<td>FGLS</td>
<td>MPML</td>
<td>EK Tobit</td>
</tr>
<tr>
<td>Common Language</td>
<td>FGLS</td>
<td>MPML</td>
<td>EK Tobit</td>
</tr>
<tr>
<td>Colony</td>
<td>FGLS</td>
<td>Random Effects</td>
<td>EK Tobit</td>
</tr>
<tr>
<td>Landlocked</td>
<td>FGLS</td>
<td>MPML</td>
<td>PPML</td>
</tr>
<tr>
<td>RTA</td>
<td>FGLS</td>
<td>ET Tobit</td>
<td>PPML</td>
</tr>
</tbody>
</table>
5.1. Robust Checks
In order to better compare the different estimation techniques, we employ some goodness of fit criteria discussed below.

Our approach is to investigate how zero values in the dependent variable affect the performance of our estimators. In particular, we are interested in if the patterns of heteroskedasticity assumed by the various estimators are acceptable. We investigate the performance in a dataset containing about 63% zero trade observations. Given the estimators considered in this study, the pattern of heteroskedasticity assumed by the models are the Constant Coefficient of Variance (CCV) assumption and the Constant Variance to Mean Ratio (CVMR) type of heteroskedasticity (c.f. Head and Mayer, 2014).

As could be seen from the previous section, the general form of the variance function of the GLM and log-linear model is given as

\[ \nu(y|x) = k((\mu(y\beta))^2) \]  

(16)

In equation 16, \( \lambda \) is non-negative and finite and its value determines the difference between GLM and log-linear models. For instance, for values of \( \lambda_i = 1 \), we obtain the Poisson model; when \( \lambda_i = 2 \), we obtain the log-linear estimators. The more efficient estimator now depends on the assumption about how its variance relates to its mean. On the one hand, the log linear model have log normal errors with constant variance (homoskedasticity assumption) and therefore it is referred to by Head and Mayer (2014) to exhibit CCV pattern of heterosckedasticity. This is a data generating process that satisfies \( \lambda_i = 2 \) - that is, its standard deviation is assumed to be proportional to its mean is said to adhere to the CCV heterosckedasticity type. On the other hand, PPML and MPML have CVMR heterosckedasticity type of pattern – i.e heteroskedasticity a la Poisson, with \( \lambda_i = 1 \) assumed.

Given the above variance function, Manning and Mullaby, (2001) suggest that the choice of the appropriate estimator could be based on a Park-type regression – a test statistic to diagnose the error term. To determine the pattern of heteroscedasticity assumed by the estimators, we therefore rely on a Park-type test (Park, 1966) which checks for the adequacy of the log linear models and the GLM models. It is a reliable method of distinguishing between the log-normal data generating process and the CVMR data generating process (Head and Mayer, 2014). To check the adequacy of the log-linear models, the test consists of estimating the following equation which can be directly derived from equation (16). This is specified as:

\[ \ln(y_i - \hat{y}_i)^2 = \ln(\lambda_0) + \lambda_i \ln \hat{y}_i + \mu_i \]  

(17)

Based on a non-robust covariance estimator, the null hypothesis is that Ho: \( \lambda_i = 2 \) (that the model is a log-linear one) is tested against the alternative that it is not. The hypothesis is accepted if the appropriate confidence interval for \( \lambda_i \) contains 2. Acceptance of this null hypothesis would be in favour of log linear model. However, because logarithmic transformation of equation (17) is only valid under restricted conditions of the conditional distribution of the dependent variable (Santos Siliva and Tenreyro, 2006 and Martinez-Zarzoso, 2013), we also estimate the modified version of the Park regression as a robust alternative. According to Manning and Mullahy, (2001) and Deb, Manning and Norton (2008), a more robust alternative is to estimate \( \lambda_i \) as:
\[(y_i - \hat{y}_i)^2 = \lambda_0 (\hat{y}_i)^{\lambda_1} + \eta_i\]

