

Man Eats Forest

Impacts of Cattle Ranching on Amazon Deforestation

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Motivation

- ▶ **Amazon deforestation** continues to be an issue, threatening
 - ▶ local *biodiversity* and *livelihoods* (Gibson et al. 2011; Villén-Pérez et al. 2022)
 - ▶ regional and global *climates* (Leite-Filho et al. 2021; Araujo et al. 2023)

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- ▶ In Brazil, **demand for land** primarily stems from **agriculture**,
 - ▶ with **cattle** and *soy* being the predominant factors (Rajão et al. 2020)
 - ▶ mining and other agricultural products play a limited role (Garrett et al. 2021)

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This paper

Uses a quasi-experimental shift-share design to **causally identify and quantify** the deforestation impacts of the **demand-driven cattle expansion** in the Legal Amazon

Legal Amazon in 2000

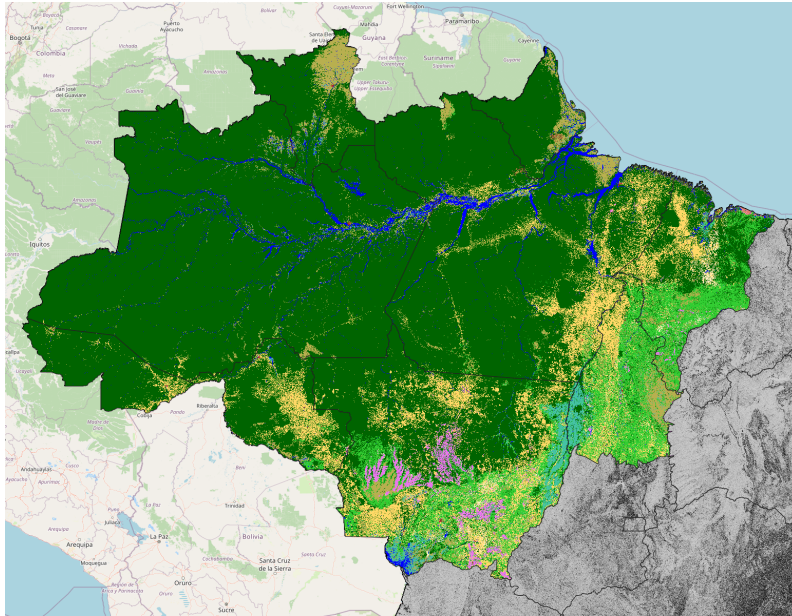


Chart: Land cover, including **forest**, **pasture**, and **croplands**, in the Legal Amazon in 2000.

Legal Amazon in 2022

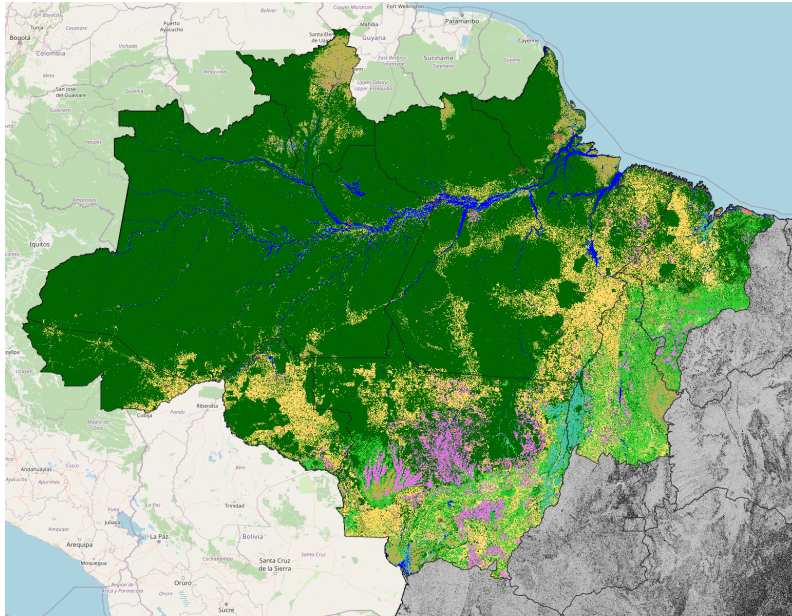


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Background, Deforestation in Brazil

