Commodity Booms, Structural Transformation and Land Inequality

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Motivation

- How commodity booms affect structural transformation?
- Developing countries have experienced a long process of structural change over the last 50 years
- Literature still lacks robust empirical evidence on push vs. pull effects
- Inequality in landownership might be working as an important channel
  - Concentration of land after the shock could be displacing workers
- Focus on Brazilian municipalities as the setting
  - Greatly affected by the last commodity super-cycle
  - Experienced significant structural change during the last decades
  - High levels of land inequality

This Paper

- Study the 2000s commodity price shocks as a source of exogenous price variations
- Construct a shift-share measure to estimate the effects of the price shocks on local reallocation of factor across sectors
- Explore the role of inequality in landholdings as a mechanism
- We find that localities that have benefited more from the shock experienced a reallocation of labor from agriculture towards manufacturing
- We also observe an increase in land inequality in those same municipalities
  - Commodity boom led to higher inequality which promoted the reallocation

Related Literature

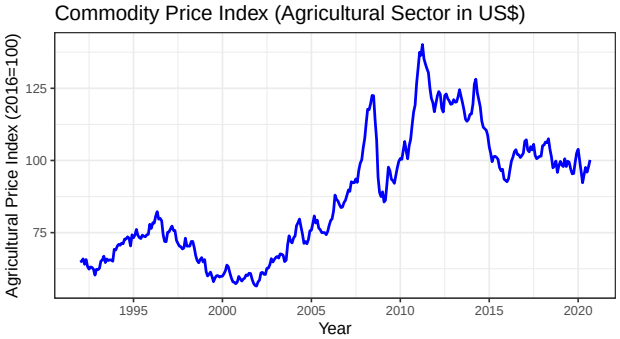
- Natural resource booms effects on local economies
  - Armed conflicts: Dube and Vargas (2013)
  - Dutch disease vs. agglomeration: Allcott and Keniston (2018)
  - Entrepreneurship: Bernstein et al. (2018)
  - Structural change and human capital: Uribe-Castro (2019)
  - Development: Cavalcanti et al. (2019)

- Agricultural productivity and structural transformation: Bustos et al. (2016); Bustos et al. (2020)

- Historical negative effects of land inequality on long-term development: Vollrath (2007); Galor et al. (2009); Wigton-Jones (2020)

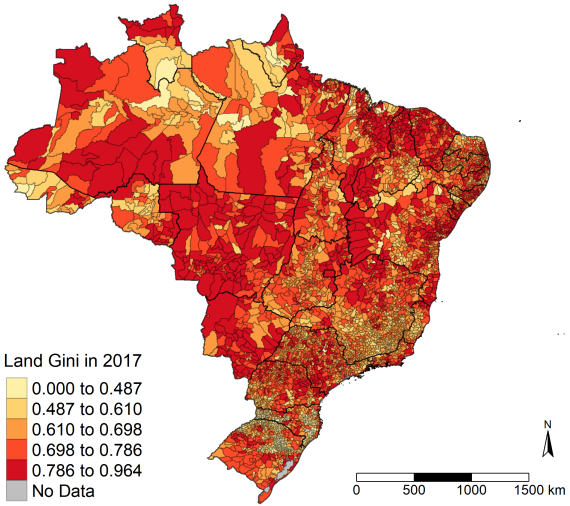
Commodity Price Shocks

- Commodity super cycle started in 2000 and peaked in 2011
- Comparable to other super-cycles
  - Post–World War II
  - 2nd Industrial Revolution
- 2000-2010 difference is our baseline



Land Inequality

- Brazil has one of the highest levels of land inequality in the world (Bauluz et al., 2020)
- Less than 1% of all farms concentrate more than half of the total rural area
- But why should we care about land inequality?
- Effect of inequality in landholdings on local outcomes
  - Might be displacing workers from agriculture



Data Sources

Summary Statistics

- PAM and PPM - IBGE
  Table
  - Production of crops and cattle for each year and municipality in metric tons
- World Bank
  - International commodity prices
- FAO-GAEZ
  - Crop potential yields in tons/hectare
- Population (1991-2000-2010) and Agricultural Census (1995-2006-2017) - IBGE
  - Employment shares, wages, land and capital intensities
  - Number and area of farms
    Land Gini Calculation
  - Baseline controls
- IPEADATA
  - Additional socio-economic and geo-climatic variables

Empirical Strategy - Predicted Shares

- Following Fiszbein (2019), we use a fractional multinomial logit to calculate predicted agricultural shares:

$$\widehat{Q}_{ki} = E[Q_{ki,99}|A_i] = \frac{e^{\beta_k A_i}}{1 + \sum_{j=1}^{K-1} e^{\beta_j A_i}}$$