The result of the Park test is presented in Table 3. We report both the confidence interval of the (park) test and the p-values gotten from the test of the hypotheses both of which check whether the pattern of heteroscedasticity assumed by each models is appropriate. Out of all the estimators, only the MPML model passed the test which suggests that the other models are inadequate given the dataset considered. For this model, first, the p-value of the statistical test of the hypothesis indicates that the estimated coefficients on $\lambda_1 = 1$ is statistically insignificantly different from zero at the 5% conventional significance level (see column 2 in Table 3). Second, as shown in column 3 of Table 3, the estimated 95% confidence interval of the coefficient on $\lambda_1$ contains the value of 1, (-2.139, 2.202). Thus, based on these two preceding results, the null hypothesis that $\lambda_1 = 1$ could not be rejected. This result is in favour of MPML and implies that the poisson proportionality assumption of the conditional mean being equal to the conditional variance cannot be rejected at the 5% , thus reinforcing that the Multinomial Poisson distribution is appropriate. Our result is in line with that of Head and Mayer (2014) who find that the selection of the most appropriate estimator to be contingent on the process generating the error term and whose simulation results reveal that the MPML model is preferable under a poisson-like error where a constant variance to mean ratio is assumed, the Poission or Multinomial PML estimators are preferable.

In contrast, PPML and all the log linear estimators did not pass the Park test. More specifically, the confidence interval of the Park test for PPML did not contain 1, and the p-value of the hypothesis of the test is statistically significantly, thus, the null hypothesis that $\lambda_1 = 1$ is unequivocally rejected. This result show that PPML is inefficient as the poisson-like hetheroscedasticity type was not satisfied. Similarly, none of the confidence interval of the entire log linear estimator contains the value of 2. Furthermore, for all the log linear models, the p-value of the hypothesis of the tests is statistically significantly, thus their null hypotheses that $\lambda_1 = 2$ were outrightly rejected. These results are indications that all the log linear estimators exhibit worse case performance.

### Table 3: Testing for the Pattern of Heteroscedasticity

<table>
<thead>
<tr>
<th>Estimator</th>
<th>Park Test (P-value)</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trun OLS</td>
<td>0.000</td>
<td>-0.198</td>
</tr>
<tr>
<td>FGLS</td>
<td>0.000</td>
<td>-0.360</td>
</tr>
<tr>
<td>FE</td>
<td>0.000</td>
<td>2.773</td>
</tr>
<tr>
<td>RE</td>
<td>0.000</td>
<td>-0.275</td>
</tr>
<tr>
<td>ET Tobit</td>
<td>0.000</td>
<td>-0.642</td>
</tr>
<tr>
<td>EK Tobit</td>
<td>0.000</td>
<td>-0.445</td>
</tr>
<tr>
<td>PPML</td>
<td>0.000</td>
<td>2.497</td>
</tr>
<tr>
<td>MPML</td>
<td>0.382</td>
<td>-2.139</td>
</tr>
</tbody>
</table>

Note: For the log linear estimator, the Park-type test that $\lambda_1 = 1$ were based on a non-robust covariance estimator. Whereas, for both PPML and MPML, modified park test which tested the hypothesis that $\lambda_1 = 2$ were based on a robust covariance estimator.

We used a (heteroscedasticity-robust) Ramsey Reset Test (Ramsey, 1969) to check the
adequacy of all the estimated models. In essence, it is a test of specification error of the functional form of the model and checks if the conditional expectations are correctly specified. The test is performed by checking the significance of an additionally constructed regressor specified as $(x' \beta)^2$, where $\beta$ is the vector of estimated parameters. The null hypothesis is that the coefficient on the test variable is 0 or insignificant. The p-values of the test is provided at the bottom of Table 1. The test reveal a statistically significant p-value for MPML estimator signifying that the estimator passed the functional form test. This points out the appropriateness of the MPML estimator for our dataset. Similar results are evidenced for truncated OLS, FGLS, fixed effects and PPML estimators. However, random effects model, ET Tobit and EK Tobit models did not pass the test as the test reject the null hypothesis that the coefficient of the test variable is significantly different from zero.

