The Extensive Margin in the Industry Trade: Estimation, Significance and Implications*

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Abstract

What determines the significance of the extensive margin (number of exporting firms) in the gravity model of trade with heterogeneous firms? Helpman, Melitz and Rubenstein (HMR) provide evidence that the neglect of the role played by firm heterogeneity can bias upward the estimates of the gravity model. However, this conclusion is not robust. In particular, when the gravity model is estimated for exports from OECD to non-OECD countries (a setting where the HMR correction should be the most apparent), firm heterogeneity plays no role. To shed light on this puzzle I further decompose the world trade data between three industries (manufacturing, mining and agriculture). The presumption is that the HMR correction should be most prominent for manufacturing trade and less so for the other industries. I confirm this prediction and find that using the trade data at an aggregate level confounds the significance of the extensive margin by mixing up the industries. In addition, I show that there is an important relationship between the HMR correction and the upward bias in the gravity estimates: the upward bias is strong only when the extensive margin is a significant determinant of the trade flows. I set up industry level HMR framework to explain these findings.

Keywords: trade flows, trade frictions, asymmetries, gravity model, estimation
JEL classification: C11, C13, F10, F12, F14

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1 Introduction

One of the most important issues in the empirical international trade literature is a consistent estimation of the volume of world trade flows. The basic question of why countries trade with each other dates back to Ricardo, but with recent improvements in the quality of the trade data it became possible to quantitatively assess this question. Starting with Tinbergen (1962), the basic framework to estimate the volume of world trade flows involved the log-log model, where the change in trade volume between any two trading countries could be predicted by the relative size of and distance between two countries. This framework is today dubbed as a classical gravity model of trade.

The key unsatisfying feature in the classical gravity model is that it can only be used to estimate trade between countries that trade with each other. The recent empirical evidence suggest that there are over 50 percent of zeros in the world trade matrix at the country level and even higher at the industry level.[1] The nature of these zeros has been widely debated. Feenstra et al. (1997) argue that trade data can suffer from many forms of errors. In particular, zeros in the trade matrix can be a result of rounding errors if the volume of trade between some countries is particularly small, or that the zeros appear simply because of poor accounting (Baranga, (2008)). However, it is hardly possible for any measurement errors to explain why so many countries do not trade with each other. These zeros are of non-random nature and therefore need to be accounted for in the gravity model of trade. There is also a large strand of the empirical trade literature that doubts the magnitude of the elasticities of trade barriers with respect to trade flows. Started by Leamer and Levinsohn (1995), this line of research emphasizes so called "distance-puzzle" - econometric evidence suggesting that the distance related elasticity of the bilateral trade has increased over time, whereas the actual transportation costs have fallen substantially.[2] From an estimation point of view the "distance puzzle" imply that the elasticity of distance with respect to trade volume is overestimated (biased upward) in the classical gravity model.

The extension of the standard trade models to include firm-level heterogeneity allowed for explaining the nature of zeros in the world trade matrix. The most prominent models by Melitz (2003), Bernard, Eaton, Jensen and Kortum (BEJK, 2003) and Yeaple (2005) were designed to relax the assumption of the representative firm in the older models, and to capture the recent empirical firm-level evidence: exporters are in the minority, more productive - more capital and technology intensive, more efficient, have more workers, pay higher wages, and more likely to become a multiplant firm and fixed (sunk) costs are a large and significant source of the export persistence.[3] While different in their approach, these models establish that the trade between countries depends on the behavior of firms. Now standard in the new trade literature, the Melitz

[1] See HMR (2008) and Belenkiy (2008) for the country level evidence; Manova (2006) and data analysis of this paper for the indutsry level evidence.

[2] More on this puzzle see Brun et al. (2004), Coe et all. (2002), and Hummels (2007) among others.

[3] See Aw and Hang (1995); Clerdis, Lach and Tybout (1998); Bernard and Jensen (1995, 1997,1999); Aw, Chung and Roberts (2000); Eaton, Kortum, Kramarz (2004); Helpman, Melitz, Yeaple (2004) and Roberts and Tybout (1997) for the details on these findings.

(2003) model allows endogenous calculation of the number of firms that decide to export. This result has opened a new way to decompose the observed trade flows into the extensive margin of trade, the number of the exporting firms, and the intensive margin of trade, the volume of trade per exporter. This decomposition gives a coherent answer as to why only few and most productive firms become exporters.

The theoretical importance of the extensive margin of trade signaled the need to re-design the classical gravity model to control for intensive and extensive margins separately. The earlier line of research by Felbermayr and Kohler (2004), and more recently by Andersson (2007) incorporated the control for extensive margin into the gravity equation. These studies used ad-hoc measures of the extensive margin, providing only reduced form estimates, but they were still able to document the significance of the extensive margin to explain the overestimated elasticities of trade flows in the classical gravity model.

In this paper I build on the framework by Helpman, Melitz and Rubenstien (2008) (HMR) to theoretically and empirically explain what determines the significance of the extensive margin in the two-stage consistent HMR gravity model. Departing from the country level set-up used by HMR and Belenkiy (2008), I use industry level data. The motivation to use more disaggregated world-trade data stems from the puzzling finding by Belenkiy (2008). In that paper, I test the robustness of the main result put forth by HMR: while omission of the extensive margin and export selection corrections result in the biased estimates of the gravity model, the extensive margin correction is the most significant of the two when estimating the trade flows. Contrary to this result, I find that when the world-trade data is sliced such that theoretically the extensive margin should overwhelm export-selection (exporter is an OECD - Northern country) the extensive margin is not significant. This result generates the "North-South" puzzle that I seek to resolve.[4]

Unlike earlier industry level studies that only estimated the gravity model for manufacturing sectors,[5] I use the trade data for agriculture, mining and manufacturing - industries with theoretically diverse firm structure. Looking at the industry level trade allows me to unmask the differences in the composition of exports that are hidden at the country level. Almost any country that is open for trade will export some fraction of goods that are produced in the different environments: from the monopoly and monopolistic competition to perfect competition. The degree of firm competition brings about different predictions about the role of the extensive margin in the trading relationships. On one hand, if the industry is characterized by competitive production, the differences among exporters will not matter, as any importing country will look for the lowest-priced exporter. Empirically, this implies that the extensive margin correction in the gravity model should not be significant. On the other hand, looking at the trade in industries where firms have monopoly power and thus considerable differences in productivity, the extensive margin should play a large role in explaining the trade flows.

[4] In any exporter-importer region pair the North collectively consists of OECD countries as of 1986, while the South consists of developing (non-OECD) countries.

[5] See for example Chaney (2006), Manova (2006), Johnson (2007).

To understand the role of the extensive margin in explaining the industry trade flows, I derive the measure of the extensive margin in the HMR model, and determine its empirical significance. I apply a combined HMR (2008) model with an aggregation mechanism found in the Melitz (2003) model and the industry related set-up of Manova (2007) to characterize an industry level trade. The key difference in my set-up is to assume that the elasticity of substitution between varieties is same within any industry, but different across these industries. The magnitude of the elasticity of substitution determines the production environment in each of these industries: in the industries with low elasticity of substitution there is monopolistic competition and in the industries with high elasticity of substitution there is perfect competition. In this study I attribute manufacturing to the monopolistic competition, agriculture and mining to a perfectly competitive production environment.[6]

My empirical framework is essentially an HMR two-stage consistent gravity model that controls for the extensive margin and export selection, in addition to fixed and variable trade barriers. I estimate this model for each of three industries to implicitly control for the production structure. The goal of each estimation is two-fold. First, I test whether the estimates of the extensive margin correction is significant for manufacturing and less so for mining and agriculture. As in Belenkiy (2008), I slice the industry trade data into region of exporter-importer origin to determine whether the "North-South" puzzle can be resolved at more disaggregated level. Second, I observe whether there is a strong upward bias in the elasticities of trade barriers with a respect to trade flows as suggested in earlier literature. In addition, following Silva et al. (2006) who argue that the strong upward bias in the elasticity estimates is just a result of heteroskedasticity in the error term of the gravity model that is estimated using log of trade volumes, I estimate the industry level Poisson models with trade volumes expressed in levels.[7]

This paper makes a number of contributions to the growing literature on empirical international trade with heterogeneous firms. First, I show that the extensive margin correction in the two-stage gravity model must be significant for trade in manufacturing, and insignificant for mining and agriculture. This analysis allows resolving "North-South" puzzle, and indentifying the necessity to control for the extensive margin in the gravity model. In particular, when the extensive margin correction is not significant, there is no need to estimate the gravity model using HMR two-stage method. Second, disaggregating world trade flows into three distinct industries, rather than focusing on various sectors in one industry, captures on average behavior of the exporting firms that is often mistreated in the related studies. For example, using only manufacturing sectors, it is not clear what drives the identification in the gravity model, as the number of zeros in the trade matrix of each sector will be very large, and the quality of the data in the developing countries will be particularly poor. Moreover, there are no trade models that can predict which manufacturing sectors a country should specialize in, though on average the pattern of trade in each distinct

[6] The production environment here means the differences in technology required to produce a unit of any variety. Since both agricultural and mining varieties are produced relatively similar, the firms in these industries are not likely to greatly differ in productivity from each other.

[7] See also Westerlund and Wilhelmsson (2006) for a similar study.

industry can be identified according to the comparative advantage. Third, this paper establishes complementarity between the implications of firm-level heterogeneity theory and pure econometrics methodology for the gravity model estimation.

To preview my results, I find that consistent with theoretical insights, the extensive margin correction is strongly significant for manufacturing and not significant for agriculture and mining in all estimated specifications. The export selection correction primarily matters for agriculture. This latter result allows resolving the "North-South" puzzle at the industry level: the extensive margin is a significant determinant of trade for the Northern manufacturing exporters alone. Thus, using the trade data at an aggregate level confounds the significance of the extensive margin by mixing the industries. Moreover, when the extensive margin is not a significant determinant of the trade flows, the estimated elasticities of the trade barriers with a respect to trade volume are not substantially overestimated as compared to the benchmark gravity model. In particular, only for manufacturing do I find strong upward bias in these estimates. As a robustness check, I apply the Bayesian estimation techniques to firm-level data by industry, and find that the manufacturing ranks first in the degree of firm-level heterogeneity followed by mining and agriculture. I use this result to confirm the predictions of the main estimation model. Finally, using two-stage HMR model and Poisson gravity model estimated by Silva et al. (2006), I find that the estimates on distance elasticities using the Poisson model are only substantially lower for manufacturing and are almost the same for agriculture as compared to the classical gravity model.

This paper is organized as follows. In Section 2, I derive the measures of the extensive and intensive margins at the industry leve,l and identify when the extensive margin should be important for the industry trade flows. Section 3 describes the empirical framework, while Section 4 describes the data used for the estimates as well as some of its silent features. Section 5 presents the main estimation results. In particular, in section 5.2 I discuss how the "North-South" puzzle is resolved. In Section 6, I discuss the relationship between the shape parameter that determines the distribution of firm-sales by industry and the ways to estimate this parameter. In addition I estimate the Poisson gravity models and offer the intuition of complementarity between Poisson and HMR estimates. Section 7 than concludes. The details of various methodologies are given in the Appendix. The Appendix is followed by the tables with estimation results and figures.

2 Extensive and Intensive Margins in the Industry Trade

2.1 The Measure of Extensive Margin

To obtain the measure of the extensive margin, I calculate the aggregate number of exporters from any country j in the industry s. To focus primarily on the exporting behavior of firms (HMR) aggregated to industry level (Manova (2007)), I apply the now familiar monopolistic competition Melitz (2003) model with heterogeneous firms . This model has the following features:

Demand:

The demand $q_{sj}(l)$ for any variety $l_s \in B_{sj,}$ where B_{sj} is a set of the available varieties produced by any industry s and country j, is derived from the CES utility:

$$U_j = \prod_s Q_{sj}^{\theta_s}, Q_{sj} = \left[\int_{l_s \in B_{js}} q_{sj}(l)^{\alpha_s} dl \right]^{1/\alpha_s}, 0 < \alpha_s < 1, 0 < \theta_s < 1.$$

The parameter α_s determines the elasticity of substitution across products available from the industry s, which is constant and defined as $\varepsilon_s \equiv \frac{1}{1-\alpha_s}$. I assume that it is the same within, but different across each industry s. Given the parameter restrictions on α_s, $\varepsilon_s > 1$. The parameter θ_s determines the share of each industry s in the total expenditure and satisfies $\sum \theta_s = 1$.[8] Using this set-up, the demand, $q_{sj}(l)$ is:

$$q_{sj}(l) = \frac{p_{sj}(l)^{-\varepsilon} \theta_s Y_j}{P_{sj}^{1-\varepsilon}} \text{ with } P_{sj} = \left[\int_{l_s \in Bs_j} p_{sj}(l)^{1-\varepsilon_s} dl \right]^{1/(1-\varepsilon_s)}, \tag{1}$$

where $p_{sj}(l)$ is the price of variety l produced in the industry s and country j , Y_j is the an income(expenditure) in country j and P_{sj} is the country's j ideal price index in the industry s.

Production for exports:

Following HMR, assume that a firm in the industry s and country j produce a variety with a cost-minimizing combination of inputs $c_{sj}a$, where c_{sj} is the cost of input bundle that is industry and country specific, and a is marginal cost of producing one unit of output. The inverse of the marginal cost $(1/a)$ is a productivity level of a firm: a firm with lower marginal cost is more productive. The productivity level is drawn from a truncated distribution with CDF $G(a)$ that is common to all industries. This distribution has the support $[a_H, a_L]$ such that $a_H > a_L > 0$. Labor is the only factor of production. The total supply of labor in country j available for any industry s is L. For convenience, I normalize the wage paid to 1.

To export from country j to country i a firm in country j incurs fixed costs of exporting $c_{sj} f_{ij}$. In addition, assuming "iceberg" type cost, $\tau_{ij} > 1$ units of a variety l_s must be sent to the country i for one unit to arrive.[9] Thus, the total cost of exporting a unit of variety for a firm in an industry s and country j, to a country i is:

$$C_{i,sj} = \tau_{ij} c_{sj} a + c_{sj} f_{ij.} \tag{2}$$

In the industries that are characterized by low elasticity of substitution ε_s the producing firms vary by productivity, and have a degree of monopoly power that is reflected in the price mark-up. The firms in these industries take the residual demand (1) as given, and choose a price to maximize profits. This yields a standard mark-up over marginal cost price charged by an exporter from an

[8] In my empirical analysis this parameter plays no role, as I do not include industry fixed effects in my estimating model. It is included here for expositional purpose.

