Do More Open Economies Lead to Export Concentration? The Case of Selected Agribusiness Goods in Brazilian Municipalities

Alan Leal
Research Associate at FGV Global Business
www.alanleal-econ.com

Michelle Márcia Vianna Martins
Professor of Economics at Federal University of Viçosa

Introdução

- Productive specialization and comparative advantages: the Ricardian perspective
- Brazilian exports specialization
- Municipalities specialization: new methods and development to measure municipal exports
- What causes exports concentration? Can an exporting economy specialized in few goods see even more concentration?

Brazilian exports characteristics

- In 2023, agribusiness was responsible for about 50% of Brazilian exports.
- Soybeans, meat, and sugar were the main contributors to this result.
- A natural question is how this productivity is spread out in the country and whether a municipality exporting more of these goods tend to specialize in fewer goods overall.
- This question is relevant given the fact that for commodities, Brazil is usually a price taker, hence specializing in exporting these goods might not be the most reasonable strategy.
- We answer this question by employing Leal and Martins (2025) export imputation method, coupled with a particular concentration exports measure. We find that for soybeans, sugar, corn, and coffee, more trade openness means exports concentration, while that does not seem to be the case for meat.

Method I

- Define k as the number of goods present in the HS6 category of goods at the HS4 level. Then, we can proxy the production direct to the foreign market in a given municipality by the following equation:

$$E_{i,\text{HS6}} = \underbrace{\alpha \mathbf{W} E_{i,\text{HS4}}}_{\text{Spatial Component}} + \underbrace{r E^{*}_{i^*,\text{HS6}}}_{\text{Adjustment Component}} \tag{1}$$

Onde:

- i is a given municipality.
- $E_{i,HS6}$ are the municipal exports estimated at the level SH6.
- $E^{*}_{i*,HS6}$ is defined as $\sum_{i=1}^{I} \alpha(E_{i*,HS4} - \mathbf{W}E_{i*,HS4})$.

Method II

- α is the proportion coefficient defined as:

$$\alpha = \frac{E_{state,HS6}}{E_{state,HS4}} \tag{2}$$

  where E means exports, hence $E_{state,HS6}$ are the state exports for a given HS6 good. $E_{state,HS4}$ is the state exports at the state level for a HS4 category.
- **W** is a spatial weight matrix $n \times n$, row-normalized, such that n is the number of municipalities and:

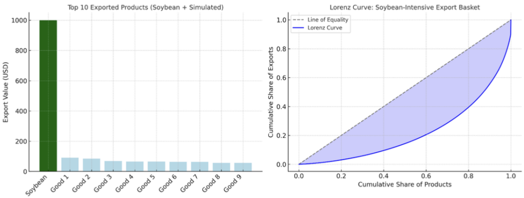
$$\sum_{j=1}^{n} w_{ij} = 1 \quad \forall i \tag{3}$$

  E $w_{ij} \geq 0 \quad \forall i, j$
- **r** is a vector $n \times 1$, that adds up to 1.
- $E_{i*,HS4}$ is a vector $n \times 1$ of observed exports at the HS4 level, where * indicates that some entries might be 0.

Good-Intensive Gini Index

1. Gini Index for Measuring Concentration
2. Impossibility to measure the true distribution of exports by a given municipality
3. Monte Carlo experiment that matches the distribution for a given good
4. Example:

Figure: Good-Intensive Gini Index creation



Fonte: Authors' elaboration.

Double Machine Learning

- Double Machine Learning: high-dimension machine learning that uses the Frisch-Waugh-Lovell theorem as a way to identify a causal effect.

$$Y = D\theta + g(X) + \varepsilon, \;\; E(\varepsilon|D, X) = 0$$

$$D = m(X) + V, \;\; E(V|X) = 0$$

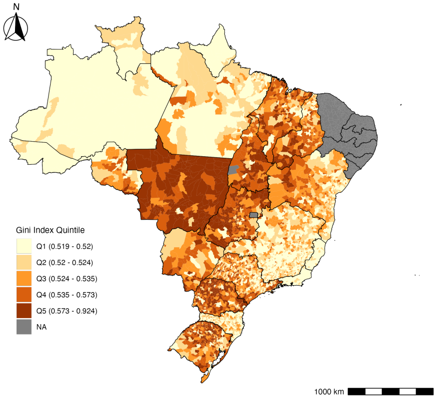
- θ measures the causal effect of interest, in our case the effect of exports-oriented trade openness on the export concentration.
- $m(X)$ and $g(X)$ are fit using random forests, hence a more flexible functional formal than a polynomial specification.

Variables I

- We use tens of variables to control for confounding effects.
- In that way, we employ added values, rain, distance to infrastructure, distance to capital, PIX variables, IBGE demographic information, ESTBAN variables, Anatel's Brazilian connectivity index, data on rural properties, data on deforestation, fiscal capacity of municipalities, data on CAR, and data on formal labor market.

Descriptive Statistics I

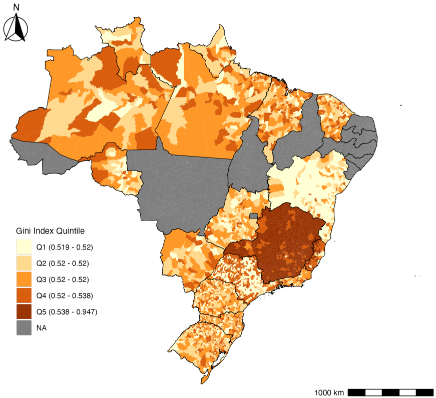
Figure: Soybeans Imputation



Fonte: Authors' elaboration.

