**Synopsis**

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**Title: International Trade Analysis Using EGM Neural Networks** **and Random Forests**

Base Paper: Neural Network Analysis of International Trade

Author: Isaac Wohl ,Jim Kennedy

**Abstract**

We will examine International Trade Flow from 1948-2019 panel data using both an Intuitive gravity model and the Extended Gravity Model including Multilateral Resistance Terms by using various econometric models like **OLS, PPML, NBMPL,GPML, FIXED EFFECT AND NLS** and compare it with **Neural Network and Random Forest Regression** analysis. We constraint our proposal to the top 18 countries which are as follows: USA, United Arab, Japan, China, Singapore, Hongkong, Belgium, UK, Germany, Korea, France, Saudi Arabia, Bangladesh,Pakistan,Italy,Myanmar, Switzerland and India. We will use databases collected from the IMF, Ministry of Commerce, World Bank , KOF.ethz and CEPII dataset.

**Introduction**

* Gravity Models are the Workhorse of International Trade. A simple Intuitive model includes variables like GDPs of two countries and distance between them. They often include dummy variables that indicate whether the trade partners share a border, a language, a colonial relationship, or a regional trade agreement.
* Problem that arises due to intuitive model is let's say how trade is being affected between countries i and j if trade costs change between i and k. This trade diversion and trade creation are such effects which come under multilateral resistance terms which intuitive gravity model does not account for.
* Anderson and Van Wincoop(2003) said the Gravity model should also incorporate Multilateral Resistance Terms because relative trade costs matter a lot.
* A common way to tackle not just multilateral resistance terms as well as other country specific , cultural terms can be done by using country fixed effects. Some gravity models use country-year fixed effects,country-pair fixed effects or both.
* Further Sections include estimation using econometric methods like OLS, Fixed Effect, PPML,GPML,NBPML and compare model’s explanatory powers.
* Finally, neural network and Random Forest Regression analysis on aggregate trade and further investigation on relative predicting powers of different Models.

**Literature Review**

* Wohl and Kennedy in their work examined international trade using neural networks and traditional gravity model approach.their findings showed higher degree of accuracy in prediction using RMSE within the traditional gravity model.
* They pointed that the neural network is a highly robust and adaptable model to deal with highly interconnected variables in trade and will be less chaotic.
* Anderson and van Wincoop(2003) noted that gravity models should also account for multilateral terms.
* Head and mayer(2014) highlighted the importance of fixed effect. By using country specific fixed effects all monadic terms including multilateral terms are captured.
* One problem aroused how to deal with zero trade flow?. Santos Silva and Tenreyro came up with Poisson pseudo maximum likelihood (PPML). Yotov(2016) prescribes use of PPML for estimating Gravity equations and it also helps in dealing with heteroscedasticity.
* Author measured the accuracy of the out of sample predictions using RMSE(root mean square error). He noted that PPML and neural network estimators RMSE is higher using country year fixed effect than compared to country fixed effect.
* They trained the neural network on the full dataset with country fixed effects from 1986-2006 and used it to predict trade between the USA and its major trading partners between 2007-2016.

**Objective**

* We will apply both intuitive and extended gravity models including multilateral resistance terms on panel data from 1948-2019 specifically including top 18 countries.
* We will apply various econometric methods like OLS, PPML, fixed effect model, NBPML,GPML and NLS and compare their model’s explanatory powers.
* We will compare intuitive gravity model with extended gravity model by comparing R square value.we will also apply Fixed effect estimation that incorporates Multilateral terms.
* We will also apply PPML, GPML,NBPML and NLS and see their explanatory terms.
* We will train neural networks and Random Forest Regression on a dataset and compare its predicting power to gravity ones using R square Value.

**Hypothesis**

* Intuitive gravity model only considers variables like GDP, distances and other dummy variables excluding the multilateral resistance terms. We wish to see that estimation using that is giving bad results as trade cost matters and the basic model does not include that.
* Extended gravity model does take multilateral terms into account which can be estimated using either through fixed effect model or the use of taylor series approximation of multilateral terms introduced by baier and bergstrand(2009) without inclusion of two dummy variables.it also helps in dealing with endogeneity.
* We wish to use the PPML model as well as it helps in dealing with zero trade flow developed by Silva and Tenreyro(2006).
* We also wish to use an extended version of PPML which is GPML which is an iterative approach and more robust. PPML is more robust than OLS and more preferred nowadays.
* We will also train the neural network and Random Forest show that R-square value is far better than the Intuitive Gravity Model.