[9] Both fixed and "iceberg" costs are same across industries.

industry s and a country j for a delivered variety in a country i :[10]

$$p_{sij}(l) = \frac{\tau_{ij} c_{sj} a}{\alpha_s}. \tag{3}$$

As in Melitz (2003) and Manova (2007), using the demand (1), the cost function (2) and the pricing rule (3), I obtain the importer quantity demanded in country i, revenues of the exporting firms in the industry s, and country j, and profits of these firms conditional on being an exporter respectively:

$$\begin{aligned} q_{sij}(a) &= \left(\frac{\tau_{ij} c_{sj} a}{\alpha_s}\right)^{-e_s} \frac{\theta_s Y_i}{P_{si}^{1-\varepsilon}}; r_{sij}(a) = \left(\frac{\tau_{ij} c_{sj} a}{P_{si}\alpha_s}\right)^{1-e_s} \theta_s Y_i; \\ \pi_{sij}(a) &= (1-\alpha)\left(\frac{\tau_{ij} c_{sj} a}{P_{si}\alpha_s}\right)^{1-e_s} \theta_s Y_i - c_{sj} f_{ij.} \end{aligned} \tag{4}$$

A firm will only find it profitable to export if it can at least break even by earning zero profits. Setting $\pi_{sij}(a) = 0$, I obtain the minimum productivity level $\gamma^*_{sij} \equiv 1/a^*_{sij}$ required for the selection into the export market. This productivity level satisfies $r_{sij}(a^*_{sij}) = \varepsilon_s c_{sj} f_{ij}$, and is equal to

$$\gamma^*_{sij} = \beta \left[\frac{\varepsilon_s c_{sj} f_{ij}}{\theta_s Y_i}\right]^{\frac{1}{\varepsilon_s - 1}} \left[\frac{\tau_{ij}}{P_{si}}\right], \tag{5}$$

where β is a selection of the constant parameters[11].

The expression for minimum productivity cut-off (5) depends on fixed and variable costs of exporting, the price index in the importing country, and the size of the import market and elasticity of substitution between products across industries s. All of these quantities affect the number of exporting firms and thus define the extensive margin of trade. First, the export productivity cutoff increases both in fixed and variable costs. This implies that high costs of exporting result in a lower number of trading partners. Second, the export cut-off falls with the size of the import market - sales are larger in the larger markets. Third, when the elasticity of substitution rises (correspondingly, mark-up over marginal cost falls), the export cut-off rises, and fewer firms are able to export. These firms will not substantially vary in productivity. They will export homogeneous varieties charging a competitive price, so that any differences in prices imply that only lowest priced exports will be sold. In the extreme case, when, the elasticity of substitution between varieties in industry s approaches infinity (the mark-up is close to zero) no firms will be able to cover the fixed costs, thus be precluded from exporting. In this case the extensive margin will not be a significant determinant of the trade flows.

To further explore the relationship between the extensive margin and the elasticity of substitution, applying the aggregation mechanism as in Melitz (2003), I find that the number of firms in

[10] This pricing rule implies that the mark-ups may vary by industry, but they are constant within the industry.

[11] More specifically $\beta = \alpha_s / c_{sij}$.

an industry s, and a country j, exporting to a country i is[12]:

$$N_{sij} = \frac{L}{\varepsilon_s(\overline{\pi}_{sij} + c_{sj} f_{ij.})}, \tag{6}$$

where $\overline{\pi}_{sij}$ is an average profits of the exporters in the industry s.

The number of exporters depends inversely on both the elasticity of substitution ε_s, across industries, and fixed costs of exporting f_{ij}. Importantly, in the industries where the elasticity of substitution is higher, the number of exporters is lower for the same level of fixed costs. Consider the firms from any two industries that face same fixed costs of exporting, but the elasticity of substitution is high in one industry (e.g. agriculture) and low in the other industry (e.g. manufacturing). In this case, in the industries where the elasticity of substitution between varieties is high, the extensive margin impact on the trade flows will be minimal. Conversely, the impact of the extensive margin on the trade flows will be high if the varieties exported by firms in that industry have a low elasticity of substitution. These observations are summarized in Proposition 1:

Proposition 1 *The number of exporters (the extensive margin of trade) from country j to country i in an industry s (N_{sij}), is inversely proportional to the elasticity of subtitution, ε_s - $\frac{\partial N_{sij}}{\partial \varepsilon_s} < 0$. In the industries where the elasticity of substitution is low the number of different exporters is high, implying that the extensive margin of trade should be a significant determinant of the trade flows. The opposite holds true for the industries where the elasticicity of substitution is high.*

The intuition for the proposition 1 can be gained from Figure A. Assuming the Pareto distribution of firms export sales, this figure plots the tails of the respective distributions of firms in the agriculture and manufacturing industries.[13] Given that the elasticity of substitution between varieties is higher in the manufacturing industry, for the same level of fixed costs the minimum productivity cutoff required to select into exporting is lower for firms in that industry as compared to agriculture and mining. This implies that the number of different exporters will be highest in the manufacturing industry and lowest in agriculture. Moreover, the lower export cutoff for the number of exporting firms in manufacturing results in bigger trade volume as compared to the trade volume for agriculture. This is represented by the shaded area to the right of the productivity cutoffs for each respective industry. With an assumption that each firm produces at most one variety for exports, Figure A show a direct link between the extensive margin (number of exporters) and the intensive margin (trade volumes per exporter): a higher number of different exporters implies larger variation in the aggregate trade volume by industry. For the manufacturing industry, I expect to have a fewer number of zeros in the trade matrix, and higher trade volume, which means that the extensive margin must play a more important role in correcting the upward bias in the gravity model as compared to agriculture. As shown in the empirical sections to follow, proposition 1 will

[12] This is same as in Melitz (2003) but with domestic fixed costs set to 0. See Appendix A for the detailed derivation.

[13] These distributions are simulated using estimated shape parameters using Monte Carlo method. Please see Section 6.1 for more details.

be helpful in explaining an apparent puzzle, the insignificance of the extensive margin in trade between the North and South, which was a highlight finding by Belenkiy (2008).

2.2 The Measure of Intensive Margin

The intensive margin of trade measures the volume of trade per exporter. The measure of the intensive margin forms the estimating gravity equation. Following HMR (2008), define the bilateral trade volume for exporters in country j and industry s as:

$$V_{sij} = \begin{cases} \int_{\gamma^*_{sij}}^{\gamma^H_{sij}} \gamma_{sij}^{\varepsilon_s - 1} dG(\gamma_{sij}) & \text{for } \gamma^H_{sij} \geq \gamma^*_{sij} \\ 0 & \text{otherwise} \end{cases}. \tag{7}$$

Using this expression, the aggregate value of country's i imports of varieties produced by firms in industry s and country j is:

$$M_{sij} = p_{sij}(l) q_{sij}(l) \theta_{is} Y_i N_{sj} V_{sij}.$$

Substitution of the appropriate expressions for price (3), demand (1), and export volumes (7) in terms of unit costs a gives:

$$M_{sij} = \left(\frac{c_j \tau_{ij}}{\alpha P_i} \right)^{1-\varepsilon_s} \theta_{is} Y_i N_{sij} V_{sij}, \tag{8}$$

where N_{sij} is given by (6), θ_{is} is a share of expenditures on the imports from industry s in country i, and P_i is an ideal price index in a country i. An expression for the aggregate value of imports (8) is a measure of the intensive margin as it gives the volume of trade for all exporting firms in the industry s. Importantly, the measure of the intensive margin does not depend on the fixed costs of entry f_{ij}, whereas these costs negatively affect the extensive margin (6). Thus, the fixed costs only affect the decision to select into the export market (affecting the extensive margin) and have no affect on the trade volume.

3 Empirical Design

In this section, I develop an empirical framework to test the prediction of Proposition 1: the measure of the extensive margin should be most significant for the industry with lowest elasticity of substitution. In addition, the assumption that elasticity of substitution is constant within any industry implies that there is going to be no variation in elasticities in estimating any pooled across-industries specification. My empirical design is strictly based on the two-stage model used by HMR (2008) and adopted by Belenkiy (2008). I choose three industries with low to high elasticity of substitution respectively: manufacturing, mining and agriculture. For each of these industries, I separately estimate the two-stage HMR (2008) model. Thus, unlike previous empirical studies that focused primarily on estimating the gravity model with pooled manufacturing data using industry fixed effects,[14] here I estimate the corrected gravity model for each industry in isolation. The advantage of this approach is it allows me to capture an average export behaviour of the exporting firms in each industry according to the patterns of comparative advantage. In addition, the estimates on the extensive margin can be ranked among these industries.

3.1 Gravity Specification

Following HMR (2008), I begin by obtaining the basic estimating gravity equation. Log-linearizing the expression for the intensive margin (8), I get:

$$m_{sij} = (\varepsilon_s - 1)\ln\alpha - (\varepsilon_s - 1)\ln c_{sj} + n_{sj} + (\varepsilon_s - 1)p_i + \ln\theta_{si} + y_i + (1-\varepsilon_s)\ln\tau_{ij} + v_{sij}. \tag{9}$$

I estimate this specification for each of the three industries: manufacturing, mining and agriculture. As the theoretical model suggests, the export volumes are affected by the number of exporters. The number of exporters in turn depends on the productivity cut-off γ^*_{sij} - the lower the cut-off the higher are the export volumes (7).

To obtain the appropriate control for the fraction of exporters (possibly zero), I assume that level productivity in each industry s ($\gamma_s \equiv 1/a_s$), has truncated Pareto distribution:[15] $G(a) = (a^{k_s} - a_L^{k_s})/(a_H^{k_s} - a_L^{k_s})$, where $k_s > (\varepsilon_s - 1)$ is a shape parameter of this distribution that varies by industry. Using the CDF of the truncated Pareto distribution, the expression for trade volumes (7) can be written as:

$$V_{sij} = \frac{k_s a_L^{k_s-\varepsilon_s+1}}{(k_s - \varepsilon_s + 1)(a_H^k - a_L^k)} W_{sij}, \text{ where } W_{sij} = \max\left\{\left(\frac{a_{sij}}{a_L}\right)^{k_s-\varepsilon_s+1} - 1, 0\right\}. \tag{10}$$

The relationship between export volume and the extensive margin in industry s can be seen through the W_{sij} term in (10). This term indentifies the selection of firms in an industry s involved in exporting. The higher the level of productivity, a_{sij}, the higher the export volume, V_{sij}, of the varieties produced by firms in an industry s. However, the higher is the elasticity of substitution, ε_s, the lower are the export volume, V_{sij}. That is, for manufacturing industry, it is much less likely to observe zero trade flows between any trading partners as compared to agriculture. In addition, the export volumes are directly proportional to the shape parameter, k, in the truncated Pareto distribution. Using (10) and letting $\tau_{ij}^{\varepsilon_s-1} \equiv D_{ij}^{\gamma} e^{-u_{ij}}$, where D_{ij} represents the symmetric distance between i and j, the gravity model (9) for a specific industry, s, becomes:

$$m_{sij} = \beta_0 + \lambda_j + \chi_i - \gamma_s d_{ij} + w_{sij} + u_{ij}, \tag{11}$$

where $\lambda_j = -(\varepsilon_s - 1)\ln c_{sj} + n_{sj}$, and $\chi_i = (\varepsilon_s - 1)\ln\alpha + \ln\theta_{si} + y_i$ are exporter and importer

[14] For example, see Chaney (2006), Manova (2007) and Johnson (2008).

[15] As discussed by HMR (2008), the choice of the truncated distribution allows to induce zero and asymmetric trade flows (such that country j exports and country i does not) between trading partners.

fixed effects respectively that are measures of trade resistance between trading partners as shown by Anderson and van Wincoop (2003). The error term is u_{ij} ˜$N(0, \sigma_u^2)$. In the specification (11), I do not have industry fixed effects, as I estimate this specification for each industry separately.

As discussed by HMR (2008) failure to control for the number of exporters in the basic gravity model leads to biased estimates on the effects of trade barriers on trade volume. The expression for the trade volume (10) depends on the number of exporters - higher number of exporters (extensive margin) implies higher trade volumes of varieties from any industry s. However, the extensive margin is negatively correlated with trade barriers in the gravity model. Thus, omitting a control for the extensive margin, w_{sij}, leads to overestimation (upward bias) of the effect of trade barriers on the trade volume ($\widehat{\gamma}$). In addition, there is a selection bias in the estimated gravity model if zero-trade pairs are excluded. This bias is likely to lead to underestimation (downward bias) in the estimate of $\widehat{\gamma}$, since the export countries with large observed trade costs are likely to have low unobserved trade costs. HMR (2008) claim that it is the failure to control for the extensive margin and not the selection explains all the biases in estimating the standard gravity model. Even though this conclusion can be challenged at the country level,[16] the results of this paper show that HMR methodology generates correct predictions of the role of the extensive margin in explaining trade flows at the industry level.

3.2 Two-Stage Model

To estimate the corrected gravity model (11) for endogenous number of exporters , I apply two-stage estimation methodology derived by HMR (2008).[17] Since the differences in productivity of the potential exporters are not observable, but the non-zero trade flows are, first define the latent variable, Z_{sij} (A4), as a ratio of the productivity of the most productive firm, $1/a_L$, to the cut-off productivity for exporting. Whenever $a_{sij} > a_L$, and $Z_{sij} > 1$ - a firm in the industry s is productive enough to select into exporting. The selection equation is a Probit specification (A6), which estimates the probability of selecting into exporting, conditional on the observed fixed and variable trade barriers. Using the estimates of the predicted probability of exporting, it is possible to obtain the consistent estimate of the extensive margin (A8).

The consistent estimate of the extensive margin, (A8), along with a control for non-random export selection (Heckman) correction, can be substituted in the gravity model (11) to obtain the final consistent estimating gravity model for each industry s:

$$m_{sij} = \beta_0 + \lambda_j + \chi_i - \underbrace{\gamma_s d_{ij}}_{\text{Intensive Margin}} + \underbrace{\ln\{\exp[\delta_s(\widehat{z}^*_{sij} + \widehat{\overline{\eta}}^*_{ij})] - 1\}}_{\text{Extensive Margin}} + \underbrace{\beta_{u\eta}\widehat{\overline{\eta}}^*_{ij}}_{\text{Non-Random Selection}} + e_{ij}, \quad (12)$$

where γ_s the elasticity of the variable trade barriers with respect to trade volume, m_{sij}, between the

[16] See Belenkiy (2008) for a details.

[17] In the following discussion, I refer to Appendix A2 for the relevant equations.

exporter in industry s, in country j, and importer, i; δ is non-linear parameter that measures the combined effect of the firm-level heterogeneity and non-random sample selection on trade volumes; $\beta_{u\eta}$ is a parameter controlling for non-random export selection, and λ_j, χ_i are the exporter, importer fixed effects respectively. Since this specification is non-linear in δ_s, I estimate this model using MLE, with normality assumption on the error term e_{ij}, which is i.i.d. and satisfies $E[e_{ij}|., T_{sij}] = 0$. The significance of the extensive margin correction in (12) depends on the magnitude and sign of $\widehat{\delta}_s \equiv \sigma_{s\eta}(k_s - \varepsilon_s + 1)/(\varepsilon_s - 1)$. For the agricultural industry the elasticity of substitution, ε_s, is high, which implies that $\widehat{\delta}_s$ will be small, while the opposite will hold for the manufacturing industry. As $\varepsilon_s \to \infty$, $\widehat{\delta}_s \to 0$, and therefore, the extensive margin will not be important in explaining the trade volumes. For some values of ε_s, the estimate of δ_s may be statistically non-zero, but small enough so that it becomes negative. In addition, the estimate of $\delta_s$contains an important relationship between the shape parameter in the Pareto distribution, k_s, and the measure of the extensive margin.[18]

4 Data

In my empirical analysis, I estimate the gravity model for a cross-section of the world trade flows for manufacturing, mining and agricultural industries separately to eliminate the effects of different production environments that are present when the trade data is pooled across all industries. This estimation requires industry level trade data, as well as appropriate measures of the trade barriers.

