Causal Inference with Network Data and Continuous Treatment: an application to trade distortions in agricultural markets

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Motivations

Countries have become dramatically **interconnected** as agri-food GVCs keep growing (Balié et al., 2017) and the international production networks become more organized under the lead of modern food processors and retailers (Minten et al., 2009; Bellemare, 2012).

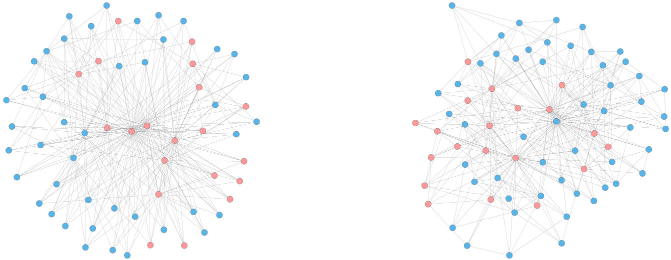

Figure: International Agro-Food Trade Network in 1990 (left) and 2010 (right). Only top 5 incoming flows are displayed for OECD (red) and Non-OECD (blue) countries

Motivations (cont'd)

A significant turnaround is expected to occur in the agricultural markets, as a result of the recent reduction in the **distortions** of OECD countries and the increase of support for agricultural producers in emerging economies (Swinnen et al., 2012).

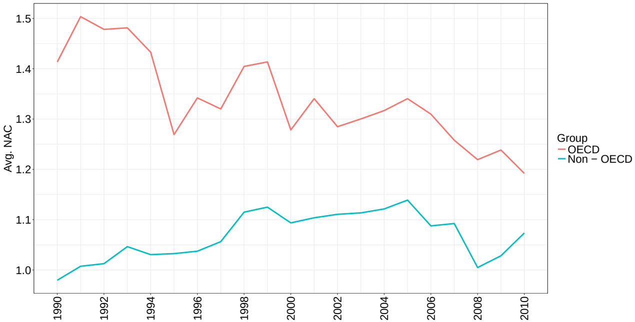

Figure: NAC values in OECD (red) and Non-OECD (blue) countries from 1990 to 2010

Aim of the paper

- We investigate whether and how policy interventions both in the country and in (commercial) partner countries affect domestic **food security**.
- Building on Forastiere et al., (2017), we develop a **joint propensity score** method that corrects for the bias resulting from both treatment selection and interference, and it allows estimating both direct and network effects of policy interventions (for continuous treatments).
- Results show that: i) a limited support to agricultural markets is beneficial to FS and ii) the bias when neglecting interference is relevant and commercial partners' distortions can alter the effects of national policies.

Policy interventions and food security

- Since both PI and FS are driven, among other factors, by the country's level of endowments and by agro-climatic conditions, there are several possible sources of endogeneity that could hinder the identification of a causal effect.
- Therefore, we rely on matching techniques (GPS by Hirano and Imbens, 2004), which allow us to control for possible sources of self-selection without the need to impose specific constraints on the relationship between PI and FS.
- Assumptions: i) weak unconfoundedness and ii) SUTVA (unique treatment and **non-interference**).

Joint Propensity Score

$$\psi(z; g; x) = P(Z_i = z, G_i = g | X_i = x)$$
$$= P(G_i = g | Z_i = z, X_i^g = x^g) P(Z_i = z | X_i^z = x^z)$$

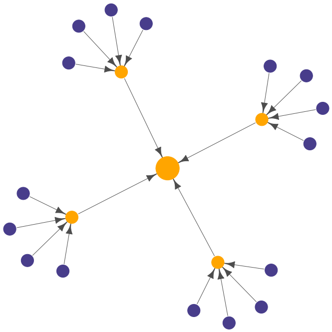

Figure: Interference toy example. Direct and Network Treatments (yellow)

Data

▸ summary

1. Treatment: Nominal Assistance Coefficient (NAC = NRA + 1) (Anderson et al., 2013)
2. Covariates: real per capita GDP, total population, per capita arable land, agricultural total factor productivity growth index, ratio of food imports to total exports, net food exports, absolute (positive and negative) percentage deviations from the trend in international food prices (Magrini et al., 2017)
3. Outcomes: food security measured as food availability, food access, food utilization and food stability (Committee on World Food Security, 2009)
4. Network: bilateral agro-food trade (FAOSTAT).

