Non-discriminatory Trade Policies in Structural Gravity Models
Evidence from Monte Carlo Simulations

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Structural Gravity Model for Trade Policy Analysis

- impacts of trade policy on trade flows, GDP and welfare
- structural gravity model (Anderson and van Wincoop, 2003)
- trade agreements: Anderson, Bergstrand, Egger, Larch, Yotov,...
- non-discriminatory trade policies (NTDP) affect all partners equally: most-favoured nation tariff, export subsidies, trade facilitation,...
- PPML with exporter(-time) and importer(-time) FE $\Rightarrow$ collinear
- "quick fixes" (Head and Mayer, 2014; Piermartini and Yotov, 2016)
- no Monte Carlo Evidence on these methods so far

Aim of the Paper

- outline estimation approaches for NDTP in SGM
- Monte Carlo simulation: bias and efficiency of estimators with SGM theory-consistent DGP
  - cross-section (computational burden!)
  - GLM: heteroscedasticity, Jensen's inequality, zero flow problem (Santos Silva and Tenreyro, 2006)
- empirical application

Structural Gravity Model

$$X_{ij} = Y_i Y_j \left(\frac{\tau_{ij}}{\Pi_i P_j} \right)^{\alpha}, \quad (1)$$

$$\Pi_i^{\alpha} = \sum_{k=1}^{N} \left(\frac{\tau_{ik}}{P_k} \right)^{\alpha} Y_k, \quad (2)$$

$$P_j^{\alpha} = \sum_{k=1}^{N} \left(\frac{\tau_{kj}}{\Pi_k} \right)^{\alpha} Y_k, \quad (3)$$

- iceberg trade costs $\tau_{ij} \geq 1$, elasticity of substitution $\sigma = 1 - \alpha$
- $E[\Pi_i \tau_{ij}] \neq 0$, $E[P_j \tau_{ij}] \neq 0$

$$E(X_{ij}) = \exp\left(e_i + m_j + \beta D_{ij} + \gamma NIP_{ij}\right)$$

- non-discriminatory import protection: $NIP_{ij} = NIP_j$
- discriminatory trade cost variable: D_{ij}

Considered Methods

Two kinds of identification methods are considered

1. data on intra-national trade flows (X_{ii}) is available
   - fixed effects - FE-intra (Heid, Larch & Yotov, 2015)
2. X_{ii} not available ("typical case", need for "quick fixes")
   - two-stage fixed effects - 2S (Eaton and Kortum, 2002)
   - Bonus-Vetus - VB (Baier and Bergstrand, 2009)
   - random intercept PPML - RI (Prehn et al., 2016)

naive gravity model as benchmark

Fixed effects with data on intra-national flows (FE-intra)

(Heid et al., 2015; Piermartini and Yotov, 2016)

$$X_{ij} = \exp\left(\lambda_i^{FE} + \chi_j^{FE} + \beta^{FE} D_{ij} + \gamma^{FE} NIP_{ij}\right) \eta_{ij}^{FE}.$$

- no direct impact of NIP_{ij} on intra-national (domestic) trade flows $NIP_{ii} = 0$
- MR terms (captured by λ_i^{FE} and χ_j^{FE}) affect all trade flows (including X_{ii})

Two-Stage Fixed Effects Model (2S)

$$
\begin{aligned}
X_{ij} &= \exp\left(\lambda_i^{2S} + \chi_j^{2S} + \beta^{2S} D_{ij}\right) \eta_{ij}^{2S} \\
\exp\left(\hat{\chi}_j^{2S}\right) &= \exp\left(\psi^{2S} + \delta^{2S} \ln Y_j + \gamma^{2S} NIP_j\right) \nu_j^{2S}.
\end{aligned}
$$

- (Eaton and Kortum, 2002; Melitz, 2008; Gylfason et al., 2015)
- (Plümper and Troeger, 2007): fixed effects vector decomposition method $\Rightarrow$ no identification under fixed effects assumption (Greene, 2011)

Bonus-Vetus Method (BV)