The performance of the log linear estimators and GLM are also tested using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). However, the results for the log linear and GLM estimators are not directly comparable due to the differences in the number of observations and differences in the specification of the dependent variables of the estimators. The results are presented at the last part of Table 1. Among the log linear estimator, the FGLS model presents the lowest AIC and BIC values, while MPML model presents the lowest AIC and BIC results among the GLM estimators, once again reinforcing its appropriateness and adequacy.

Overall, first, we find strong support for the CVMR heteroscedasticity type when we used the MPML estimator, implying that the estimator is efficient. Second, there is no evidence of functional form misspecification based on the Ramsey Reset test. Therefore, as pointed out by these robust checks points, the prediction of the MPLM technique is rather very good for our kind of dataset which is characterized by very low trade values and many zeros.

### 6.0 CONCLUSION

The issues of zero trade observations and the validity of the log linear transformation of the gravity equation in the presence of heteroscedasticity have generated a number of claims and controversies in the literature. Subsequently, various estimation techniques have been proposed to address these problems, with differing claims and conclusions about the best performing model. This paper seeks to validate the claims in the literature concerning the best performing estimator using African dataset on fish exports to the EU. We provide an in-depth review of methods that have been employed in solving these problems. Our survey of studies at the forefront of the current debate show that each estimator is not without its pros and cons.

As an empirical analysis, we adapted the Anderson and van Wincoop (2003) specification of the gravity equation and control for multilateral trade using Baier and Bergstrand (2009) approximation. Given our dataset and the gravity equation specified, we assess the performance of the log linear and generalized linear models in a dataset whose independent variable contains about 63% zero trade flows observations. Our estimations reveal results that are evidently in favour of only the MPML technique.

Conclusively, the choice of the most appropriate estimator for our dataset is contingent on the process generating the error term. This particular African dataset and the resulting data generating process underlying the structure of the error term, gives strong evidence that the data generating process follows a constant variance mean ratio type of heteroscedasticity, which indicate a strong support for the Multinomial PML as the most appropriate estimation
The estimation technique not only produces efficient estimate of the trade effect of standards, it also provides a natural solution to deal with the zero trade observations which is frequent in our dataset.

REFERENCES


gravity model in international trade: advances and applications. Cambridge Univ Press, Ch. 4, pp. 88(134).


Boulhol, H., Bosquet, C., 2012. Applying the GLM variance assumption to overcome the scale dependence of the Negative Binomial QGPML Estimator.


# APPENDIX

## Table A1: List of Countries in the Dataset

<table>
<thead>
<tr>
<th>Country Groups</th>
<th>Members</th>
</tr>
</thead>
<tbody>
<tr>
<td>Importers (EU27)</td>
<td>Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuanian, Luxembourg, Malta, Netherlands, Poland, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom</td>
</tr>
</tbody>
</table>

## Table A2: Summary Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Untransformed</th>
<th>Demeaned as in Baier and Bergstrand (2010)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Export</td>
<td>3054.829</td>
<td>20937.11</td>
</tr>
<tr>
<td>Log of Export</td>
<td>4.902</td>
<td>3.648</td>
</tr>
<tr>
<td>Export Share</td>
<td>0.104</td>
<td>0.449</td>
</tr>
<tr>
<td>Log of Exporter's GDP</td>
<td>16.161</td>
<td>1.536</td>
</tr>
<tr>
<td>Log of Importer's GDP</td>
<td>19.271</td>
<td>1.674</td>
</tr>
<tr>
<td>Fish Standard</td>
<td>-5.541</td>
<td>18.725</td>
</tr>
<tr>
<td>Log of Distance</td>
<td>8.582</td>
<td>0.439</td>
</tr>
<tr>
<td>Language Dummy</td>
<td>0.106</td>
<td>0.308</td>
</tr>
<tr>
<td>Colonial Links Dummy</td>
<td>0.040</td>
<td>0.196</td>
</tr>
<tr>
<td>Landlocked Variable</td>
<td>0.389</td>
<td>0.488</td>
</tr>
<tr>
<td>Trade Agreement Dummy</td>
<td>0.276</td>
<td>0.447</td>
</tr>
</tbody>
</table>
Table A: The Zero Trade and Logarithmic Transformation in Gravity Modeling – A Summary of the Debate