Individual and Neighborhood Propensity Scores

	$\phi(z; x^z)$	$\phi(g; z; x^g)$
(l1.ln) pc real gdp	2.268* (1.367)	14.357*** (2.696)
(l1.ln) pc real gdp^2	−0.236 (0.167)	−1.949*** (0.330)
(l1.ln) pc real gdp^3	0.009 (0.007)	0.088*** (0.013)
(l1.ln) pc arable land	−0.127*** (0.019)	0.152*** (0.039)
(l1.ln) pop	−0.072 (0.045)	0.694*** (0.090)
(l1.ln) pop^2	0.003* (0.002)	−0.019*** (0.004)
(l1) agr. tfp	−0.095 (0.109)	0.239 (0.214)
(l1) food imp/tot exp	0.249** (0.115)	1.601*** (0.226)
(l1) food imp/tot exp^2	0.034 (0.035)	0.679*** (0.068)
(l1) net exp	−0.184*** (0.025)	−0.266*** (0.051)
(l1) pos dev food	−1.601*** (0.446)	−0.721 (0.885)
(l1) neg dev food	−0.897*** (0.346)	−0.176 (0.685)
food volatility	−3.608** (1.448)	0.890 (2.867)
food crisis	−0.167*** (0.045)	−0.143 (0.090)
Z		−0.205* (0.119)
Constant	−7.755** (3.730)	−40.855*** (7.353)
Observations	1,233	1,233
R^2	0.454	0.760
Adjusted R^2	0.446	0.756
Residual Std. Error	0.404 (df = 1214)	0.797 (df = 1213)
F Statistic	56.069*** (df = 18; 1214)	201.736*** (df = 19; 1213)
Regional dummies	Yes	Yes

Note: **p<0.1;* ***p<0.05;* ****p<0.01. l1 stands for one year lag.*

Food availability

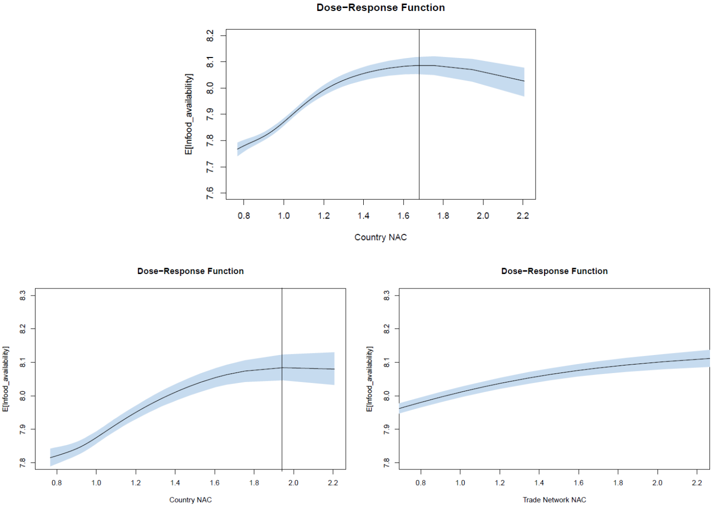

Figure: Marginal dose-response function no-interference (top) and marginal dose-response function $\mu^Z(g)$ of direct NAC (bottom left) and marginal dose-response function $\mu^G(z)$ of network NAC (bottom right) on food availability (log scale)

Conclusions

- GVCs triggered an unprecedented integration of DCs into the global economy, with significant consequences on FS, especially when considering the variety, quality, and safety of food products and the composition of people's diets.
- PIs matter and they have a non-linear impact on FS, as a excessive support for the primary sector may have detrimental effect.
- Bias when neglecting interference is relevant and commercial partners' distortions can alter the effects of national policies. It is therefore crucial to assess a country's level of trade integration when designing evidence-based policy interventions.