(Baier and Bergstrand, 2009; Baier and Bergstrand, 2010)

$$
\begin{aligned}
X_{ij}/(Y_i Y_j) &= \exp\left(\psi^{BV} + \beta^{BV} D_{ij}^{MRS} + \gamma^{BV} NIP_{ij}^{MRS}\right) \eta_{ij}^{BV} \\
x_{ij}^{MRS} &= x_{ij} - \sum_{k=1}^{N} x_{kj} \frac{1}{N} - \sum_{l=1}^{N} x_{il} \frac{1}{N} + \sum_{k=1}^{N} \sum_{l=1}^{N} x_{kl} \frac{1}{N^2}
\end{aligned}
$$

- derived for log-linear model, but also used in GLM (Hoekman and Nicita, 2011; Bratt, 2017)
- MC in (Head and Mayer, 2014): estimates on D_{ij} are unbiased in log-linear model

Poisson Random Intercept Model (RI)

Prehn, Brümmer and Glauben (2016) - Appl. Econ. Lett.

$$
\begin{aligned}
X_{ij} &= \exp\left(\lambda_i^{RI} + \chi_j^{RI} + \beta^{RI} D_{ij} + \gamma^{RI} NIP_{ij}\right)\eta_{ij}^{RI}, \\
\lambda_{0i}^{RI} &\sim N(0, \sigma^2_{\lambda_{0i}}), \\
\chi_{0j}^{RI} &\sim N(0, \sigma^2_{\chi_{0j}}),
\end{aligned}
$$

- generalized linear mixed model, Poisson family, normal priors
- in large samples effect of prior vanishes and Laplace approximation pushes estimates to fixed effects ML-estimates (Santos-Silva)
- use glmer function of R package *lme4* with default settings as in (Prehn et al., 2016)

Data Generating Process - deterministic part $E(X_{ij})$

(Egger and Staub, 2016)

- endowment economy: $Y_i = p_i H_i$
- draw correlated auxiliary variables $z_{ij}^H, z_{ij}^D, z_{ij}^{NIP} \sim \mathcal{MVN}\left(\mu_z, v_z \Sigma_z\right)$
- set α (baseline: -4) and derive H_i, D_{ij}, NIP_j (Egger and Staub, 2016)
- $\ln \tau_{ij}^{\alpha} = \beta D_{ij} + \gamma NIP_{ij}$ with $\beta = \gamma = 1$
- solve for equilibrium price

$$p_i^{1-\alpha} = \frac{1}{H_i} \sum_{j=1}^{N} \frac{\tau_{ij}^{\alpha} p_j H_j}{\sum_{k=1}^{N} p_k^{\alpha} \tau_{kj}^{\alpha}}$$

- compute Y_i and deterministic $E(X_{ij})$

$$E(X_{ij}) = \frac{p_i^{\alpha} \tau_{ij}^{\alpha} Y_j}{\sum_{k=1}^{N} p_k^{\alpha} \tau_{kj}^{\alpha}},$$

DGP - Stochastic Part η_{ij}

heteroscedastic log-normal distribution

$$\eta_{ij} = \exp\left(z_{ij}^{\eta}\right), \quad z_{ij}^{\eta} \sim N(-0.5\sigma^2_{\eta,ij}, \sigma^2_{\eta,ij}).$$

- $E(\eta_{ij}) = 1$
- baseline: $\sigma^2_{\eta,ij} = \ln\left(1 + E(X_{ij})^{-1}\right) \Rightarrow$ PPML asymp. efficient
- compute trade flows

$$X_{ij} = E(X_{ij})\eta_{ij}.$$

Monte Carlo Experiments

- 10,000 replications for $N = 10$ (100 obs.) and $N = 50$ (2,500 obs)
- each approach estimated by PPML
- compute mean bias and sd

1. Baseline
2. zero correlation between NIP_j and importer effect m_j $\Rightarrow$ no collinearity!
3. increase dispersion in endowments
4. higher elasticity of substitution $\Rightarrow$ dispersion trade costs/flows
5. increase variance of noise
6. missing data: 10 and 50 percent of countries are randomly dropped
7. different variance functions DGP: Gamma and Negative Binomial