<table>
<thead>
<tr>
<th>Model/Estimator</th>
<th>Scholar</th>
<th>Characteristics/Merit</th>
<th>Criticism/Demerit</th>
<th>Response to Critics</th>
</tr>
</thead>
</table>
| Tobit                            | Anderson and Marcoiller (2002), Rose (2004), Martin and Pham (2008). | - To deal with the zero trade problem due to unobservable trade flows or measurement error from rounding up.  
- Applied to fit dataset that is only observable over some range.  
- Applicable there is difference between actual outcomes and desired outcomes. | - Linder and de Groot (2006) opined that zero trade occur due to binary decision making on the profitability of trade and not from censoring that the model posited, which makes it inappropriate to take care of the zero trade.  
- Frankel (1979) argued that the estimator is liable to measurement errors, which will impact on the result due to the artificial censoring of positive small trade values.  
- In response to the position of Martin and Pham (2008), Santoa Silva and Tenreyro (2011) find the threshold Tobit model to have large bias that rise with sample size, which makes it an inconsistence estimator in a simulation exercise. | - Martin and Pham (2008) suggested the use of Eaton and Tamura (1994) threshold Tobit model that gives the lowest bias and outperform all other estimators in a simulation exercise. |
| Poisson Pseudo Maximum Likelihood (PPML) | Santos Silva and Tenreyro (2006, 2008, 2009,) | - It is used to deal with the zero trade and logarithm transformation. | - Burger et al. (2009) argued that the model is vulnerable to over- | - Santo Silva and Tenreyro (2011) opined that despite the |
The gravity equation is specified at levels in order to avoid the problem that arose using OLS under logarithm transformation. It takes into consideration observed heterogeneity; zero trade dealt with through the multiplicative form of the fixed effects in PPML and avoid under-prediction of large trade volume by generating estimates of trade flows rather than the log of trade flows. Gives the lowest bias among estimators. Proponents suggest the estimator as the workhorse for the gravity model.

- The assumption of equidispersion in the dependent variable leads to overdispersion due to unobserved heterogeneity.
- Martinez-Zarzoso (2013) opined that PPML is not always the best estimator as its estimates are outperformed by both OLS and FGLS estimates in out of sample forecast, so, it is not always the best estimator.
- The PPML assumption regarding the pattern of heteroscedasticity is rejected by the data in most cases (Martinez-Zarzoso 2013).

- PPML identified overdispersion and excessive zero trade problems, PPML is consistent and generally well-behaved in the presence of overdispersion in the dependent variable and large zero trade will not affect its performance.
- Soren and Bruemmer (2012) argued that PPML performs quite well under overdispersion, and show that the PPML is well-behaved under bimodal distributed trade data.
- Santo Silva and Tenreyro (2008) responded by justifying the use of PPML as the best estimator in gravity model, but acknowledged that PPML estimator can be outperformed by other estimators in some cases.
Zarzoso, 2013).
- Martin and Pham (2008) argue that PPML is not robust to the joint problems of zero trade and heteroscedasticity.
- Staub and Winkelman, 2012).
- Santo Silva and Tenreyro (2011) responded to the critics of PPML arguing that the studies of the critics of PPML did not generate its data through a constant elasticity model, with which their study did.
- Also, Santo Silva and Tenreyro (2011) re-investigate the performance of PPML in the presence of large zero trade data in a constant elasticity model. The results show that PPML estimator is consistent, well-behaved with large zero trade and not affected by overdispersion in the dependent variable.