Thank you

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Summary statistics

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	Variable	Mean	St. Dev.	Max	Min
Outcomes	food availability	2812.12	548.80	3828.00	1516.00
	food access	98.98	109.46	615.00	1.00
	food utilization	38.32	24.98	89.50	6.10
	food variability	15.58	15.97	85.00	0.00
Covariates	pc real gdp	12743.10	13856.17	52118.09	323.26
	pc arable land	0.32	0.33	2.81	0.03
	pop (/100)	3,0230.99	164,009.143	1,337,705.00	0.27
	agr tfp	111.58	16.25	179.82	49.13
	food imp/tot exp	0.02	0.03	0.26	0.00
	net exp	1.66	2.15	24.35	0.01
	pos dev food	0.01	0.03	0.14	0.00
	neg dev food	0.05	0.04	0.14	0.00
	food volatility	0.02	0.01	0.05	0.01
	food crisis	0.09	0.29	1.00	0.00
Treatment	NAC (Z)	1.15	0.26	2.29	0.71

Coefficients of the outcome models

	Food Availability	Food Utilization	Food Variability	Food Access
z	4.090*** (0.632)	−8.573*** (2.027)	−0.205 (4.168)	−9.623* (5.396)
z^2	−2.659*** (0.458)	6.544*** (1.471)	1.390 (3.019)	6.855* (3.904)
z^3	0.553*** (0.104)	−1.588*** (0.336)	−0.589 (0.687)	−1.631* (0.886)
$\phi(z; X_i^z)$	−0.685*** (0.176)	1.350** (0.566)	−1.952* (1.173)	3.272** (1.542)
$\phi(z; X_i^z)^2$	−0.415 (0.362)	2.584** (1.161)	0.966 (2.398)	5.495* (3.118)
$\phi(z; X_i^z)^3$	0.404* (0.217)	−1.543** (0.696)	−0.442 (1.434)	−3.857** (1.872)
$z * \phi(z; X_i^z)$	0.535*** (0.059)	−2.158*** (0.189)	0.937** (0.388)	−4.453*** (0.522)
g	0.309*** (0.028)	−0.938*** (0.090)	0.074 (0.183)	−4.547*** (0.506)
g^2	−0.035*** (0.004)	0.093*** (0.013)	0.012 (0.026)	1.863*** (0.210)
g^3	0.002*** (0.0002)	−0.005*** (0.001)	−0.0004 (0.002)	−0.231*** (0.034)
$\lambda(g; z; X_i^g)$	−0.186 (0.390)	2.970** (1.261)	−0.535 (2.558)	−26.975*** (4.658)
$\lambda(g; z; X_i^g)^2$	1.359 (1.624)	−10.254** (5.216)	−14.127 (10.601)	94.139*** (17.963)
$\lambda(g; z; X_i^g)^3$	−2.341 (1.901)	14.041** (6.088)	20.684* (12.392)	−88.330*** (20.198)
$g * \lambda(g; z; X_i^g)$	0.003 (0.027)	−0.206** (0.087)	0.643*** (0.175)	−2.651*** (0.704)
$z * g$	−0.112*** (0.015)	0.373*** (0.048)	−0.115 (0.098)	1.499*** (0.296)
Constant	5.989*** (0.269)	6.746*** (0.860)	2.937* (1.771)	9.978*** (2.317)
Observations	1,204	1,233	1,205	1,007
R^2	0.611	0.663	0.265	0.615
Adjusted R^2	0.606	0.659	0.255	0.610
Residual Std. Error	0.126 (df = 1188)	0.411 (df = 1217)	0.831 (df = 1189)	1.016 (df = 991)
F Statistic	124.215*** (df = 15; 1188)	159.672*** (df = 15; 1217)	28.509*** (df = 15; 1189)	105.750*** (df = 15; 991)

Note: *p<0.1; **p<0.05; ***p<0.01