The data to estimate the main gravity specification (12) comes from two sources: Feenstra's NBER-United Nations Trade Data, 1962-2000 for 1986, and HMR's constructed variable and fixed trade barriers data set.[19] NBER-United Nations Trade Data contains bilateral trade volume by commodity according to SITC-4 classification. The large number of zeros in the trade matrix associated with fairly disaggregated 4-digit data will not allow me to appropriately identify the gravity model for sub-sectors in these industries. To overcome this issue, I aggregate the trade data to 1-digit SIC level. This process requires a careful matching of commodities within 4-digit to 1-digit aggregate industry groups. The final estimating data sets are obtained by merging 1-digit SIC data with the HMR data for 158 countries . This gives me three data sets to estimate the gravity model for each of the three industries with 24,806 observations for the World-World trade.[20] The consequence of splitting the data by industry yields far more zeros in the trading relationships in agricultural and mining industries compared to the manufacturing industry. The list of all countries can be found in Tables A1 and A2.

The descriptive statistics in Table 1 (A-C) help in explaining the "North-South" trade puzzle. Table 1(A) highlights the extent of zeros in the World-World trade matrix by industry in 1986. The number of zero trade flows in the respective matrices for each industry plays an important role

[18] See section 6 for details.

[19] These trade barriers are constructed from the country level-data and come from the three sources: the Penn World Tables, the World Bank's World Development Indicators and the CIA'S World Factbook.

[20] Agriculture - SIC 0; Mining -SIC 1; Manufacturing - SIC 2,3. World-World trade implies no particular location for the trading partners pair.

in the model identification. If the number of zeros is too small, it is not possible to separate the effects of the extensive margin and non-random selection corrections on the trade flows. In this case, both effects may be insignificant or have incorrect signs. The same scenario might occur if the number of zeros is too large. In this case, the trade data points could be too sparse, resulting in a low or insignificant correlation between these corrections and the trade flows. The former problem is relevant for estimating the gravity model at the country level, while the latter problem can arise from using disaggregated sector data within any industry. The largest number of zeros is found for mining followed by agriculture and manufacturing.[21] This suggests that the selection effect will be highest for agriculture and mining and less so for manufacturing. This is consistent with the idea that in the industries like agriculture and mining the selection effect must be more important in explaining the trade flows as compared to adjustment on the extensive margin.

In Table 1(B), I calculate the fraction of zeros in the trade matrix by industry and region of origin of trading partners. In particular, consider the North-South trading region. While the largest fraction of exports from the North to South is in manufacturing products where the extensive margin correction should be most important for a consistent gravity estimation, exports in mining and agriculture together account for 47 percent of this region's pair trade. However, for these industries the fraction of zeros in the trade matrix is very large (79 percent for mining and 71 percent for agriculture), which implies that the extensive margin correction is far less important than export selection. This finding suggests that when one applies HMR methodology using country level data, the extensive margin correction appears to be non-significant in the gravity estimation for North-South trade. For this trading region pair this result can be explained by export selection correction overwhelming the extensive margin when country level trade data is used.

In Table 1(C), I calculate the number of trading partners for the top three exporting countries and the median exporters by industry. Interestingly, the top three exporters in each industry are developed countries that are in the North group, while the median exporters are developing countries in the South group. The top exporter in agriculture is the Netherlands with 144 non-zero trading partners, while Uganda has only 22. A similar pattern applies to mining and manufacturing. Thus, it appears that since the trade from the Northern countries dominate the Southern trade regardless of the industry, the importance of the extensive margin can be muted at the country level HMR's estimation.

5 Significance of the Extensive Margin in the Data

In this section, I estimate the gravity model (12) to test whether the estimation results are in accord with the prediction of proposition 1: the extensive margin must be most significant for the trade flows in the industry with low elasticity of substitution between varieties. Moreover, it is of interest to verify the direction of bias when the extensive margin correction is omitted. Using

[21] Belenkiy (2008) finds this reasoning as an explanation of the insignificance of the extensive margin and non-random selection corrections for North-North trade.

country level data, HMR showed that extensive margin control in the gravity model corrects for the strong upward bias in the effects of trade barriers on trade volumes. However, the extensive margin correction is not always significant, generating the "North-South" puzzle. For this region pair, the estimates of gravity model (12) at the country level reveal the upward bias in the simple gravity model, but bias decomposition shows that extensive margin alone cannot explain this fact.[22] The stylized analysis of zeros in the trade matrix of each industry provided evidence that the significance of the extensive margin for the North-South region pair may be confounded at the country level by mixing up all the industries. The estimation results below confirm this conjecture.

5.1 World - World Industry Trade

I begin by reporting the results of estimating gravity model (12) when the location of the exporter does not matter. I estimate the gravity model for each of three industries to compare the significance of the extensive margin against the export selection and the ability of these corrections to explain the biases in the benchmark model.[23] Table 2 (A-C) gives the estimating results of the gravity model for agriculture, mining and manufacturing industries respectively. Column (1) in each of the Tables 2 (A-C) gives the estimates of the first stage Probit model (A7) that determines the probability of exporting for firms in each industry when they face the variable and fixed trade barriers. Compared to the benchmark estimates of column (2), it appears that the trade barriers that negatively/positively affect the trade volume also negatively/positively affect the probability of exporting of firms in all three industries, which confirms the validity of the first stage.

The main interest lies in the estimates of the two-stage corrected gravity model (12) in column (3). As argued by HMR (2008) and Manova (2006), the estimation of this two-stage model requires an exclusion restriction. The key requirement for a valid exclusion restriction is that this variable significantly affects the probability of the export selection, but it is not important once such a decision has been made (this variable is not correlated with second-stage estimated residuals). Moreover, this exclusion restriction must vary by industry.[24] For the three industries, the variable island satisfies the exclusion restriction requirement for agriculture, and a common religion does so for mining and manufacturing.

When comparing the estimates of the corrected two-stage model in columns (3) to the benchmark estimates in columns (2) for all three industries, the estimates for both variable and fixed trade barriers are overestimated in the benchmark model, but substantially so only for manufacturing. For example, the distance is overestimated by over 1 percent for manufacturing and only 0.05 percent for agriculture. Moreover, for the manufacturing industry exports, the elasticity of distance barrier is significantly greater than 1 (-1.5) even when the extensive margin correction is applied. This result suggests that compared with agriculture and mining, distance is much larger

[22] See Belenkiy (2008) for these estimates

[23] A benchmark model is a classical gravity equation (without any corrections) of type: $m_{sij} = \beta_0 + \lambda_j + \chi_i - \gamma d_{ij} + u_{ij}$, where all the variable as previosly defined.

[24] These variables can potentially affect exports form each industry equally, but since I estimate the gravity model for each of these industries separately this requirement can be relaxed.

impediment to trade for exporters in the manufacturing industry. Since the distance raises the productivity threshold to select into exporting the large effect of distance on trade volume for manufacturing implies significant importance of the extensive margin correction in the gravity model for this industry.[25] On one hand, for manufacturing with the largest upward bias among the three industries, the extensive margin correction is both large in magnitude and significance, whereas the non-random selection correction is not significant. On the other hand, for both agriculture and mining the extensive margin correction is either insignificant or much smaller in magnitude as compared to export selection. This analysis provides support for proposition 1: the extensive margin correction is strongly significant for the manufacturing industry where varieties have low elasticity of substitution and, insignificant or smaller in the mining and agriculture industries where the elasticity of substitution between varieties is high. Moreover, in agriculture, where the export selection correction is most relevant, the classical gravity OLS model estimates do not differ substantially from two-stage corrected gravity model.

To further understand the role of each correction in explaining industry trade flows, I estimate two additional specifications. First, I estimate the gravity model (12) without non-random selection correction. This estimation allows me to gauge the full effect of the extensive margin. If proposition 1 holds true, this correction alone must be strongest in manufacturing. Second, I estimate (12) controlling only for non-random selection. This correction should be most important for agriculture and mining. In addition, this bias decomposition allows verifying of the direction of the biases in the benchmark gravity model as predicted by HMR. The extensive margin correction must correct for the upward bias in the benchmark model, while non-random selection must correct for the downward bias.

The bias decomposition estimates for three industries are shown in Table 3 (A-C). It is apparent that for all three industries the HMR argument holds: the estimates of the trade barriers with respect to trade volume are overestimated in the benchmark model (column 1). However, the extensive margin correction explanation for this bias does not hold uniformly across all industries. Consider the bias decomposition for agriculture (Table 3 (A)). This industry is characterized by high elasticity of substitution between the exported varieties. Consistent with a prediction of proposition 1, the extensive margin correction, $\widehat{\overline{z}}^*_{rij}$ (-0.089), is not a significant determinant of the trade flows. Moreover, this estimate is negative, which is consistent with fact that a high elasticity of substitution can result in the negative estimate of the extensive margin correction. On the other hand, the non-random selection (Heckman) correction is significant in both the two-stage (column 2) and decomposed model (column 4). HMR predict that non-random selection correction alone underestimates the true effect of the trade barriers on the trade flows, as reflected in the distance coefficient in column 4 being larger than the same estimate in columns 2 and 3. However, I cannot reject the null hypothesis that the estimates on distance are statistically different for both corrections. Thus, even though the two-stage model corrects for the *upward* bias, it is the export selection correction that matters in explaining the trade flows for agriculture industry.

[25] This can be seen from the expression for minimum productivity level γ^*_{sij} (5)

For the manufacturing industry (Table 3 (C)) the results are opposite. While the two-stage model estimates show that the coefficients on the trade barriers are overestimated in the benchmark model, it is now the extensive margin that corrects for this upward bias. These results support proposition 1, and confirm that for the manufacturing industry trade data the HMR model works as expected, while for agriculture the extensive margin correction is not necessary.

5.2 "North-South" Puzzle

In trying to explain the "North-South" puzzle, I slice the industry trade data such that the exporter from each industry is a Northern (OECD) country and the importer is a Southern (non-OECD) country.[26] Similar to Belenkiy (2008), I estimate the gravity model (12) for the North-South region,[27] obtain bias decomposition and check whether at the industry level the estimates are consistent with proposition 1: the extensive margin correction must be most significant for exports from manufacturing industry for this region pair.

I begin with a check of consistency between the original HMR data set and the industry level data for the North-South region. I aggregate the industry level data to the country level by adding the non-zero export volume for each exporter by industry. This aggregation results in 2275 non-zero observations, 700 less than in HMR's country level data set for this region pair. This discrepancy can arise from not exhaustively using all producing industries in each country. To make these data sets comparable, I restrict the HMR data for North-South to having only 2275 non-zero observations. I estimate gravity model (12) and perform bias decompositions for each of these data sets. These estimates are reported Tables 4 and 5 respectively. Comparing the estimates from these tables, I first observe that even after matching non-zero observations between both data sets, the estimates of the two-stage gravity model and bias decomposition specifications, while close to each other in magnitude, are not the same in statistical significance. This suggests for a possible measurement error between the data sets. Second, the upward bias in the elasticity estimates remains in the both benchmark models. Third, once the data is aggregated, the estimates in Table 4 reveal the presence of the "North-South" puzzle: the extensive margin correction (column (2)) $\widehat{\delta}$, is not significant and the non-random selection is much larger in magnitude in the bias decomposition (columns (3) and (4)). The estimates in Table (5) are somewhat surprising. In the bias decomposition using HMR unrestricted country level data, Belenkiy (2008) finds that the extensive margin correction is not significant, but non-random selection is. With restricted data, the significance is reversed. However, the estimate of the extensive margin in two-stage model (column (2)) is barely significant and small compared to non-random selection. Notwithstanding a possible measurement error from the dropped observations in the HMR country level data set, the estimates using aggregate industry data seem to be a valid benchmark comparison for the gravity estimates at the industry level.

Next, I estimate the gravity model (12) for each of the three industries. I report the estimating

[26] The OECD membership is up until 1986.

[27] The estimates for other three region pairs (N-N, S-N, S-S) are consistent with HMR model at the country level and are not discussed here.

results in Table 6 (A). Comparing the estimates across three industries, the non-random export selection is uniformly significant, but largest in magnitude for agriculture. The extensive margin correction is significant for all three industries, but as predicted it is largest for manufacturing. For the mining industry, the number of non-zero observations is rather small, generating a very small and economically negligible estimate for the extensive margin correction. The significance of the extensive margin correction for all three industries suggest, that at least for Northern exporters, the productivity differences matter even in the industries with high elasticity of substitution between the varieties. It is also important to note that both variable and fixed trade barriers appear to have the largest effect on the trade volumes for manufactures. For example, the distance elasticity is much larger than 1 for manufactures and below 1 for mining and agriculture. This perhaps is not surprising, as exporting of manufactured varieties is associated with substantial transportation costs as compared to agriculture and mining, even though these costs have been in decline recently.[28]Given the large effects of the trade barriers for manufacturing, these estimates suggest an important role for the extensive margin correction in explaining the trade flows for this industry.

To get a clear picture of the contribution of each correction in explaining the industry trade flows, I estimate bias decomposition specifications by industry for the North-South region pair. I report these estimates in Table 6 (B). To understand why the "North-South" puzzle arises at the country level, I focus on the estimates of each correction by industry. Consider the estimate of the extensive margin correction: it is only significant for manufacturing - an industry with low elasticity of substitution between varieties as predicted by proposition 1. The non-random selection correction is significant for agriculture and mining - industries that export relatively homogeneous varieties with little differences in productivity between the exporting firms. Thus, for the North-South trading pair, the HMR model seems to be verified by the data at the industry level. The fact that this model fails at the country level suggests that at the aggregate level the effect of the extensive margin on the trade flows is confounded as the result of pooling all industries with diverse production structure. Once the model is estimated separately for each industry the extensive margin appears to be significant for the manufacturing industry alone.

6 Additional Insights

6.1 The Empirical Role of the Shape Parameter k.

I now consider the empirical association between the shape parameter in the Pareto distribution and the magnitude of the extensive margin through its relationship with the elasticity of substitution. This analysis allows determining the importance of the extensive margin in explaining the trade flows by exploiting the differences in distribution of the firm level productivity within each industry.