  - A_i: vector of crop-specific potential yields
  - $Q_{ki,99}$: average local crop k endowment share in municipality i over 1995-1999

- Draws from optimal crop choice model of McFadden et al. (1973)
  - Profit-maximizer and price-takers farmers choose crop production given the vector of productivity

Empirical Strategy - Exposure Measure

- We then construct a shift-share measure which defines the relative exposure of each location to the shock:

$$CE_{it} = \sum_{k} \widehat{Q}_{ki} \cdot \log P_{kt}$$

  - P_{it}: international price of crop k at time t

- The shares sum up to 1 and prices are used in logs to avoid OVB as discussed in Borusyak and Hull (2020)

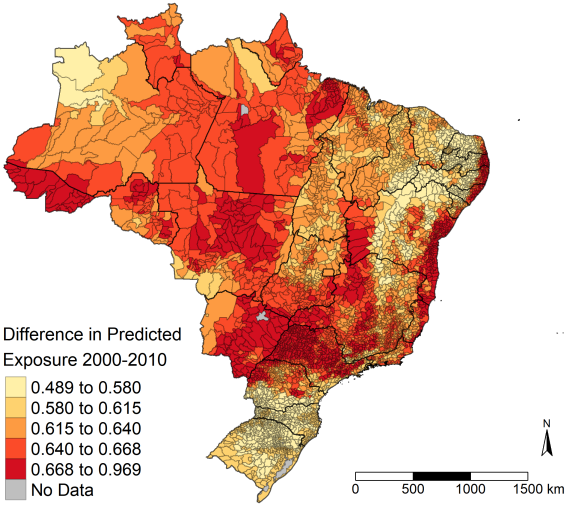
- This measure is related to several others in the literature:
  - Dube and Vargas (2013)
  - Allcott and Keniston (2018)
  - Bernstein et al. (2018)

Predicted Measure

- **Exogeneity:** Cross-sectional (shares) + time variation (prices)
- Predicts the agricultural frontier expansion
  - Midwest region
  - Matopiba
  - Amazon

▸ Actual Measure and Cattle

▸ Correlation



Empirical Strategy - Main Specification

- Our main equation is:

$$y_{it} = \beta \times CE_{it} + \delta' X_{i,1991} + \alpha_i + \gamma_t + u_{it}$$

  - CE_{it}: exposure to the shock in municipality i, year t
  - $X_{i,1991}$: vector of baseline controls
  - α_i: municipality fixed effects
  - γ_t: year fixed effects
  - u_{it}: error term

- Identification: $\mathbb{E}\left[u_{it} CE_{it} | X_{i,1991}, \alpha_i, \gamma_t\right] = 0$

- We use first differences for the agricultural and population census

- $X_{i,1991}$ controls for heterogeneous initial characteristics across municipalities
  - Population density, income per capita, illiteracy rate and share of rural population

Population Census Outcomes

	Δ Employment Share Agriculture	Δ Employment Share Manufacturing	Δ Employment Share Services	Δ Log Wages Agriculture	Δ Log Wages Manufacturing
Δ CE	−0.136***	0.174***	0.005	0.523***	−0.348***
	(0.018)	(0.014)	(0.012)	(0.089)	(0.131)
Adj. R^2	0.081	0.037	0.170	0.014	0.005
Observations	5,482	5,482	5,482	5,482	5,482

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Observations	5,482	5,482	5,482	5,482	5,482
Standard Errors Robustness Checks					
Cluster at microregion	(0.035)***	(0.035)***	(0.015)	(0.124)***	(0.136)**
Conley 50km	(0.037)***	(0.033)***	(0.018)	(0.129)***	(0.156)**
Conley 100km	(0.051)***	(0.047)***	(0.022)	(0.162)***	(0.163)**
Conley 200km	(0.069)**	(0.070)**	(0.026)	(0.184)***	(0.161)**
AKM	(0.035)***	(0.044)***	(0.021)	(0.119)***	(0.085)***
AKM0	(0.056)**	(0.070)**	(0.033)	(0.187)**	(0.143)*

Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

▸ Alternative Measures

Discussion - Structural Change

- Results show a sizeable reallocation of labor from agriculture to manufacturing
  - Corroborate the findings of Bustos et al. (2016) on labor-saving technology
  - But evidence on widespread agricultural productivity change in the last decades points in the other direction (Moscona, 2018)
- The overall effect across a wide range of commodities points to a relevant push effect
  - Possible heterogeneous effect on the type of crop
- Results in line with Gollin et al. (2016) model
  - Natural resource rents can drive structural change just as industrial development
- We find no effect on services share
  - Analysis is only at the municipality level
  - The effect on the demand for services in the aggregate economy is not present