Results: baseline and no collinearity

	N=10				N=50			
	NIP_{ij}		D_{ij}		NIP_{ij}		D_{ij}	
	Bias	SD	Bias	SD	Bias	SD	Bias	SD
Baseline								
naive	-2.44	0.40	-0.07	0.03	-2.51	0.15	-0.02	0.00
BV	1.92	3.33	-0.13	0.05	13.54	6.83	-0.04	0.01
2S	-2.56	0.57	0.00	0.04	-2.56	0.18	0.00	0.01
RI	-2.58	0.67	0.00	0.00	-2.57	0.43	0.00	0.00
FE-intra	0.00	0.09	0.00	0.03	0.00	0.03	0.00	0.01
No Collinearity								
naive	-0.15	0.09	-0.15	0.06	-0.04	0.02	-0.04	0.01
BV	-0.15	0.48	-0.15	0.05	-0.04	0.52	-0.04	0.01
2S	-0.02	0.18	0.00	0.03	0.00	0.04	0.00	0.01
RI	0.00	0.04	0.00	0.00	0.00	0.01	0.00	0.00
FE-intra	0.00	0.10	0.00	0.03	0.00	0.03	0.00	0.01

Note: All estimations are performed by PPML. Results are based on 10,000 repetitions.

Results: FE-intra flows

	N=10				N=50			
	NIP_{ij}		D_{ij}		NIP_{ij}		D_{ij}	
	Bias	SD	Bias	SD	Bias	SD	Bias	SD
(1) baseline	0.00	0.09	0.00	0.03	0.00	0.03	0.00	0.01
(2) no collinearity	0.00	0.10	0.00	0.03	0.00	0.03	0.00	0.01
(3) disp. endowments	0.01	0.11	0.00	0.03	0.00	0.03	0.00	0.01
(4) disp. costs/flows	0.01	0.07	0.00	0.03	0.00	0.02	0.00	0.00
(5) increased noise	0.00	0.32	0.03	0.13	0.00	0.11	0.00	0.03
(6) missing 90%/50%	0.00	0.10	0.00	0.03	0.00	0.03	0.00	0.01
(7a) Gamma	-0.06	0.52	0.00	0.14	-0.03	0.28	0.00	0.03
(7b) Negative Binomial	-0.06	0.53	0.00	0.14	-0.03	0.27	0.00	0.03

Note: All estimations are performed by PPML. Results are based on 10,000 repetitions.

Empirical Application - Data Description

- CEPII's 'TradeProd' (de Sousa et al., 2012)
- industry 311 'Food products' in year 2000
- MFN-tariff taken from WITS
- distance, border, common language: CEPII GeoDist database (Mayer and Zignago, 2011)
- RTA: 'Mario Larchs Regional Trade Agreements Database' (Egger and Larch, 2008)
- 63 countries, 3,963 observations

Empirical Results

	(1) FE-intra	(2) BV	(3) 2S	(4) RI[1]	(5) naive
$\ln(1+MFN_{ij})$	-5.48***	-175.60***	-1.04	-0.78	-0.68
	(0.733)	(25,59)	(1.12)	(1.51)	(0.68)
$\ln Dist_{ij}$	-0.87***	-0.90***	-0.85***	-0.85***	-0.60***
	(0.06)	(0.09)	(0.06)	(0.01)	(0.09)
$BORDER_{ij}$	0.55***	0.47***	0.56***	0.56***	0.68***
	(0.13)	(0.15)	(0.10)	(0.01)	(0.15)
RTA_{ij}	0.33***	0.44***	0.50***	0.50***	0.14
	(0.09)	(0.14)	(0.11)	(0.01)	(0.17)
$COMLANG_{ij}$	0.25**	-0.001	0.29**	0.29***	0.36***
	(0.10)	(0.14)	(0.12)	(0.01)	(0.12)
Two-way fixed effects	Yes	No	(Yes)	(Yes)	No
X_{ii} included	Yes	No	No	No	No
Obs.	3963	3900	3900 / 62	3900	3900

Note: All estimations were performed by PPML with heteroscedasticity-robust sandwich standard errors (except for random intercept model). [1] Robust standard errors are currently not supported for generalised linear mixed models in the lme4 package. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Conclusions

- "quick fixes" yield highly biased results $\Rightarrow$ collinearity
- data on domestic flows needed for identification $\Rightarrow$ still scarce
- FE-intra shows desirable behavior in MC
- plausible value for MFN-tariff i.e. $\hat{\sigma}$ in empirical application
- efficiency issues: $\Rightarrow$ conditional likelihood (Charbonneau, 2013), difference out FE (GMM) (Jochmans, 2017)

References I

Anderson, J. E. and van Wincoop, E. (2003).
Gravity with Gravitas: A Solution to the Border Puzzle.
The American Economic Review, 93(1):170–192.