It has been long recognized that the firm distribution can be well approximated by thick-tailed distribution families. In particular, with the firm-level heterogeneity in the productivity levels, only

[28] See Anderson and Wincoop (2004) for the survey of the trade costs.

a few firms will be of the highest productivity, and thus will be in the "tail" of the distribution. The most popular choice of fitting firm-level data is a Pareto distribution with the CDF of the following form:

$$F_s(a) = 1 - a^{-k_s}, \tag{13}$$

where k_s is a shape parameter to be estimated. In regard to this study, this specification is a departure from the bounded Pareto distribution of the productivity used by HMR to match the trade data. However, given the HMR specification, all the firms are at least productive enough to serve the domestic market. Since the estimation of the shape parameter k_s, for each industry s requires firm-level data, the availability of only US firm-level data means that with US being a relatively closed economy there is a sufficient mass of firms that serves the US market. Thus, with the US firm-level data, I do not need to bound the distribution from above. Differentiating (13) with a respect to a, I obtain the PDF of this distribution[29]:

$$f(a|k_s) = k_s a^{-(k_s+1)} da, \tag{14}$$

with $a \geq 1$ ($\beta = 1$) and the appropriate restrictions such that $k_s > 2$ and $k_s > \varepsilon - 1$.[30] As shown by Chaney (2008), the inverse of k_s measures the degree of heterogeneity in industry s. In addition, this second assumption ensures that in the equilibrium, the firm distribution of the has a finite mean.

One of the important implications of the Melitz (2003) model is that a more productive firm (smaller a) will be larger: it will have larger output and revenues and thus sales. This implication suggests that the firm-level productivity ($1/a$) can be proxied using the data on the ordered (largest first) firm sales by industry. That is, the firm-level sales in the industry s are Pareto distributed: $Sls_s \tilde{} Pareto(k_s, 1)$ with the following PDF:

$$f(Sls_s|k_s) = k_s Sls_s^{-(k_s+1)}. \tag{15}$$

In the Appendix B, I discuss the methodologies of estimating the shape parameter k_s, using US firm-level sales data by industry. Unlike the traditional rank-order regression approach, I use Bayesian techniques due to non-linearity in distribution of firm sales as shown in Figures 1-3.

There is an important relationship between the shape parameter k_s that defines the degree of firm-level heterogeneity in an industry s, and the extensive margin of trade, W_{sij}. The following proposition establishes this relationship:

Proposition 2 *The estimated extensive margin of trade (the number of the exporting firms) is*

[29] For any arbitrary random variable $\theta \tilde{} Pareto(\alpha, \beta)$, where α is a shape parameter and β is a scale parameter, the pdf of the Pareto distribution is:

$$f(\theta|a, \beta) = \alpha\beta^{\alpha}\theta^{-(\alpha+1)}.$$

The distribution for the unobserved productivity level is a special case with a scale parameter set to one.

[30] These restrictions imply infinitely large size firms, which cannot be found in the data. Hence the actual estimates of k_s could be less than 2.

directly proportional to the degree of the firm-level heterogeneity as determined by the inverse of the shape parameter k_s

Proof. The estimated fraction of the exporting firms in the industry s is given by (A8):

$$\widehat{W}_{sij} = \max\left\{ (Z^*_{sij})^{\widehat{\delta}_s} - 1, 0 \right\},$$

where $\widehat{\delta}_s \equiv \widehat{\sigma}_{s\eta}(\widehat{k}_s - \varepsilon_s + 1)/(\varepsilon_s - 1)$. To prove the proposition I calculate $\partial\widehat{W}_{sij}/\partial\widehat{k}_s$ and show that $0 < \partial\widehat{W}_{sij}/\partial\widehat{k}_s < 1$. This partial derivative is:

$$\frac{\partial\widehat{W}_{sij}}{\partial\widehat{k}_s} = \frac{\partial\widehat{W}_{sij}}{\partial\widehat{\delta}_s}\frac{\partial\widehat{\delta}_s}{\partial\widehat{k}_s} = \widehat{\delta}_s(Z^*_{sij})^{\widehat{\delta}_s - 1}\frac{\widehat{\sigma}_{s\eta}}{(\varepsilon_s - 1)}.$$

By construction, all parameters are positive. As the elasticity of substitution ε_s becomes larger, this derivative remains positive but it becomes smaller. High elasticity of substitution ε_s corresponds to the industries with more homogeneous firms, which implies a thinner tail in the Pareto distribution, and thus, higher k_s. Thus, with the larger shape parameter k_s the fraction of exporting firms $\widehat{W}_{sij}$ rises, but at the diminishing rate. ■

Proposition 2 implies that the distribution of firms within an industry s has a direct implication on the significance of the extensive margin in the gravity model (12). In industries that are composed of firms that produce a large volume of the differentiated products (e.g. manufacturing) the extensive margin of trade must play a significantly larger role in explaining trade flows than in the industries where there is little firm-level heterogeneity (e.g. agriculture). Proposition 2 is a complement to Proposition 1: as the elasticity of substitution rises the number of differential exporters in an industry s falls , which in turn by proposition 2 implies a higher value of the shape parameter k_s, and a lower degree of firm-level heterogeneity in that particular industry. Thus, the estimates of the shape parameter k_s can be used as a robustness check to the estimates of the extensive margin in the gravity model (12). If the predictions of Proposition 2 are correct, the estimate for the shape parameter k_s must be smallest for the manufacturing industry and largest for the agricultural industry. This in turn means the largest and smallest degree of the firm-level heterogeneity respectively.

To test proposition 2 I use COMPUSTAT firm-level data by industry for 1987. The COMPUSTAT data contains extensive characteristics of publicly traded firms according to 6-digit NAICS classification. In particular, the value of firm net final sales can be ranked, the largest value of sales first. As I argue in Appendix B, the measure of firm sales can be used as a good approximation to the firm productivity that is assumed to be drawn from the truncated Pareto distribution, and thus can be used to estimate the shape parameter in this distribution. To match the data used to estimate the main gravity equation, I aggregate the firm-level data to the 1-digit level. This aggregation gives 920, 77 and 7 observations for manufacturing, mining and agriculture industries respectively. It is apparent that a small number of observations, for agriculture in particular, means that the regression approach would not yield appropriate estimates for the shape parameter k_s. I use Bayesian techniques to overcome this problem.

The estimates of the shape parameter k_s for each of the three industries are reported in Tables 7 and 8. While I do not estimate the rank-size regression for agriculture due to data limitation, both estimation approaches confirm the relative ranking of the shape parameter k_s: the magnitude of the shape parameter rises as the industry becomes more homogeneous. None of the estimates are close to 2, which was the theoretical restriction on the parameter k_s.[31] The 95 % credible intervals in Table 8 for manufacturing and mining appear to be quite tight around the posterior mean, indicating a good distribution fit. Note that none of these intervals include the rank-size estimates for manufacturing and mining that are reported in the Table 7. Thus, it appears that rank-size methodology applied to the firm-level data produces underestimated parameters as there is significant non-linearity in rank-sales firm relationship. The parameter for the agriculture industry has very wide credible intervals and, thus is estimated imprecisely. Still, ranking the estimates of the shape parameter k_s for each industry, I find that $k_{mnfg} < k_{mng} < k_{agr}$, which implies largest degree of firm-level heterogeneity for manufacturing and smallest for agriculture. Thus, I find empirical support for Proposition 2: the estimated extensive margin must be most significant for the industry with smallest value of the shape parameter k_s, which appears to be manufacturing. This conjecture is consistent with the main estimation results discussed in the previous section.

6.2 Another Econometric Test

Even though there is a general consensus that the estimates in the classical gravity model are overestimated, there are multiple ways to explain this finding: from a pure econometrical standpoint as shown by Silva et. al (2006), and by using a theory to derive the consistent estimating gravity equation (HMR (2008)). Silva et. al (2006) argue that when the model is estimated using logarithm of trade flows rather than levels, the upward bias in the gravity model is associated with large heteroskedasticity in the error term. HMR (2008) estimates log gravity relationship, but with extensive margin and export selection correction. HMR is also able to show the upward bias in the gravity estimates. It is of interest now, whether these two methodologies are substitutes or complements. Using the industry level data, I find the latter: for the manufacturing industry the estimates of the elasticities of trade barriers with a respect to trade volume in the classical gravity model are substantially overestimated, but they are barely overestimated for agriculture.

Recall that in the classical gravity model the extensive margin correction derived by HMR appears as an omitted variable. This variable is shown to generate an upward bias in the estimates of the classical model as the number of exporters is negatively correlated with the trade barriers and is an important determinant of the trade volume. According to Proposition 2, the extensive margin is directly proportional to the degree of the firm-level heterogeneity. A statistically larger degree of firm-level heterogeneity implies that the error term in the classical gravity model has a

[31] Using rank-size regression on the Compustat data for the US firms Chaney (2008) finds the shape parameter k to be around $0.7 < 2$.

larger variance and by definition is more heteroskedastic. Applying Silva et. al (2006) results to this reasoning, it appears that estimating the classical gravity in log form will result in a larger overestimation of the elasticities of trade barriers with respect to trade volume for manufacturing as compared to agriculture. That is, the econometric reasoning of Silva complements the theoretically derived two-stage gravity model by HMR.

Following Silva et. al (2006), I apply the Poisson pseudo-maximum-likelihood (PPML) estimation technique to industry level data used for the main estimation. I drop the extensive margin and export selection corrections from (12) and use the Poisson regression to estimate the following gravity model:

$$M_{sij} = \exp(\beta D_{ij} + \lambda_j +, \chi_i) + e_{ij}, \tag{16}$$

where D_{ij} is a vector of trade barriers, M_{sij} is a trade volume between the exporter in industry s in country j and importer i expressed in *levels*; λ_j, χ_i are the exporter, importer fixed effects respectively and e_{ij} is an error term satisfying $E[e_{ij}|,..,D_{ij}] = 0$. The model (16) is estimated assuming that the conditional variance $V[M_{sij}|D_{ij}]$ is proportional to the conditional mean $E[M_{sij}|D_{ij}]$ i.e. $V[M_{sij}|D_{ij}] \propto E[M_{sij}|D_{ij}]$. To take a full account of heteroskedasticity in the model, all inference has to be based on an Eicker-White (Eicker, 1963; White, 1980) robust covariance matrix estimator clustered by exporter-importer pair.

The estimation results of the model (16) for each industry s are reported in Table 9. Comparing the PPML estimates to the benchmark and MLE estimates in Table 2 (A-C) and focusing on distance, I note two key features. First, as expected, the PPML estimates significantly differ for manufacturing, only slightly for mining and almost same as benchmark estimates for agriculture. Since the exporters in agriculture do not substantially vary in productivity the error term in the benchmark model has a low variance producing almost unbiased estimates. The results for manufacturing is completely opposite with distance being substantially overestimated in the benchmark gravity model. Second, the two-stage consistent model (MLE) and PPML estimates produce almost identical estimates. For example, the distance elasticity in manufacturing is -1.522 when estimated by MLE and -1.325 when estimated by PPML. Thus, the pure econometric correction of the log gravity model and two-stage consistent gravity model lead to the same predicted biases in the classical gravity model. However, the latter model is more desirable as it has proper theoretical underpinnings.

7 Conclusion

This paper contributes to the existing empirical trade literature with heterogeneous firms in providing a more comprehensive industry level analysis of the two-stage consistent model proposed by HMR. In particular, I explore the ability of the extensive margin to explain the trade flows at a more disaggregated data level. While earlier studies that used industry data focused mostly on manufacturing sub-sectors, I choose industries according to their market structure. I modify the

HMR theoretical framework to account for the industry trade. By assuming that the elasticity of substitution is the same within the industry but different across the industries, I obtain the condition that determines the significance of the extensive margin for industry trade.

There are several important points that emerge from this study. First, the extensive margin correction is only significant for manufacturing across all specifications, while export selection primarily matters for agriculture. These results are consistent with the evidence that firms in manufacturing substantially differ in productivity, but firms in agriculture are more homogeneous. The results on mining are somewhat mixed, but export selection appears to be most important in explaining the trade flows for this industry as well. Second, I verify the strong upward bias in elasticity of the trade barriers with a respect to trade flows in the classical gravity model as compared to the two-stage HMR model. However, this bias is only substantial whenever the extensive margin correction is significant (manufacturing). For agriculture, the estimates of these elasticities hardly differ from each other. Third, I successfully resolve the "North-South" puzzle. I find that the extensive margin correction is significant for the Northern trade, but only in manufacturing. It appears that at the aggregate level the significance of the extensive margin for this region pair is counfounded by mixing the industries. Fourth, I establish a relationship between the distribution of firm-level sales, as determined by its shape parameter, and the importance of the extensive margin. My results verify this relationship and thus serve as a robustness check to the main estimation. Finally, I link the earlier attempts to explain the upward bias in the classical gravity model from an econometric standpoint (Silva et al. (2006)) to the theoretically robust two-stage model derived by HMR. I find an important complementarity in these estimates.

More generally, the results of this paper suggest the needed caution when applying the two-stage HMR gravity model to some sets of the trade data. I determine that while the HMR extensive margin correction should be selectively applied at the aggregate level, it performs well on more disaggregated data.

A Various Derivations

A.1 Number of Exporters

Using the aggregation mechanism as in the Melitz (2003) model, I can obtain the number of firms in an industry s and a country j exporting to a country i (6).