Descriptive Statistics II

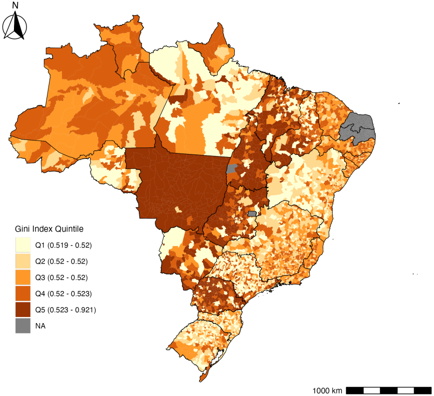
Figure: Coffee Imputation



Fonte: Authors' elaboration.

Descriptive Statistics III

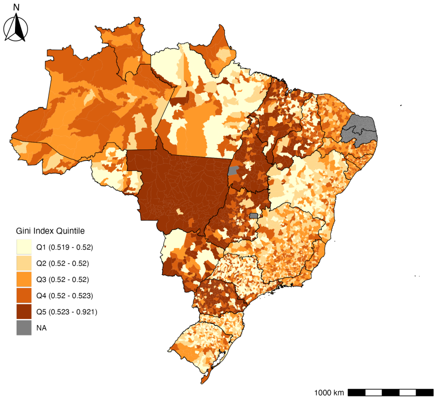
Figure: Corn Imputation



Fonte: Authors' elaboration.

Descriptive Statistics IV

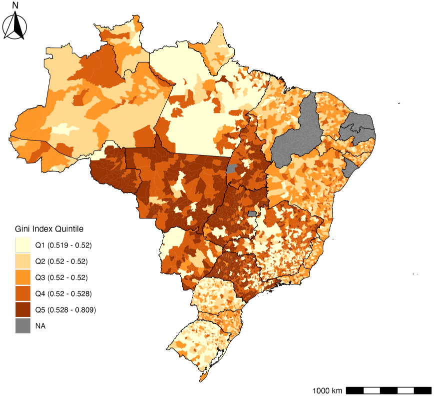
Figure: Sugar Imputation



Fonte: Authors' elaboration.

Descriptive Statistics V

Figure: Meat Imputation



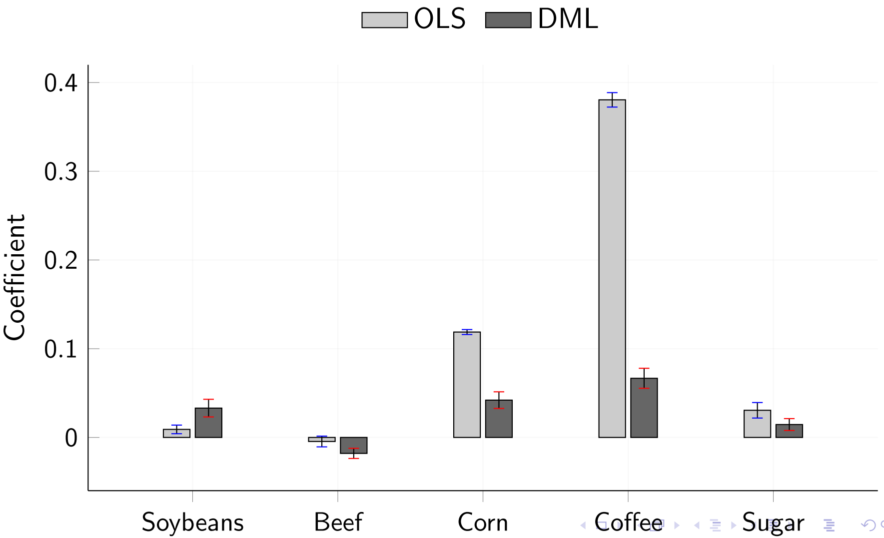
Fonte: Authors' elaboration.

Econometric Results

Good	**OLS**	**Double Machine Learning**	**Observations**
Soybeans	0.00907***	0.03306***	4,632
	(0.00485)	(0.00994)	
Beef	-0.00456	-0.01798**	4,879
	(0.00606)	(0.00573)	
Corn	0.11880***	0.04206***	5,178
	(0.00280)	(0.00938)	
Coffee	0.38050***	0.06667***	4,291
	(0.00815)	(0.01128)	
Sugar	0.03060***	0.01454**	5,039
	(0.00874)	(0.00669)	

Notes: Authors' elaboration. Standard errors in parentheses.
*** Significant at 1%; ** at 5%; * at 10%.

Impact of municipal export openness on export concentration



Results I

- Beef puzzle: why exporting more beef means less export concentration?
- Coffee result is concerning given our total price-taking behavior
- Other agrarian goods working as expected
- Is it possible not to concentrate? By aggregating more value to Brazilian exports

References I

Leal, A. and Martins, M. M. V. (2025). Brazilian exports imputation: A new algorithm for estimating the municipal production directed at the foreign market. *Revista Brasileira de Estudos Regionais e Urbanos*, 19(2):266–288.