**Model and Methodology**

* **Gravity Model**

Writing gravity model in its Basic Form:

(GDPi)𝝱1(GDPj)𝝱2

Tij = ɑ  \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

(Dij)𝝱3

Writing gravity model as OLS estimators:

lnXij,t = θ0 + θ1ln(GDPi,t) + θ2ln(GDPj,t) + θ3ln(Distij) + θ4Contigij + θ5Comlangij+ θ6Colij + θ7ln(Infrai) + θ8ln(Infraj)+ θ9Oborij + θ10Aseanij + θ11Eacij + θ12Sadcij + eijt

Adding some fixed country effects:

lnXij,t = θ0 + θ1ln(GDPi,t) + θ2ln(GDPj,t) + θ3ln(Distij) + θ4Contigij + θ5Comlangij+ θ6Colij + θ7ln(Infrai) + θ8ln(Infraj)+ θ9Oborij + θ10Aseanij + θ11Eacij + θ12Sadcij + 𝜇i + ɑj +eijt

Alternatively, with country year fixed effects:

lnXij,t = θ0 + θ1ln(GDPi,t) + θ2ln(GDPj,t) + θ3ln(Distij) + θ4Contigij + θ5Comlangij+ θ6Colij + θ7ln(Infrai) + θ8ln(Infraj)+ θ9Oborij + θ10Aseanij + θ11Eacij + θ12Sadcij + 𝜇it + ɑjt +eijT

* **Neural networks**

An Artificial Neural Network input has an associated weight(w)which is assigned on the basis of its relative importance to other inputs.

Y = f(w1x1 + w2x2 + b)

There are different types of Activation function in the literature defined as follows:

sigmoid(x) = 1/(1 + exp(−x))

tanh(x) = 2\*sigmoid(2x) − 1

ReLU(x) = max(0, x)

* **Random Forest Regression**

Supervised learning model which prevents Overfitting of the data. It uses multiple decision Trees which increases accuracy

frfB(x) = (1/B)\*(∑Bb=1Tb(x))

Var((1/B)\*(∑Bb=1Tb(x))) = 𝜌𝜎2 + 𝜎2((1 - 𝜌)/B)

Here B is the number of trees.

Tb = Random Forest Tree

**Variable Description**

|  |  |
| --- | --- |
| **Variables** | **Description** |
| Tradeflow\_comrade\_o | Trade flow as reported by the exporter (in thousands current US$) (source: Comtrade) |
| iso3 | ISO3 alphabetic code |
| Country | Country name |
| Contig | Dummy equal to 1 if countries are contiguous |
| Distw | Population-weighted distance between most populated cities (km) |
| Distwces | Population-weighted distance between most populated cities (km) using CES formulation with θ = −1 |
| Comlang\_off | 1 if countries share common official or primary language |
| Comlang\_ethno | 1 if countries share a common language spoken by at least 9% of the population |
| Comcol | 1 if countries share a common colonizer post 1945 |
| Comrelig | Religious proximity index |
| Pop | Population (in thousands) |
| Gdpcap | GDP per capita (current thousands US$) |
| Comcur | 1 if pair currently shares the same currency |
| Gatt | 1 if country currently is a GATT member |
| wto | 1 if country currently is a WTO member |
| rta | 1 if the pair currently has a RTA (source: WTO) |
| Rta\_coverage | Indicates whether the RTA covers goods only or goods and services (source: WTO) |
| Rta\_type | Indicates the type of RTA (customs union for instance) |

**Tentative Conclusion**

* Neural networks have a high degree of accuracy in prediction compared to R Square within the Gravity model.
* Model’s explanatory power increased by using the Fixed effect model and it clearly underlines the importance of multilateral resistance terms.
* PPML is more preferred to Other econometric methods.
* Neural network and Random Forest Regression R Square is much better than gravity ones which clearly indicates that in future we should move onto use the machine learning models for estimating international trade patterns as it helps in dealing with large datasets which have numerous interconnected variables.

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**Datasets:**

1. <https://data.imf.org/?sk=9d6028d4-f14a-464c-a2f2-59b2cd424b85&sId=1390030341854>
2. <https://data.worldbank.org/>
3. <https://commerce.gov.in/>
4. <http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp>
5. <https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html>