Define the aggregate productivity of exporting firms in industry s, and country j as function of γ^*_{sij} :

$$\widetilde{\gamma}_{sij}(\gamma^*_{sij}) = \left[\frac{1}{1-G(\gamma^*_{sij})}\int_{\gamma^*_{sij}}^{\gamma^L_{sij}} \gamma^{\varepsilon-1} g(\gamma) d\gamma\right]^{\frac{1}{\varepsilon-1}}. \tag{A1}$$

Using (A1), average export revenues and average, profits of exporters in the industry s are:

$$\overline{r}_{sij} = r(\widetilde{\gamma}_{sij}) = \left[\frac{\widetilde{\gamma}_{sij}}{\gamma^*_{sij}}\right]^{\varepsilon-1} \theta_s r(\gamma^*_{sij}); \overline{\pi}_{sij} = \overline{\pi}(\widetilde{\gamma}_{sij}) = \left[\frac{\widetilde{\gamma}_{sij}}{\gamma^*_{sij}}\right]^{\varepsilon-1} \frac{\theta_s r(\gamma^*_{sij})}{\varepsilon_s} - c_{sj} f_{ij.} \tag{A2}$$

In addition, average export revenues can be written as:

$$\overline{r}_s = \overline{\pi}_s + c_{sj} f_{ij.} \tag{A3}$$

In the aggregate revenues $R_s = L$ i.e. aggregate revenues must equal to total payments to labor. Using this condition, (A2) and (A3), I obtain (6):

$$N_{sij} = \frac{R_{sij}}{\overline{r}_{sij}} = \frac{L}{\varepsilon_s(\overline{\pi}_{sij} + c_{sj} f_{ij.})}.$$

A.2 Two-Stage Model

A.2.1 Firm Export Selection

Denote the latent variable Z_{sij} to be the ratio of the variable export profits of the most productive firm in an industry s (with productivity $\frac{1}{a_L}$) to the fixed export costs for exports from j to i:

$$Z_{sij} = \frac{(1-\alpha)\left(P_i \frac{\alpha}{c_{sj}\tau_{ij}}\right)^{\varepsilon-1} \theta_{si} Y_i a_L^{1-\varepsilon}}{c_{sj} f_{ij}}. \tag{A4}$$

Assume that f_{ij} are stochastic fixed costs due to unmeasured i.i.d friction $v_{ij}\tilde{}N(0,\sigma_v^2)$ that may be correlated with u_{ij} and are defined as follows:

$$f_{ij} \equiv \exp(\phi_{EX,j} + \phi_{IM,i} + \mu\phi_{ij} - v_{ij}), \tag{A5}$$

where $\phi_{IM,i}$ is a fixed trade barrier imposed by the importing country, $\phi_{EX,j}$ is a measure of fixed export costs common across all export destinations and ϕ_{ij} is an observed measure of any additional country-pair specific fixed trade costs[32]. With this assumption the latent variable Z_{sij} in (A4) can now be expressed as:

$$z_{sij} \equiv \ln(Z_{sij}) = \gamma_0 + \xi_j + \zeta_i - \gamma d_{ij} - \mu\phi_{ij} + \eta_{ij,} \tag{A6}$$

[32] See Appendix C for the list of such costs

where $(\varepsilon_s - 1)\ln\tau_{ij} \equiv \gamma d_{ij} - u_{ij}$; $\eta_{ij} \equiv u_{ij} + v_{ij}\tilde{}N(0, \sigma_u^2 + \sigma_v^2)$ is i.i.d. but correlated with an error term u_{ij} in the gravity model (11); $\xi_j = -\varepsilon_s \ln c_{sij} + \phi_{EX,j}$, $\zeta_i = (\varepsilon_s - 1)p_i + y_i + \ln\theta_{si} - \phi_{IM,i}$ are exporter and importer fixed effects respectively. Even though z_{ij} is unobserved, it is positive whenever j exports to i i.e. there is non-zero value of the export volumes in the bilateral trade matrix and it is zero otherwise.

To obtain the export selection equation, define the indicator variable $T_{sij} = 1$ if the industry s in a country j exports to country i and zero otherwise. Let ρ_{sij} be the probability that the country j exports to the country i conditional on the observed variables. The export selection equation is the following Probit specification:

$$\rho_{sij} = \Pr(T_{sij} = 1|\text{observed variables}) = \Phi(\gamma_0^* + \xi_j^* + \zeta_i^* - \gamma^* d_{ij} - \mu^*\phi_{ij}), \tag{A7}$$

where $\Phi(\bullet)$ is a CDF of the unit-normal distribution, and every starred coefficient represents the original coefficient divided by σ_η.

To obtain the consistent estimate of W_{sij} , let $\widehat{\rho}_{sij}$ be the predicted probability of exports from j to i that can be obtained from the estimated residuals in the Probit equation (A7). Given the vector of these predicted probabilities, the estimated fraction of exporting firms can be backed out by taking an inverse of the unit-normal CDF $\Phi(\bullet)$ - $\widehat{z}_{sij}^* = \Phi^{-1}(\widehat{\rho}_{sij})$. A consistent estimate for W_{ij} is:

$$W_{sij} = \max\{(Z_{sij})^{\delta_s} - 1, 0\}, \tag{A8}$$

where $\delta_s \equiv \sigma_{s\eta}(k_s - \varepsilon_s + 1)/(\varepsilon_s - 1)$ and δ_s needs to be estimated for each industry s.

A.2.2 Consistent Estimation of the Gravity Model

There are two requirements to obtain consistent estimate of γ in the gravity specification (11). There should be a control variable for endogenous number of exporters (via w_{sij}) $E[w_{ij}|., T_{sij} = 1]$ and a control variable for selection of a country into the trading partner $E[u_{ij}|., T_{sij} = 1]$. Both of these terms depend on $\widehat{\overline{\eta}}_{sij}^* \equiv E[\eta_{ij}^*|., T_{sij} = 1]$. Also $E[u_{ij}|., T_{sij} = 1] = corr[(u_{ij}, \eta_{ij}), (\frac{\sigma_u}{\sigma_\eta})\overline{\eta}_{ij}^*]$. Since $\overline{\eta}_{ij}^*$ has a CDF of the unit-normal distribution, a consistent estimate $\widehat{\overline{\eta}}_{ij}^*$ can be obtained from the inverse Mills ratio: $\widehat{\overline{\eta}}_{ij}^* = \frac{\phi(\widehat{z}_{sij}^*)}{\Phi(\widehat{z}_{sij}^*)}$, or estimated from Heckman procedure available from any statistical package provided a valid exclusion restriction. Finally $\widehat{\overline{z}}_{sij}^* \equiv \widehat{z}_{sij}^* + \widehat{\overline{\eta}}_{ij}^*$ is a consistent estimate for $E[z_{sij}^*|., T_{sij} = 1]$ and $\widehat{\overline{w}}_{sij}^* \equiv \ln\{\exp[\delta_s(\widehat{z}_{sij}^* + \widehat{\overline{\eta}}_{sij}^*)] - 1\}$ is a consistent estimate for $E[w_{sij}|., T_{sij} = 1]$ from (A19). Hence the consistent estimating gravity model is now given by:

$$m_{sij} = \beta_0 + \lambda_j + \chi_i - \gamma_s d_{ij} + \ln\{\exp[\delta_s(\widehat{z}_{sij}^* + \widehat{\overline{\eta}}_{ij}^*)] - 1\} + \beta_{u\eta}\widehat{\overline{\eta}}_{ij}^* + e_{ij}, \tag{A9}$$

where $\beta_{u\eta} \equiv corr[(u_{ij}, \eta_{ij}), (\frac{\sigma_u}{\sigma_\eta})]$ and e_{ij} is i.i.d. distributed error term satisfying $E[e_{ij}|., T_{sij} = 1] = 0$. Since (A20) is non-linear in δ_s, I estimate it using MLE.

B Details on Estimating the Shape Parameter in Pareto Distribution

B.1 Regression-Based Approach

To estimate the shape parameter k_s in the Pareto distribution, recent studies[33] have applied the rank-size regression approach. Considering distribution of sales, the probability that firm i has a value of sales above a firm of a certain size falls with a rank. Thus, the firm that ranked first in terms of value of its sales will be in the tail of the distribution. It follows that there exists negative relationship between rank and sales that can be captured by estimating the following specification:

$$\log(Rank_i^s - \frac{1}{2}) = \alpha - \beta_s \log(Sls_i^s) + \varepsilon, \tag{B1}$$

where $Rank_i^s$ is an ordering of firms in an industry s by the largest sales first, β_s is to be estimated for each sector s and ε is an idiosyncratic mean zero error term. Gabaix and Ibragimov (2007) show that $\widehat{\beta}$ is an unbiased and a consistent estimator of the shape parameter in the Pareto distribution when number of the firms N is large enough.

While simple to estimate using OLS, the specification (B1) when applied to the sales data by industry sectors has a few caveats. First, the assumption that there is a linear relationship between rank and sales does not hold in any of the industries. Figures 1 - 3 plot the rank as a function of the sales for manufacturing, mining and the agriculture respectively. None of these plots appear to have a linear relationship, but by construction, these relationships are negative. However, it appears that the tails of these distributions resemble a linear relationship. Thus the estimate of β_s in (B1) will have a correct sign, but it will be underestimated for the firms with a small sales and overestimated for the firms with a large sales. One way to deal with this non-linearity is to remove some fraction of the firms with lower sales until the distribution is approximately linear. This approach considerably reduces the number of observations and introduces a selection bias. Second, only manufacturing industry data has enough observations to consistently estimate β_s. The data on the mining industry with 77 observation and the data on agriculture with only 7 observation for the USA in 1987 cannot produce OLS estimates of β_s with any acceptable precision. Therefore, I set up an alternative methodology to estimate the shape parameters k_s for each industry, but use the rank-size regressions as a robustness check.

B.2 Bayesian Markov Chain - MonteCarlo (MCMC) Approach

To obtain the estimates for k_{aggr}, k_{mng} and k_{mnfg}, I depart from the existing literature approach and apply the Bayesian techniques. Using Bayesian techniques gives a key advantage over the method used by Chaney (2008): with a limited number of observations, particularly in the agriculture, the Bayesian sampling allows me to obtain the estimates of the shape parameters with correspoding credible intervals that indicate the probability that an estimate lies witin an interval range. In addition, I do not need to impose any specific functional relationship and allow the data to produce the estimates. The Bayesian estimates will yield the posterior mean and variance for the shape parameters by industries.

The estimation of the shape parameters k_s, require a specification of the prior distribution function for the parameter k. Together with a likelihood function, I can obtain the joint posterior distribution, which can be numerically estimated using the Markov Chain-Monte Carlo (MCMC)

[33] See for example Krugman (1996), Helpman, Melitz and Yeaple (2004), Chaney (2008) among others.

sampling algorithm. With an assumption that sales are distributed Pareto, using (15) the joint likelihood function is:

$$f(\underset{\sim}{Sls_s}|k_s, \beta = 1) = \prod_{i=1}^{n} k_s Sls_s^{-(k_s+1)} = k_s^n \left(\prod_{i=1}^{n} Sls_{i,s}\right)^{-(k_s+1)}. \tag{B2}$$

With a known scale parameter $\beta = 1$, a conjugate prior family for k_s is a Gamma family with the following prior density[34]:

$$f(k_s) = k_s^{c-1} \frac{d^c \exp^{-dk_s}}{\Gamma(c)}, \tag{B3}$$

where $k_s > 0$, and $c > 0$ is a shape parameter, $d > 0$ is a rate parameter, and $\Gamma(\bullet)$ is a Gamma function. More compactly, the shape parameter k_s has a prior Gamma distribution - $k_s\tilde{}\gamma(c, d)$.

The choice of the shape parameter c in the prior distribution for k_s is based on restrictions placed on k_s, as well as its hypothetical values for a specific industry. Chaney (2008) estimates that the average shape parameter for manufacturing is approximately equals to 2. He also notes that industries with high value of the shape parameter k are more homogeneous - more output is concetrated among the smallest and least productive firms. Thus, it is reasonable to assume that the initial values of c for mining and agriculture should be higher than for manufacturing. I set them equal to average benchmark industry elasticities[35]. Futhermore, I intialize k_s to the prior mean which is $\mu_{k_s} = \frac{c}{d} = c$, where I set the rate parameter $d = 1$. Table B1 summarizes the parameter initialization by industry.

Table B1 - Parameter Intialization for Bayesian Estimation

Parameter	Agriculture	Mining	Manufacturing
c	5	11	7

The sufficient statistic based on the sample of ordered sales $Sls = (Sls_1, Sls_2, ..., Sls_n)$ when $\beta = 1$ is:

$$u = \sum_{i=1}^{n} \log(Sls_i). \tag{B4}$$

The posterior distribution for k_s using (B2),(B3) and (B4) is proportional to:

$$f(k_s|Sls, \beta = 1) \propto k_s^{n+c-1} \exp^{-(u_s+d_s)k_s},$$

which implies that the shape parameter k_s for each industry s is distributed as:

$$k_s|Sls, \beta\tilde{}\gamma(n_s + c_s, u_s + d_s). \tag{B5}$$

To obtain the estimates of k_s, I apply the Gibbs step in the MCMC algorithm to sample the shape parameter k_s for each industry s and calculate the posterior mean of the each sample. In addition, I calculate the variance and the 95% credible intervals for each estimated parameter k_s.

[34] See Arnold and Press (1983) for the detailed discussion on the Bayesian techniques to estimate parameters in the Pareto distribution.

[35] Surprisingly, the estimates of the benchmark eslasticities show higher average elasticity of substitution in the manufacturing industry as compared to the agriculture, but smaller than in the mining industry.

C Description of the Main Variables

Dependent Variables

- *trade* volume - Unidirectional value of trade volumes between the exporter in the industry s from $i - j$ country pair (in logs unless stated otherwise).
- trade - a binary variable which is equal to one if *trade volume* is non-zero,and is zero otherwise.

Explanatory Variables

Variable Trade Barrier

- *distance* - the symmetric distance between the importer's i and the exporter's j capitals (in logs).

Fixed Trade Barriers

- *common* border - a binary variable which is equal to one if the importer i and the exporter j share same physical border, and is zero otherwise.
- *island* - a binary variable which is equal to one if the importer i and the exporter j are both islands, and is zero otherwise.
- *landlocked* - a binary variable which is equal to one if the importer i and the exporter j have both no coastline or direct access to the sea, and zero otherwise.
- *colonial ties* - a binary variable which is equal to one if the importer i had ever colonized the exporter j or vice versa, is zero otherwise.
- *currency union* - a binary variable that is equal to one if the importer i and the exporter j use same currency or if within the country pair money was interchangeable at 1:1 exchange rate for an extended period of time (see Rose (2000), Glick and Rose (2002) and Rose (2004)), and is zero otherwise.
- *legal system* - a binary variable that is equal to one if the importer i and the exporter j share the same legal origin, and is zero otherwise.
- *religion* - (% Protestants in country i · % Protestants in country j) + (% Catholics in country i · % Catholics in country j) + (% Muslims in country i · % Muslims in country j) .
- *FTA* - a binary variable that is equal to one if the importer i and the exporter j belong to a common regional trade agreement, and is zero otherwise.
- *language* - a binary variable that is equal to to one if the importer i and the exporter j speak the same language, and is zero otherwise.