<p>| Negative Binomial Pseudo Maximum Likelihood (NBPML) and Zero | Burger et al. (2009) | To correct for the overdispersion in the dependent variable and the vulnerability of the model. | One of the drawbacks of NBPML and PPML is the excessive number of zero trade. | Burger et al. (2009) opined that even though the Poisson model and NBPML... |</p>
<table>
<thead>
<tr>
<th>Inflated Models</th>
<th>PPML to excessive trade zero.</th>
<th>trade that is derived from non-Poissoness of the model (Johnson and Kotz, 1969).</th>
</tr>
</thead>
<tbody>
<tr>
<td>e.g. Zero Inflated Pseudo Maximum Likelihood (ZIPML) technique, Zero Inflated Binomial Pseudo Maximum Likelihood (ZINBPML).</td>
<td>It incorporates unobserved heterogeneity into the condition mean and thus, takes care of unobserved heterogeneity.</td>
<td>Turkson (2011) argued that these estimation techniques cannot handle excessive zero.</td>
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<td>Staub and Winkelmann (2012) posit that both ZIPML and ZINBPML are inconsistent if the models are misspecified.</td>
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<td>The Zero Inflated Models perform better as they corrected excessive zeros and overdispersion in the dependent variables.</td>
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<td>- Consistent in the presence of excessive zero trade.</td>
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<td>- Unaffected by unobserved heterogeneity.</td>
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<td>- It is robust to misspecification as it consistently estimate the regression coefficients irrespective of the true distribution of the counts,</td>
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<td>- ZINPQL can be less efficient compared to zero inflated estimators when the zero inflated models are correctly specified.</td>
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<td>model can technically handle zero trade, however, both are not well positioned in the case where the number of observed zeros trade value is greater than the number of zero predicted by the model.</td>
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<td>The Zero Inflated Models perform better as they corrected excessive zeros and overdispersion in the dependent variables.</td>
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<td>The models theoretically well situated in Poisson and non-Poisson estimation.</td>
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while ZIPML and ZINBPML demonstrate considerable bias in the medium sample.

- It is an efficient estimator among the class of least square estimators.  
- Variance of the disturbances needs to be re-estimated to correct for heteroscedasticity errors.  
- The comparison of the best estimators should be between FGLS and other generalized least models (GLMs) such as; Non-linear least square (NLS), Gamma Poisson Maximum Likelihood (GPML) and PPML.  
- Gamma Psuedo Maximum Likelihood (GPML) techniques is more efficient under the log-scale residuals have high kurtosis. | - Santos Silva and Tenreyro (2008) debunked the claim of FGLS proponents and provided justification for the PPML estimator in the context of log-linear gravity model.  
- Santos Silva and Tenreyro (2011) found GMPL to be consistent and well-behaved under Monte Carlo simulation with excessive zero trade values in a constant elasticity model, but has a larger bias than the PPML.  
- Martine-Zarzoso (2013) argued that the GMPL may suffer from substantial loss of precision whenever the variance function is misspecified or when the log-scale residuals have high kurtosis. | Martinez-Zarzoso (2013) argued that the choice of the best estimator is a function of the dataset and there is no absolute best estimator for all typology of dataset. Thus, the most appropriate estimator is data specific and could be determined by model selection tests. |
| Heckman Selection Model | Heckman (1979), Linder and de Groot (2006), Munasib and Roy (2011). | assumption that the conditional variance depends on higher power of the conditional mean, thus, given more weight to conditional mean.  
- NLS assigns more weight to noisier observations.  
- NLS consistent in the modeling of zero.  
- NLS gives more weight to observations with large variance. | - NLS efficiency is reduced due to its allocation of more weight to noisier observation (Santos Silva and Tenreyro, 2006). Also, NLS is inefficient because it generally ignores heteroscedasticity in the data. | - Burger et al. (2009) argued that in both Heckman and HMR models, it is difficult to satisfy the exclusion restriction because the instrumental variable is often difficult to find.  
- The transformation of these models into logarithmic form before estimation might cause biased coefficient (Haworth and Vincent, 1979; Santos Silva and Tenreyro, 2006).  
- posited that these models did not control for heteroscedasticity that are pervasive in trade data.  
- excluded variables and imposed the normality of the error term. |  
- It extended the Heckman model by controlling for both sample selection bias and firm heteroscedasticity.  
- It solves the zero trade problem with a two-step estimation procedure.  
- It measures the effects of the number of exporting firms and volume of trade.  
- First, it estimates the probit regression for probability of trading at the firm’s levels (extensive margin).  
- Using the first stage estimation result to estimate the intensive trade margin.  
- It assumes homoscedasticity.  