Baier, S. L. and Bergstrand, J. H. (2009).
Bonus vetus OLS: A simple method for approximating international trade-cost effects using the gravity equation.
Journal of International Economics, 77:77–85.

Baier, S. L. and Bergstrand, J. H. (2010).
Approximating general equilibrium impacts of trade liberalizations using the gravity equation.
In Van Bergeijk, P. and Brakman, S., editors, *The Gravity Model in International Trade: Advances and Applications*, chapter 4, pages 88–134. Cambridge University Press, Cambridge.

Bratt, M. (2017).
Estimating the bilateral impact of nontariff measure on trade.
Review of International Economics, 25(2):1–25.

Charbonneau, K. B. (2013).
Multiple Fixed Effects in Theoretical and Applied Econometrics.
PhD thesis, Princeton University.

de Sousa, J., Mayer, T., and Zignago, S. (2012).
Market access in global and regional trade.
Regional Science and Urban Economics, 42(6):1037 – 1052.
special issue In honor of Jacques Thisse.

References II

Eaton, J. and Kortum, S. (2002).
Technology, Geography and Trade.
Econometrica, 70(5):1741–1779.

Egger, P. and Larch, M. (2008).
Interdependent Preferential Trade Agreement Memberships: An Empirical Analysis.
Journal of International Economics, 76(2):384–399.

Egger, P. and Staub, K. (2016).
GLM estimation of trade gravity models with fixed effects.
Empirical Economics, 50:137–175.

Greene, W. (2011).
Fixed Effects Vector Decomposition: A Magical Solution to the Problem of Time-Invariant Variables in Fixed Effects Models?
Political Analysis, 19:135–146.

Gylfason, T., Martínez-Zarzoso, I., and Wijkman, P. M. (2015).
Free Trade Agreements, Institutions and the Exports of Eastern Partnership Countries.
Journal of Common Market Studies, 53(6):1214–1229.

Head, K. and Mayer, T. (2014).
Gravity Equations: Workhorse, Toolkit, and Cookbook.
In Gopinath, G., Helpman, E., and Rogoff, K., editors, *Handbook of International Economics*, volume 4, pages 131–195. Amsterdam: Elsevier.

References III

Heid, B., Larch, M., and Yotov, Y. V. (2015).
A Simple Method to Estimate the Effects on Non-discriminatory Trade Policy within Structural Gravity Models.
unpublished.

Hoekman, B. and Nicita, A. (2011).
Trade Policy, Trade Costs, and Developing Country Trade.
World Development, 39:2069–2079.

Jochmans, K. (2017).
Two-way models for gravity.
Review of Economics and Statistics, 99(3):478–485.

Mayer, T. and Zignago, S. (2011).
Notes on CEPIIs distances measures: The GeoDist database.
CEPII, WP No 2011-25.

Melitz, J. M. (2008).
Languate and Foreign Trade.
European Economic Review, 52:667–699.

Piermartini, R. and Yotov, Y. V. (2016).
Estimating Trade Policy Effects with Structural Gravity.
CESifo Working Paper 6009.

References IV

Plümper, T. and Troeger, V. E. (2007).
Efficient Estimation of Time-Invariant and Rarely Changing Variables in Finite Sample Panel Analyses with Unit Fixed Effects.
Political Analysis, 15:124–139.

Prehn, S., Brmmer, B., and Glauben, T. (2016).
Gravity model estimation: fixed effects vs. random intercept Poisson pseudo-maximum likelihood.
Applied Economics Letters, 23(11):761–764.

Santos Silva, J. M. C. and Tenreyro, S. (2006).
The Log of Gravity.
The Review of Economics and Statistics, 88(4):641–658.