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Table 1(A) - Extent of Zeros by Industry

Word-World Trade	Agriculture	Mining	Manufacturing
Number of Non-Zeros	4309	2506	6853
Fraction of Zeros (%)	82.7	89.9	72.4
Number of Trading Pairs	24, 806	24, 806	24, 806

Table 1(B) - Extent of Zeros by Industry and Region

	North-North	North-South	South-North	South-South
	Manufacturing			
Number of Non-Zeros	632	2254	1766	658
Fraction of Zeros (%)	2.8	34.3	48.5	96.2
	Mining			
Number of Non-Zeros	452	711	658	658
Fraction of Zeros (%)	30.4	79.3	80.8	96.2
	Agriculture			
Number of Non-Zeros	557	991	1540	1221
Fraction of Zeros (%)	14.3	71.1	55.1	92.9
Number of Trading Pairs	650	3, 432	3, 432	17, 292

Table 1(C) - Trading Partners by Industry and Country

Agriculture		Mining		Manufacturing	
Country	Partners	Country	Partners	Country	Partners
Netherlands	144	Germany / UK	98	Italy	147
France	140	US / Netherlands	97	Japan / UK	146
USA	137	France	95	France / Germany	145
Uganda	22	Ecuador	9	Zimbabwe	28

Table 2 (A) - The Consistent Gravity Model Estimation by Industry
World-World Trade Flows

AGRICULTURAL, FORESTRY, AND FISHERY PRODUCTS (SIC 0)			
Year 1986	(1)	(2)	(3)
Variables	(Probit) T_{ij}	Benchmark	MLE
Distance	-0.0295***	-0.755***	-0.702***
	(0.002)	(0.037)	(0.043)
Language	0.00317	0.0687	0.0778
	(0.003)	(0.073)	(0.069)
FTA	-0.0132*	0.585***	0.287**
	(0.007)	(0.15)	(0.14)
Colonial	0.145***	0.777***	0.649***
	(0.035)	(0.12)	(0.13)
Legal	0.0174***	0.243***	0.225***
	(0.003)	(0.054)	(0.053)
Border	0.0159*	0.313**	0.215
	(0.009)	(0.14)	(0.14)
Religion	0.0239***	0.446***	0.402***
	(0.005)	(0.12)	(0.12)
Landlocked	-0.00514	-0.263	-0.325
	(0.008)	(0.23)	(0.22)
Currency Union	-0.00958	1.493***	1.830***
	(0.007)	(0.56)	(0.54)
δ (from $\widehat{\overline{w}}^{*}_{rij}$)			0.218***
			(0.080)
$\widehat{\overline{\eta}}^{*}_{rij}$			1.131***
			(0.086)
Observations	21460	4309	4309
Fraction Missing or Non-Zero	13.4%	17.3%	17.3%
R^2	0.619	0.58	

Notes:
Raw # of observations = 24,806; Missing observations are reported for Probit;
Exporter and Importer Fixed Effects;
Island is an excluded variable and it is not reported;
Pseudo R-Squared is reported for Probit;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 (B) - The Consistent Gravity Model Estimation by Industry
World-World Trade Flows

MINING AND CONSTRUCTION PRODUCTS (SIC 1)			
Year 1986	(1)	(2)	(3)
Variables	(Probit) T_{ij}	Benchmark	MLE
Distance	-0.0201***	-0.732***	-0.537**
	(0.002)	(0.058)	(0.211)
Language	0.005**	-0.137	-0.219*
	(0.002)	(0.120)	(0.115)
FTA	0.0189	0.342*	-0.228
	(0.014)	(0.177)	(0.194)
Colonial	0.042***	0.518***	0.376
	(0.015)	(0.171)	(0.244)
Legal	0.010***	0.309***	0.257**
	(0.002)	(0.082)	(0.111)
Border	-0.004*	0.375**	0.258
	(0.002)	(0.182)	(0.178)
Island	-0.0004	0.225	0.128
	(0.004)	(0.266)	(0.242)
Landlocked	-0.009**	-1.139**	-1.001**
	(0.004)	(0.445)	(0.437)
Currency Union	0.0160	0.317	0.506
	(0.019)	(0.497)	(0.432)
δ (from $\widehat{\overline{w}}^*_{rij}$)			0.491
			(0.349)
$\widehat{\overline{\eta}}^*_{rij}$			0.956***
			(0.296)
Observations	17184	2506	2506
Fraction Missing or Non-Zero	30.7%	10.1%	10.1%
R^2	0.594	0.625	

Notes:
Raw # of observations = 24,806; Missing observations are reported for Probit;
Exporter and Importer Fixed Effects;
Religion is an excluded variable and it is not reported;
Pseudo R-Squared is reported for Probit;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 (C) - The Consistent Gravity Model Estimation by Industry
World-World Trade Flows

LIGHT AND HEAVY MANUFACTURING (SIC 2,3)			
Year 1986	(1)	(2)	(3)
Variables	(Probit) T_{ij}	Benchmark	MLE
Distance	-0.104***	-2.527***	-1.522***
	(0.005)	(0.072)	(0.078)
Language	0.0278***	0.622***	0.342**
	(0.001)	(0.140)	(0.134)
FTA	-0.0243	-0.202	1.121***
	(0.028)	(0.337)	(0.284)
Colonial	0.222**	2.192***	0.657***
	(0.090)	(0.245)	(0.242)
Legal	0.0398***	1.166***	0.735***
	(0.007)	(0.111)	(0.109)
Border	-0.0417***	0.907***	1.876***
	(0.013)	(0.298)	(0.288)
Religion	-0.0381**	-0.811***	-0.330
	(0.016)	(0.288)	(0.280)
Landlocked	-0.0641***	-0.786*	0.030
	(0.018)	(0.434)	(0.415)
Currency Union	0.0497	2.697***	2.204**
	(0.0437)	(1.010)	(1.012)
δ (from $\widehat{\overline{w}}^*_{rij}$)			2.401***
			(0.119)
$\widehat{\overline{\eta}}^*_{rij}$			0.011
			(0.140)
Observations	22052	6853	6853
Fraction Missing or Non-Zero	11.1%	27.6%	27.6%
R^2	0.688	0.749	

Notes:
Raw # of observations = 24,806; Missing observations are reported for Probit;
Exporter and Importer Fixed Effects;
Island is an excluded variable and it is not reported;
Pseudo R-Squared is reported for Probit;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 3(A) - Bias Decompositon at the Industry Level
World-World Trade Flows

AGRICULTURAL, FORESTRY, AND FISHERY PRODUCTS (SIC 0)				
Year 1986	(1)	(2)	(3)	(4)
COEFFICIENT	Benchmark	MLE	Firm Heterogeneity	Heckman Selection
Distance	-0.755***	-0.702***	-0.804***	-0.944***
	(0.037)	(0.043)	(0.12)	(0.04)
Language	0.0687	0.0778	0.073	0.101
	(0.073)	(0.069)	(0.075)	(0.073)
FTA	0.585***	0.287**	0.551***	0.067
	(0.15)	(0.14)	(0.17)	(0.190)
Colonial	0.777***	0.649***	0.880***	1.145***
	(0.12)	(0.13)	(0.26)	(0.131)
Legal	0.243***	0.225***	0.268***	0.367***
	(0.054)	(0.053)	(0.085)	(0.056)
Border	0.313**	0.215	0.327**	0.261**
	(0.14)	(0.14)	(0.14)	(0.133)
Religion	0.446***	0.402***	0.485***	0.613***
	(0.12)	(0.12)	(0.16)	(0.112)
Landlocked	-0.263	-0.325	-0.276	-0.382*
	(0.23)	(0.22)	(0.23)	(0.228)
Currency Union	1.493***	1.830***	1.451***	1.707***
	(0.56)	(0.54)	(0.56)	(0.38)
δ (from $\widehat{\overline{w}}^*_{rij}$)		0.218***		
		(0.080)		
$\widehat{\overline{\eta}}^*_{rij}$		1.131***		1.101***
		(0.086)		(0.082)
$\widehat{\overline{z}}^*_{rij}$			-0.089	
			(0.24)	
Observations	4309	4309	4309	4309
R^2	0.58		0.58	

Notes:
Exporter and Importer Fixed Effects;
Island is an excluded variable and it is not reported;
Robust standard errors with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 (B) - Bias Decompositon at the Industry Level
World-World Trade Flows

MINING AND CONSTRUCTION PRODUCTS (SIC 1)				
Year 1986	(1)	(2)	(3)	(4)
COEFFICIENT	Benchmark	MLE	Firm Heterogeneity	Heckman Selection
Distance	-0.732***	-0.537**	-0.512	-1.063***
	(0.058)	(0.211)	(0.429)	(0.066)
Language	-0.137	-0.219*	-0.203	-0.114
	(0.120)	(0.115)	(0.143)	(0.11)
FTA	0.342*	-0.228	0.225	0.021
	(0.177)	(0.194)	(0.279)	(0.23)
Colonial	0.518***	0.376	0.334	0.855***
	(0.171)	(0.244)	(0.429)	(0.179)
Legal	0.309***	0.257**	0.213	0.492***
	(0.082)	(0.111)	(0.197)	(0.082)
Border	0.375**	0.258	0.411*	0.103
	(0.182)	(0.178)	(0.215)	(0.168)
Island	0.225	0.128	0.233	0.112
	(0.266)	(0.242)	(0.266)	(0.245)
Landlocked	-1.139**	-1.001**	-1.015**	-1.348***
	(0.445)	(0.437)	(0.512)	(0.43)
Currency Union	0.317	0.506	0.209	0.768
	(0.497)	(0.432)	(0.536)	(0.506)
δ (from $\widehat{\overline{w}}^*_{rij}$)		0.491		
		(0.349)		
$\widehat{\overline{\eta}}^*_{rij}$		0.956***		1.142***
		(0.296)		(0.125)
$\widehat{\overline{z}}^*_{rij}$			0.265	
			(0.531)	
Observations	2506	2506	2506	2506
R^2	0.625		0.58	

Notes:
Exporter and Importer Fixed Effects;
Religion is an excluded variable and it is not reported;
Robust standard errors with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 3 (C) - Bias Decompositon at the Industry Level
World-World Trade Flows

LIGHT AND HEAVY MANUFACTURING (SIC 2,3)				
Year 1986	(1)	(2)	(3)	(4)
COEFFICIENT	Benchmark	MLE	Firm Heterogeneity	Heckman Selection
Distance	-2.527***	-1.522***	-1.826***	-2.628***
	(0.072)	(0.078)	(0.078)	(0.069)
Language	0.622***	0.342**	0.384***	0.733***
	(0.140)	(0.134)	(0.138)	(0.134)
FTA	-0.202	1.121***	1.172***	-0.624
	(0.337)	(0.284)	(0.278)	(0.399)
Colonial	2.192***	0.657***	1.111***	2.310***
	(0.245)	(0.242)	(0.242)	(0.263)
Legal	1.166***	0.735***	0.859***	1.219***
	(0.111)	(0.109)	(0.113)	(0.103)
Border	0.907***	1.876***	1.628***	0.867***
	(0.298)	(0.288)	(0.285)	(0.274)
Island	-0.811***	-0.330	-0.417	-0.879***
	(0.288)	(0.280)	(0.289)	(0.423)
Landlocked	-0.786*	0.030	-0.232	–0.183*
	(0.434)	(0.415)	(0.438)	(0.423)
Currency Union	2.697***	2.204**	2.025**	2.989***
	(1.010)	(1.012)	(1.027)	(0.739)
δ (from $\widehat{\overline{w}}^*_{rij}$)		2.401***		
		(0.119)		
$\widehat{\overline{\eta}}^*_{rij}$		0.011		0.947***
		(0.140)		(0.141)
$\widehat{\overline{z}}^*_{rij}$			1.431***	
			(0.089)	
Observations	6853	6853	6853	6853
R^2	0.749		0.58	

Notes:
Exporter and Importer Fixed Effects;
Religion is an excluded variable and it is not reported;
Robust standard errors with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 4 - Two-Stage Gravity Model Estimations at the Country Level

North-South Trade Flows				
Aggregate Industries				
Year 1986	(1)	(2)	(3)	(4)
Variables	Benchmark	MLE	F-H	Heckman
Distance	-1.104***	-0.981***	-1.067***	-1.139***
	(0.0634)	(0.0622)	(0.0648)	(0.053)
Language	0.0591	0.112	0.0747	0.096
	(0.0872)	(0.0832)	(0.0871)	(0.084)
FTA	0.777**	-0.104	1.175***	0.797**
	(0.346)	(0.328)	(0.386)	(0.344)
Colonial	1.375***	1.047***	1.284***	1.387***
	(0.135)	(0.139)	(0.140)	(0.134)
Legal	0.464***	0.279***	0.414***	0.492***
	(0.0716)	(0.0722)	(0.0745)	(0.067)
Border	0.389	0.561**	-0.251*	0.402
	(0.311)	(0.269)	(0.147)	(0.252)
Island	-0.319**	-0.168	-0.218	-0.334*
	(0.146)	(0.143)	(0.230)	(0.167)
Landlocked	-0.304	-0.134	0.396	-0.336
	(0.228)	(0.217)	(0.302)	(0.209)
Currency Union	1.335**	-0.318	2.191***	1.440***
	(0.558)	(0.676)	(0.654)	(0.374)
δ (from $\widehat{\overline{w}}^*_{rij}$)		0.126		
		(0.107)		
$\widehat{\overline{\eta}}^*_{rij}$		0.845***		0.317***
		(0.0844)		(0.112)
$\widehat{\overline{z}}^*_{rij}$			0.122**	
			(0.0507)	
Observations	2275	2275	2275	2275
R^2	0.774		0.774	

Notes:
Raw # of observations = 24,806;
Exporter and Importer Fixed Effects;
Religion is an excluded variable and it is not reported;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 5 - Two-Stage Gravity Model Estimations at the Country Level

North-South Trade Flows				
HMR Trade Data				
Year 1986	(1)	(2)	(3)	(4)
Variables	Benchmark	MLE	F-H	Heckman
Distance	-1.123***	-1.013***	-1.082***	-1.131***
	(0.0595)	(0.0567)	(0.0612)	(0.048)
Language	0.0661	0.104	0.0769	0.083
	(0.0796)	(0.0767)	(0.0801)	(0.076)
FTA	1.046***	0.400	1.461***	1.040***
	(0.363)	(0.335)	(0.405)	(0.312)
Colonial	1.269***	0.998***	1.172***	1.272***
	(0.123)	(0.117)	(0.126)	(0.125)
Legal	0.509***	0.349***	0.456***	0.516***
	(0.0676)	(0.0637)	(0.0715)	(0.060)
Border	0.611*	0.745***	-0.375***	0.623***
	(0.313)	(0.269)	(0.139)	(0.228)
Island	-0.441***	-0.307**	-0.247	-0.433***
	(0.136)	(0.132)	(0.205)	(0.152)
Landlocked	-0.334*	-0.182	0.613**	-0.331*
	(0.203)	(0.193)	(0.301)	(0.191)
Currency Union	1.303**	0.103	2.189***	1.309***
	(0.527)	(0.625)	(0.615)	(0.340)
δ (from $\widehat{\overline{w}}^*_{rij}$)		0.006*		
		(0.003)		
$\widehat{\overline{\eta}}^*_{rij}$		0.722***		0.017
		(0.0808)		(0.102)
$\widehat{\overline{z}}^*_{rij}$			0.126**	
			(0.0491)	
Observations	2275	2275	2275	2275
R^2	0.794		0.795	

Notes:
Raw # of observations = 24,806;
Exporter and Importer Fixed Effects;
Religion is an excluded variable and it is not reported;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 (A) - Two-Stage Gravity Model Estimations at the Industry Level
North-South Trade Flows