Agricultural Census Outcomes

	Δ Land Gini 2017-2006	Δ Land Gini 2017-1995	Δ Land Gini 2006-1995	Δ Log Land Intensity	Δ Log Machine Intensity
Δ CE	0.063***	0.112***	0.037*	0.270***	0.582**
	(0.012)	(0.024)	(0.022)	(0.104)	(0.226)
Adj. R^2	0.067	0.081	0.013	0.0415	0.006
Observations	5,452	4,928	4,928	5,452	5,452

Agricultural Census Outcomes

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	(0.012)	(0.024)	(0.022)	(0.104)	(0.226)
Adj. R^2	0.067	0.081	0.013	0.0415	0.006
Observations	5,452	4,928	4,928	5,452	5,452
Standard Errors Robustness Checks					
Cluster at microregion	(0.028)**	(0.037)***	(0.028)	(0.135)**	(0.300)
Conley 50km	(0.027)**	(0.039)***	(0.033)	(0.139)*	(0.315)*
Conley 100km	(0.029)**	(0.049)**	(0.040)	(0.161)	(0.376)
Conley 200km	(0.030)**	(0.056)**	(0.047)	(0.197)	(0.556)
AKM	(0.025)***	(0.048)**	(0.041)	(0.185)	(0.293)*
AKM0	(0.048)	(0.078)	(0.068)	(0.290)	(0.507)*

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

▸ Alternative Measures

Discussion - Channels

- Preliminary results point to land inequality as an important channel
- Rising concentration of land could be displacing of workers away from agriculture
- More specifically, this effect could be driven by the type of landownership
  - Large landowners acquiring nearby land and increasing concentration
- Evidence on greater capital intensity at farms
  - Substituting labor
- Heterogeneous effect on the type of industry
  - Sub-sectors related to processing the agricultural products
  - Agroindustry

Next Steps

- Alternative measures:
  - Predicted shares and international prices as an IV for local quantities and prices
  - Explore other measures used in the literature
- Further explore channels, mechanisms and heterogeneous effects
  - Agribusiness and food processing
  - Crop heterogeneity
  - Type of landownership
  - Technological change via new type of seeds
- Build a simple model of structural change and land inequality
- Further robustness checks:
  - High inputs in potential yields data
  - Aggregate at microregions and AMCs
  - Placebo tests

Thank You!

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Agricultural Endowments

Back

	Number of Municipalities	
	2000	2010
Cattle	5471	5518
Maize	5329	5176
Rice	4071	3084
Banana	3795	3555
Orange	3634	3006
Sugarcane	3483	3695
Coffee	2008	1822
Soybean	1446	1800
Cotton	1272	411
Tobacco	958	892
Wheat	802	895
Yerba Mate	555	474
Sorghum	469	604
Cocoa	264	282
Barley	173	135

Summary Statistics

Back

	2000		2010		Δ 2010-2000		
	Mean	SD	Mean	SD	Mean	SD	Observations
Panel A: Population Census							
Employment Share Agriculture	0.425	0.204	0.356	0.182	-0.068	0.081	5,482
Employment Share Manufacturing	0.010	0.087	0.101	0.090	0.002	0.055	5,482
Employment Share Services	0.315	0.108	0.324	0.088	0.008	0.055	5,482
Log Wage in Agriculture	6.167	0.606	6.391	0.577	0.221	0.393	5,482
Log Wage in Manufacturing	6.375	0.618	6.629	0.557	0.254	0.560	5,482
Panel B: Exposure Measure							
Commodity Exposure	6.345	0.381	6.876	0.347	0.532	0.064	5,482
	2006		2017		Δ 2017-2006		
	Mean	SD	Mean	SD	Mean	SD	Observations
Panel C: Agricultural Census							
Land Gini	0.694	0.130	0.676	0.118	-0.018	0.084	5,452
Log Land Intensity	-0.630	0.772	-0.654	0.801	-0.019	0.472	5,452
Log Machine Intensity	-5.893	1.762	-5.500	1.683	0.392	0.831	5,452

Land Gini Calculation

Back

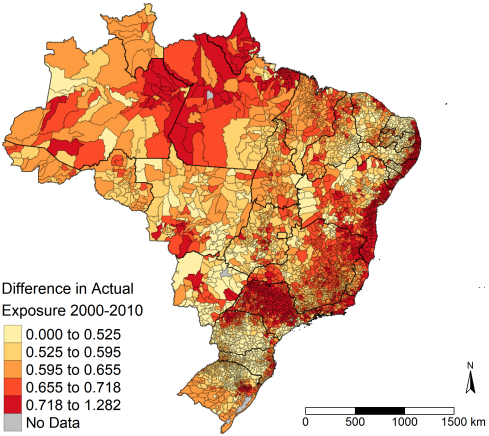
- Area and number of rural properties is reported into different area intervals
- We follow Nunn (2008) to obtain the Gini coefficient as follows:

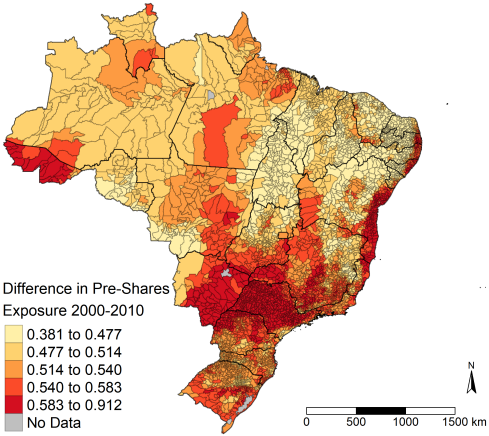
$$\text{Land Gini} = 1 + \left(\frac{1}{n}\right) - \frac{2\sum_1^n (n - i + 1)\, a_i}{n \sum_i^n a_i}$$

  - n: number of farms
  - a_i: farm size in acres
  - i: denotes the rank in ascending order of a_i

Actual Measure and Cattle

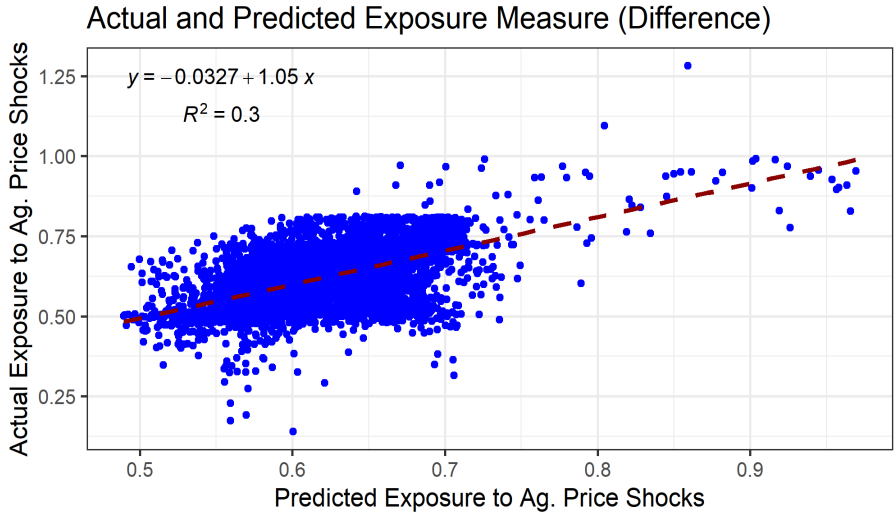
Back





Correlation Between Measures

Back



Population Census Outcomes - Alternative Measures

Back

	Δ Employment Share Agriculture	Δ Employment Share Manufacturing	Δ Employment Share Services	Δ Log Wages Agriculture	Δ Log Wages Manufacturing
Top 10% Δ CE	−0.024***	0.028***	−0.003	0.0810***	−0.006
	(0.003)	(0.003)	(0.002)	(0.017)	(0.023)
Top 25% Δ CE	−0.021***	0.026***	−0.002	0.074***	−0.016
	(0.002)	(0.002)	(0.001)	(0.013)	(0.018)
Bottom 10% Δ CE	0.012***	−0.005***	−0.008***	−0.027	0.036
	(0.004)	(0.002)	(0.003)	(0.018)	(0.028)
Bottom 25% Δ CE	0.007**	−0.011***	−0.002	−0.001	0.064***
	(0.003)	(0.002)	(0.002)	(0.014)	(0.022)
Observations	5,482	5,482	5,482	5,482	5,482

Robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Agricultural Census Outcomes - Alternative Measures

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	Δ Land Gini 2017-2006	Δ Land Gini 2017-1995	Δ Land Gini 2006-1995	Δ Log Land Intensity	Δ Log Machine Intensity
Top 10% Δ CE	0.012***	0.007	−0.006	0.008	−0.115***
	(0.004)	(0.004)	(0.004)	(0.020)	(0.030)
Top 25% Δ CE	0.007**	0.006*	−0.001	0.016	−0.046**
	(0.002)	(0.003)	(0.003)	(0.015)	(0.022)
Bottom 10% Δ CE	0.004	−0.018***	−0.0202***	−0.038*	−0.326***
	(0.004)	(0.005)	(0.004)	(0.021)	(0.056)
Bottom 25% Δ CE	−0.003	−0.019***	−0.014***	−0.042**	−0.202***
	(0.003)	(0.004)	(0.004)	(0.020)	(0.038)
Observations	5,452	4,928	4,928	5,452	5,452

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$