Generate auxiliary variables for trade costs

DGP extends (Egger and Staub, 2016)

$$z_{ij}^{H}, z_{ij}^{D}, z_{ij}^{NIP} \sim \mathcal{MVN}\left(\mu_z, \Sigma_z\right) \tag{4}$$

$$\Sigma_z = v_z \times \begin{pmatrix} \sigma_H^2 & r_{12} \times \sigma_H \sigma_D & r_{13} \times \sigma_H \sigma_{NIP} \\ r_{12} \times \sigma_D \sigma_H & \sigma_D^2 & r_{23} \times \sigma_D \sigma_{NIP} \\ r_{13} \times \sigma_{NIP} \sigma_H & r_{23} \times \sigma_{NIP} \sigma_D & \sigma_{NIP}^2 \end{pmatrix}, \tag{5}$$

parametrization follows (Egger and Staub, 2016)

- $\mu_z = (3, -2, 0)$, $\sigma_H = 3\sqrt{N}/4$, $\sigma_D = \sigma_{NIP} = 5$ and $r_{12} = r_{13} = r_{23} = 0.95$
- variance scaling factor $v_z = 0.1$ in baseline

Generate endowments and trade cost variables

$$H_i = \exp\left(\sum_{j=1}^{N} z_{ij}^{H}/N\right) N, \tag{6}$$

$$D_{ij} = \left(\frac{\exp\left(z_{ij}^{D}\right)}{1+\exp\left(z_{ij}^{D}\right)}\right)^{-\alpha/4}, \tag{7}$$

$$NIP_j = \left(1/N\sum_{i=1}^{N}\frac{\exp\left(z_{ij}^{NIP}\right)}{1+\exp\left(z_{ij}^{NIP}\right)}\right)^{-\alpha/4}, \tag{8}$$

- $\alpha = -4$ in the baseline scenario, following (Anderson and van Wincoop, 2003)
- using full set of N^2 trade flows

MC - Data Properties

	Baseline		Variations with $N = 50$			
	$N = 10$	$N = 50$	$\rho(NIP_j, m_j) = 0$	$v_z = 0.3$	$\alpha = -9$	$v_\eta = 9$
$CV(H_i)$	0.23	0.24	0.24	0.42	0.24	0.24
$CV(\tau_{ij}^{\alpha})$	1.13	1.07	1.03	1.18	2.18	1.07
$CV(X_{ij})$	1.05	1.12	1.10	1.39	2.08	1.34
$CV(D_{ij})$	-0.57	-0.57	-0.71	-0.82	-0.57	-0.57
$CV(NIP_{ij})$	-0.42	-0.18	-	-0.20	-0.18	-0.18
$CV(e_i)$	0.18	0.11	0.11	0.23	0.23	0.11
$CV(m_j)$	0.59	0.32	0.27	0.47	0.55	0.32
$\rho(\tau_{ij}^{\alpha}, H_i)$	0.23	0.12	0.12	0.11	0.09	0.12
$\rho(D_{ij}, NIP_{ij})$	0.16	0.08	-0.60	0.09	0.07	0.08
$\rho(NIP_j, m_j)$	-0.79	-0.65	0.00	-0.53	-0.72	-0.65
$pseudo - R^2$	0.95	0.96	0.96	0.98	0.99	0.68

Note: The table contains the mean statistics of 10,000 repetitions.

BV-method: PPML vs. OLS

		DGP - OLS				DGP - GLM			
		NIP_{ij}		D_{ij}		NIP_{ij}		D_{ij}	
Sample	BV on	Bias	SD	Bias	SD	Bias	SD	Bias	SD
		Baseline							
N^2	both	0.00	0.25	0.00	0.05	-0.18	0.15	-0.16	0.05
N^2	D_{ij}	-0.18	0.26	0.00	0.05	-0.29	0.32	-0.15	0.09
$N^2 - N$	both	2.37	4.62	0.01	0.05	1.90	3.32	-0.13	0.05
$N^2 - N$	D_{ij}	-0.49	0.59	0.01	0.05	-0.54	0.65	-0.12	0.09
		No Correlation $\rho(NIP_{ij} m_j) = 0$							
N^2	both	0.00	0.21	0.00	0.05	-0.15	0.14	-0.15	0.05
N^2	D_{ij}	-0.92	0.09	-0.05	0.05	-0.93	0.10	-0.21	0.09
$N^2 - N$	both	0.00	0.05	0.00	0.70	-0.15	0.48	-0.15	0.05
$N^2 - N$	D_{ij}	-0.91	0.09	-0.01	0.05	-0.93	0.10	-0.15	0.09

Note: Estimates in the left (right) panel are obtained via OLS and PPML. Results are based on 10,000 repetitions for $N = 10$.