Year 1986	(1)	(2)	(3)
	Agriculture (SIC 0)	Mining (SIC 1)	Manufacturing (SIC 2,3)
COEFFICIENT	MLE	MLE	MLE
Distance	-0.852***	-0.618***	-2.758***
	(0.114)	(0.136)	(0.160)
Language	-0.0614	-0.107	0.646***
	(0.142)	(0.186)	(0.222)
FTA	0.653	-0.211	1.340
	(0.398)	(0.342)	(0.968)
Colonial	0.510**	0.755***	2.150***
	(0.235)	(0.241)	(0.369)
Legal	0.208**	0.016	0.948***
	(0.105)	(0.124)	(0.190)
Border	0.168	0.534	1.164*
	(0.286)	(0.333)	(0.699)
Landlocked	-5.242***	-0.696	-0.137
	(0.527)	(1.105)	(0.609)
Currency Union	2.455***	0.478	1.722
	(0.596)	(0.583)	(1.718)
δ (from $\widehat{\overline{w}}^*_{rij}$)	0.472*	0.0013***	0.830***
	(0.252)	(6.06e-05)	(0.202)
$\widehat{\overline{\eta}}^*_{rij}$	1.724***	1.053***	1.070***
	(0.192)	(0.208)	(0.220)
Observations	991	711	2254
Underlying Observations	3432	3432	3432

Notes:
Exporter and Importer Fixed Effects;
Island is an excluded variable in second stage estimations for Agriculture;
Religion is an excluded in Mining and Manufacturing - both are not reported;
Robust standard errors with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 6 (B) - Bias Decompositon at the Industry Level
North-South Trade Flows

Year 1986	(1)	(2)	(3)	(4)	(5)	(6)
	Agriculture (SIC 0)		Mining (SIC 1)		Manufacturing (SIC 2,3)	
COEFFICIENT	F- H	H-S	F- H	H-S	F- H	H-S
Distance	-0.911***	-1.167***	-0.794***	-.923***	-2.872***	-3.050***
	(0.127)	(0.108)	(0.269)	(0.134)	(0.169)	(0.140)
Language	-0.056	-0.078	-0.164	-0.132	0.568**	0.625***
	(0.157)	(0.152)	(0.214)	(0.181)	(0.232)	(0.221)
FTA	0.775*	0.583	0.318	0.103	3.779***	2.378***
	(0.461)	(0.516)	(0.499)	(0.547)	(1.181)	(0.895)
Colonial	0.660**	0.973***	1.081***	1.140***	2.611***	2.961***
	(0.257)	(0.235)	(0.386)	(0.247)	(0.359)	(0.360)
Legal	0.253**	0.350***	0.108	0.143	1.152***	1.358***
	(0.117)	(0.117)	(0.165)	(0.133)	(0.196)	(0.174)
Border	0.142	0.001	0.626*	0.452	0.853	0.881
	(0.299)	(0.363)	(0.363)	(0.355)	(0.785)	(0.655)
Landlocked	-5.041***	-6.680***	-1.156	-1.007	-0.234	-0.511
	(0.579)	(1.20)	(1.198)	(1.486)	(0.644)	(0.548)
Currency Union	2.220***	2.460***	1.128	1.232*	6.490***	3.541***
	(0.652)	(0.613)	(0.791)	(.637)	(1.679)	(0.974)
$\widehat{\overline{\eta}}^*_{rij}$		1.403***		0.718***		0.180
		(0.210)		(0.220)		(0.293)
$\widehat{\overline{z}}^*_{rij}$	-0.205		-0.151		0.427***	
	(0.151)		(0.228)		(0.138)	
Observations	991	991	711	711	2254	2254
R^2	0.623		0.576		0.748	

Notes: F- H - Firm Heterogeneity and H-S - Heckman Selection;
Exporter and Importer Fixed Effects;
Island is an excluded variable in second stage estimations for Agriculture;
Religion is an excluded in Mining and Manufacturing - both are not reported;
Robust standard errors with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 7 - Rank-Size Firm Level Estimates

Year 1987	(1)	(2)
	Manufacturing	Mining
Variables	$\log(rank - 1/2)$	$\log(rank - 1/2)$
Sales $\left(\widehat{\beta}_s\right)$	-0.165***	-0.188***
	(0.005)	(0.013)
Implied Shape Parameter $\left(\widehat{k}_s\right)$	0.165	0.188
Observations	920	77
R^2	0.841	0.895

Notes:

Absolute value of the estimate $\widehat{\beta}_s$ is the shape parameter in the Pareto distribution;
The implied shape parameter $\widehat{k}_s$ is reported for convenience;
Agriculture estimates are not reported as number of the observations is prohibitively small;
Robust Standard Errors are in parenthesis;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table 8 - Posterior Estimates for the Shape Paramter k_s by Industry

Industry (k_s)	Gamma Prior Distribution			
	Number of Firms	k_s	Standard Error	95% Credible Intervals
Manufacturing (k_{mnfg})	920	0.213	$1.6e-06$	$[0.199, 0.227]$
Mining (k_{mng})	77	0.300	0.0001	$[0.239, 0.372]$
Agriculture (k_{aggr})	7	0.347	0.005	$[0.167, 0.597]$

Table 9- PPML Estimates of the Gravity Model by Industry

World-World Trade Flows			
Year 1986	(1)	(2)	(3)
	Agriculture (SIC 0)	Mining (SIC 1)	Manufacturing (SIC 2,3)
Variables	M_{sij}	M_{sij}	M_{sij}
Distance	-0.774***	-0.528***	-1.325***
	(0.0525)	(0.126)	(0.126)
Language	0.0633	-0.336*	-0.277
	(0.109)	(0.178)	(0.245)
FTA	0.487***	0.0755	0.915***
	(0.129)	(0.252)	(0.232)
Colonial	0.574***	0.684***	0.388
	(0.149)	(0.209)	(0.300)
Legal	0.471**	0.0257	0.476
	(0.187)	(0.304)	(0.655)
Border	0.0475	0.194*	0.0401
	(0.0719)	(0.114)	(0.154)
Island	0.311***	1.209***	1.144***
	(0.113)	(0.317)	(0.213)
Religion	-0.272	1.585***	1.541**
	(0.259)	(0.395)	(0.680)
Landlocked	-0.784***	-1.028**	-0.492
	(0.230)	(0.504)	(0.362)
Currency Union	1.170**	-1.300*	0.675
	(0.523)	(0.779)	(3.769)
Observations	4309	2506	6853

Notes:
Raw # of observations = 24,806; Missing observations are reported for Probit;
Exporter and Importer Fixed Effects;
Robust Standard Errors are in parenthesis with country pair clustering;
*significant at 10%; ** significant at 5%; *** significant at 1%

Table A1 - List of the OECD (Northern) Countries

Country	Year of Accession	Country	Year of Accession
AUSTRALIA	1971	KOREA	1996
AUSTRIA	1961	MEXICO	1994
BELGIUM-LUX	1961	NETHERLANDS	1961
CANADA	1961	NEW ZEALAND	1973
CZECH REPUBLIC	1995	NORWAY	1961
DENMARK	1961	POLAND	1996
FINLAND	1969	PORTUGAL	1961
FRANCE	1961	SLOVAK REPUBLIC	2000
GERMANY	1961	SPAIN	1961
GREECE	1961	SWEDEN	1961
HUNGARY	1996	SWITZERLAND	1961
ICELAND	1961	TURKEY	1961
IRELAND	1961	UNITED KINGDOM	1961
ITALY	1962	UNITED STATES	1961
JAPAN	1964		

Source: Organisation for Economic Co-operation and Development (OECD), www.oecd.org

Table A2 - List of the Developing/Emerging (Southern) Countries

AFGHANISTAN	COTE D IVOIRE	ISRAEL	PAKISTAN	UNTD ARAB EM
ALBANIA	CUBA	JAMAICA	PANAMA	UNTD RP TNZ
ALGERIA	CYPRUS	JORDAN	PAPUA N.GUIN	URUGUYA
ANGOLA	DJIBOUTI	KENYA	PARAGUAY	VENEZUELA
ARGENTINA	DOMINICAN RP	KIRIBATI	PERU	VIETNAM
BAHAMAS	ECUADOR	KOREA DPR	PHILLIPINES	WESTERN SAHA
BAHRAIN	EGYPT	KUWAIT	QATAR	YEMEN
BANGLADESH	EL SALVADOR	LAOS	REUNION	ZAIRE
BARBADOS	EQ. GUINEA	LEBANON	ROMANIA	ZAMBIA
BELIZE	ETHIOPIA	LIBERIA	RWANDA	ZIMBABWE
BENIN	FIJI	LIBYA ARAB	SAUDI ARABIA	
BERMUDA	FM USSR	MADAGASCAR	SENEGAL	
BHUTAN	FM YUGOSLAVI	MALAWI	SEYCHELLES	
BOLIVIA	FRENCH GUIAN	MALAYSIA	SIERRA LEONE	
BRAZIL	GABON	MALDIVES	SINGAPORE	
BRUNEI	GAMBIA	MALI	SOLOMON ISLD	
BULGARIA	GHANA	MALTA	SOMALIA	
BURKINA FASO	GREENLAND	MAURITANIA	SOUTH AFRICA	
BURUNDI	GUADELOUPE	MAURITIUS	SRI LANKA	
CAMBODIA	GUATEMALA	MONGOLIA	ST KITTS NEV	
CAMEROON	GUINEA	MOROCCO	SUDAN	
CAYMAN ISLDS	GUINEA-BISSA	MOZAMBIQUE	SURINAM	
CENTRAL AFR.	GUYANA	MYANMAR	SYRN ARAB RP	
CHAD	HAITI	NEPAL	TAIWAN	
CHILE	HONDURAS	NETH ANTILLE	THAILAND	
CHINA	HONG KONG	NEW CALEDONI	TOGO	
COLOMBIA	INDIA	NICARAGUA	TRINIDAD-TOB	
COMOROS	INDONESIA	NIGER	TUNISIA	
CONGO	IRAN	NIGERIA	TURKS CAICOS	
COSTA RICA	IRAQ	OMAN	UGANDA	

Source: The HMR Data Set

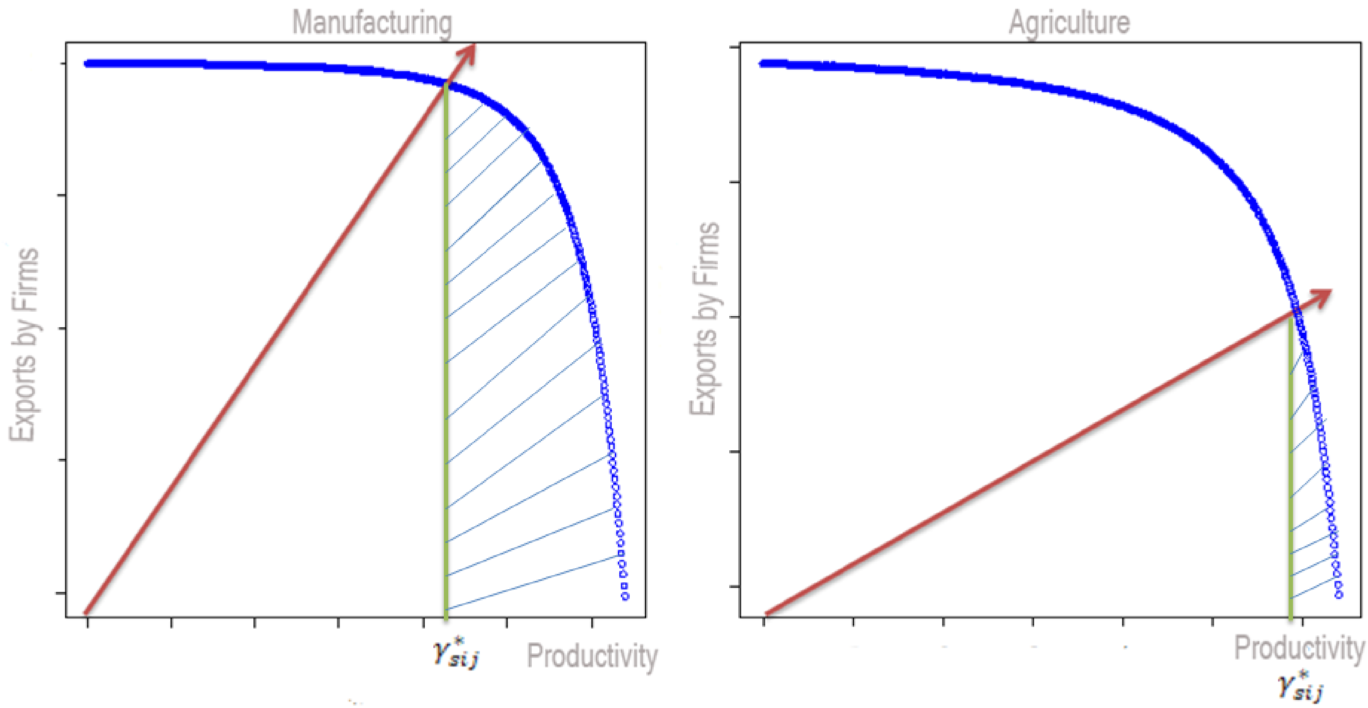
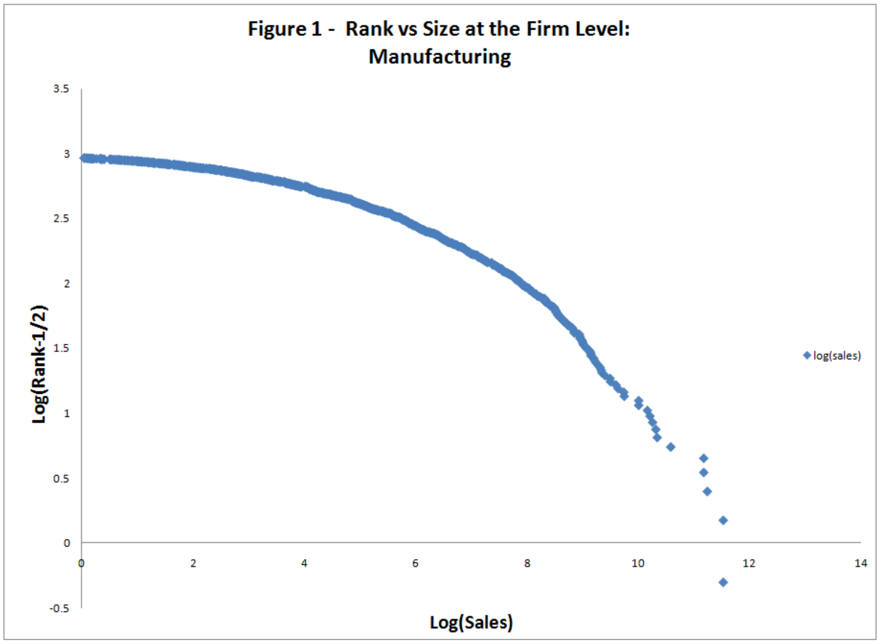
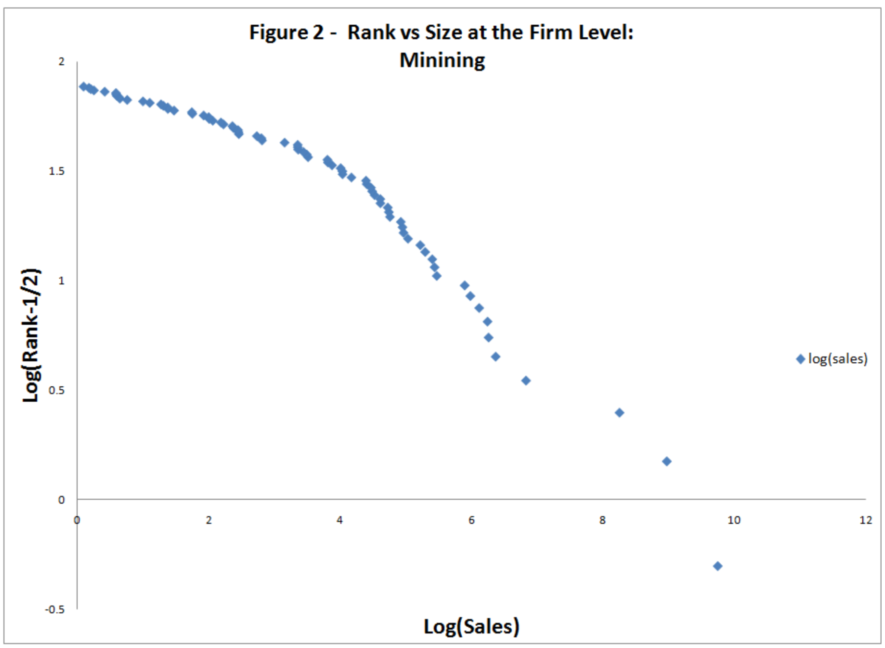


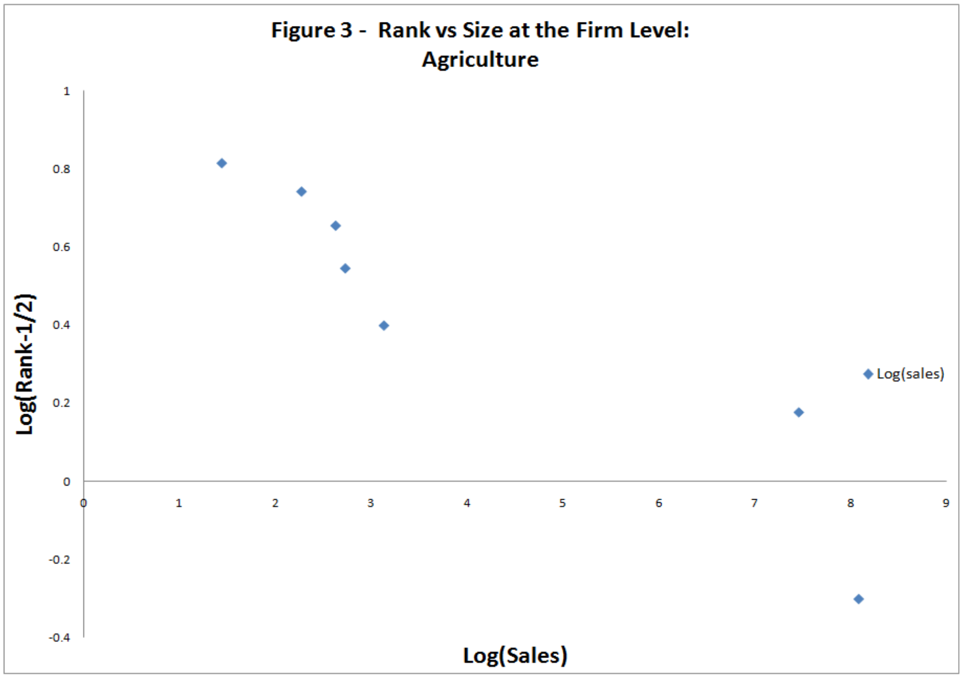
Figure A - The variation of export volumes by industry



Source: Compustat - US Firms, 1987



Source: Compustat - US Firms, 1987



Source: Compustat - US Firms, 1987

Figure 4A - Trace Plot for Paramater k - Manufacturing

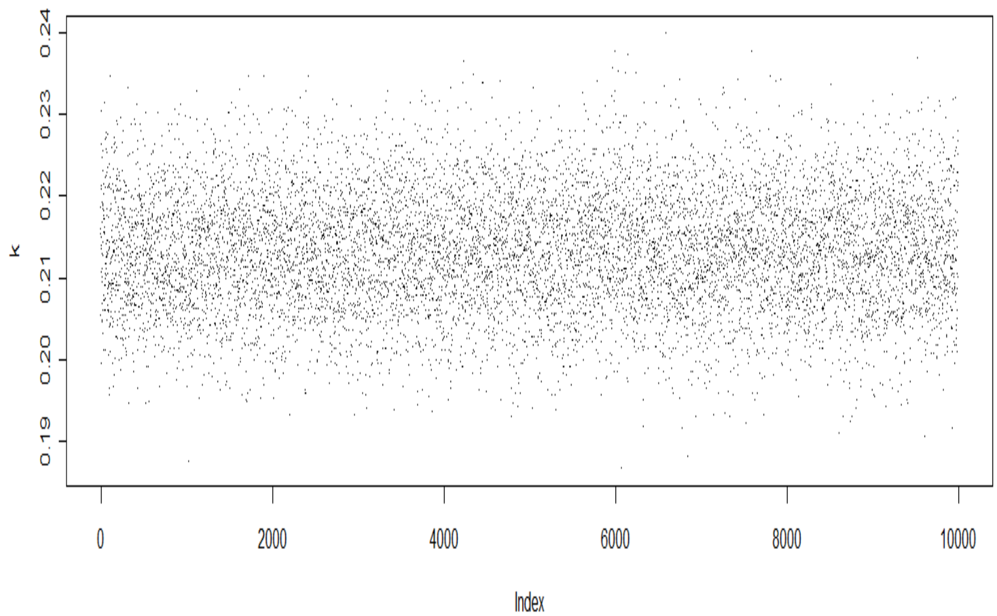
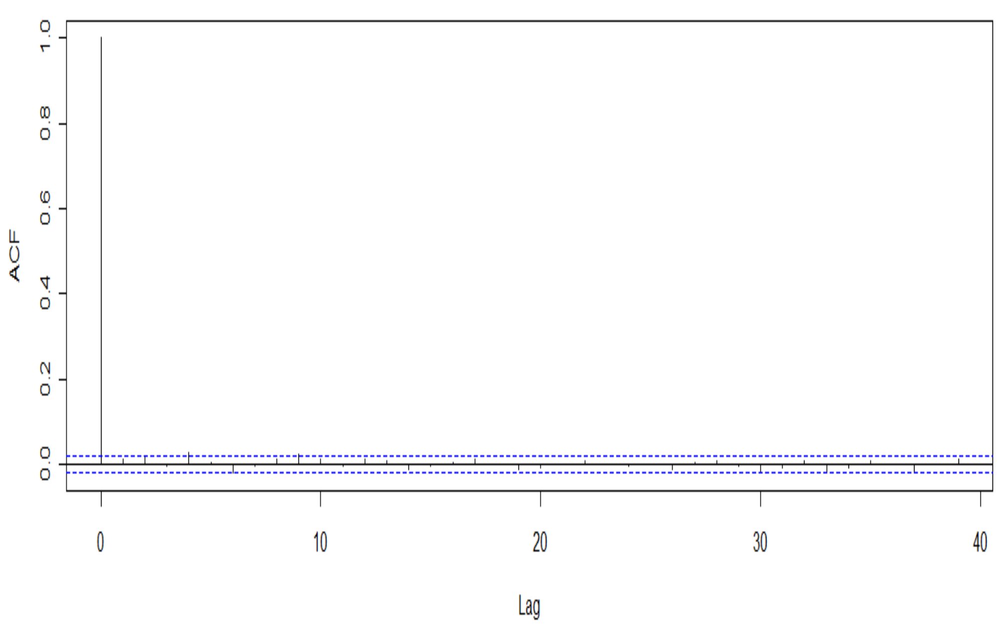


Figure 4B - Autocorrelation Plot for Parameter k - Manufacturing



Source - Author's Calculations

Figure 5A - Trace Plot for Paramater k - Mining

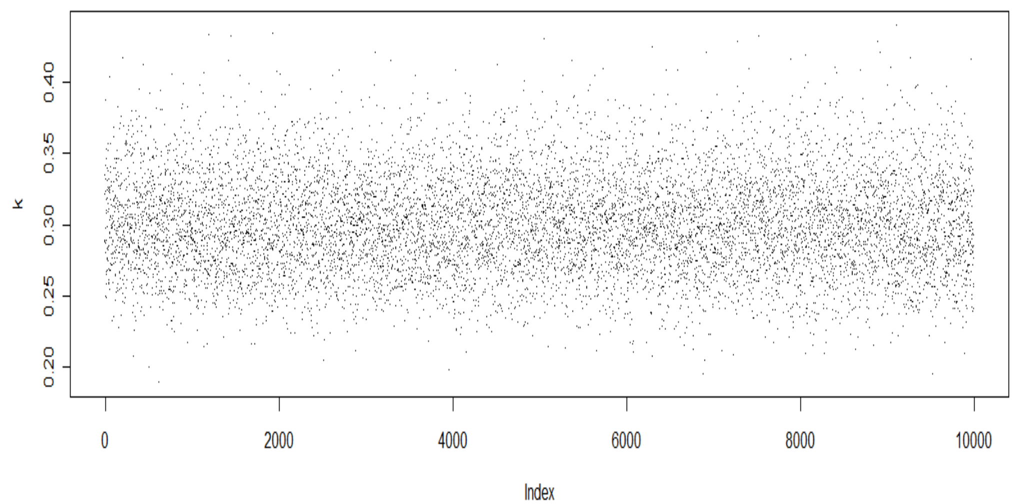
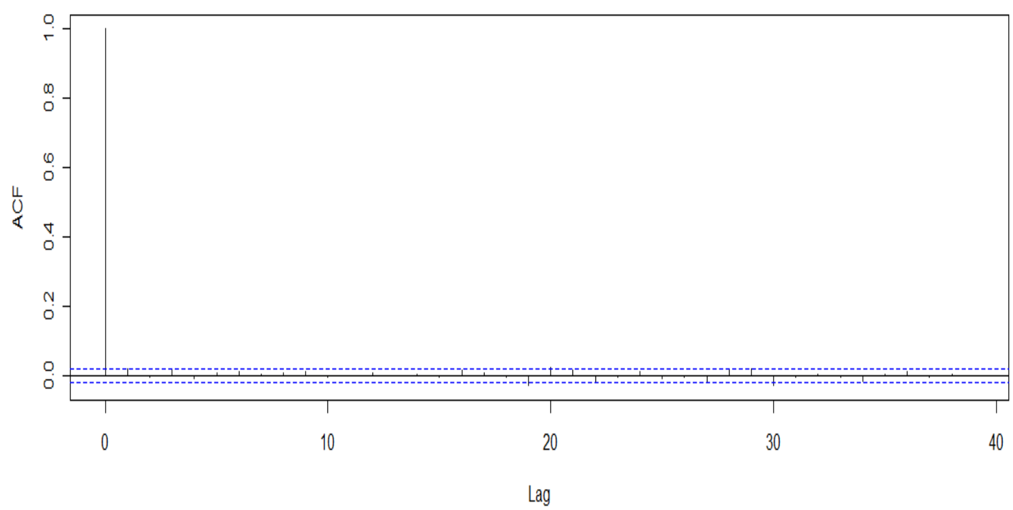


Figure 5B - Autocorrelation Plot for Parameter k - Mining



Source - Author's Calculations

Figure 6A - Trace Plot for Paramater k - Agriculture

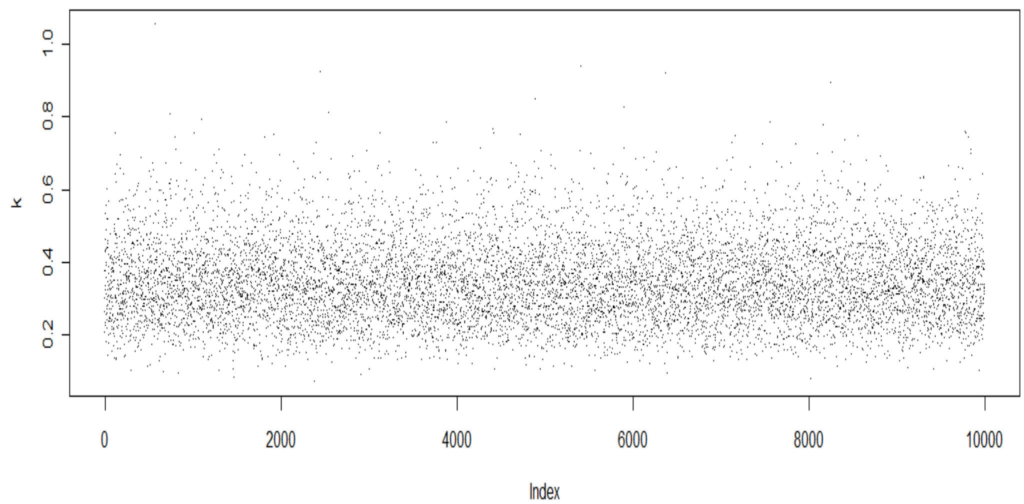
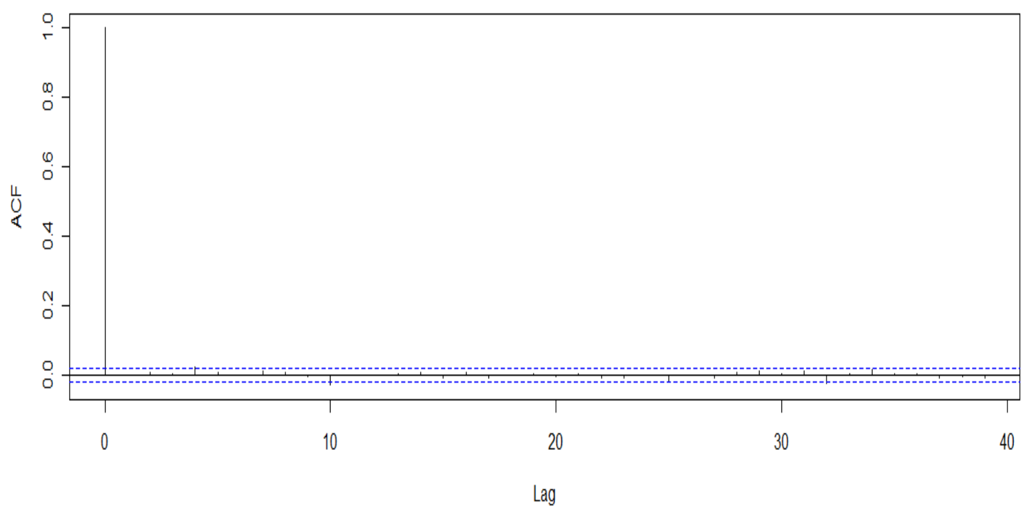


Figure 6B - Autocorrelation Plot for Parameter k - Agriculture



Source - Author's Calculations