Reasons for high levels and resurgence include:

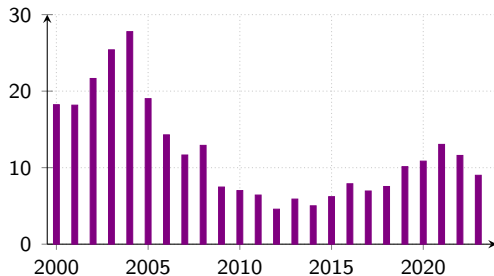


Chart: Deforestation in the Brazilian Amazon (in 1,000 km²).

- a. Cusack et al. 2021; Pendrill et al. 2022.
- b. Reydon, Fernandes, and Telles 2020.
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Reasons for high levels and resurgence include:

- ▶ strong and rising **demand for agricultural products**, especially **beef products**^a
 - ▶ can be met with *intensification*, or deforestation at the *extensive margin*.

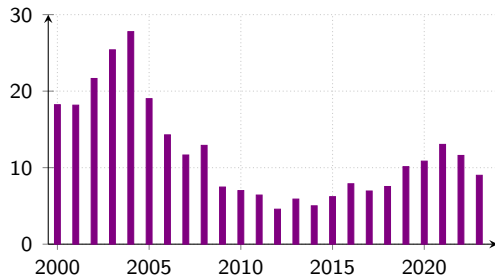


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- ▶ weak *land governance* enabling speculative **land appropriation**^b
 - ▶ forest is cut, agricultural activities are feigned, and ownership is claimed.

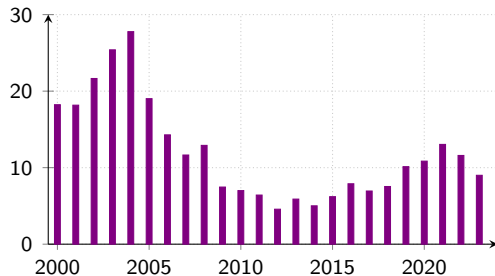


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- ▶ *policy interventions* being **not resilient** with respect to political influence^c

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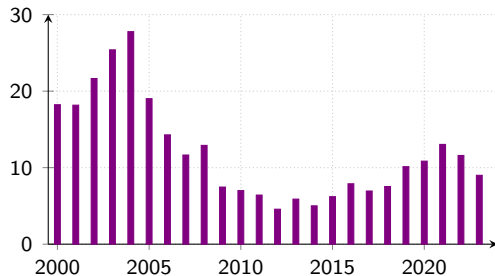


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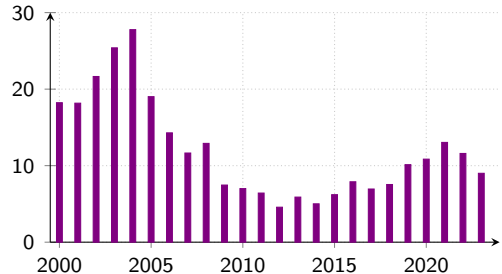


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- ▶ ...is important for the national economy at **8% of GDP** (CEPEA 2023), and the livelihoods of **local farmers** specifically (Ermgassen et al. 2020),

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- ▶ ...is important for the national economy at **8% of GDP** (CEPEA 2023), and the livelihoods of local farmers specifically (Ermgassen et al. 2020),
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- ▶ ...is linked to deforestation that accounts for a **fifth of global land use emissions** from the tropics, 500MT per year (Pendrill et al. 2019),

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- ▶ ...is linked to deforestation that accounts for a **fifth of global land use emissions** from the tropics, 500MT per year (Pendrill et al. 2019),
- ▶ ...and, due to the mobility of cattle, acts as the **main intermediary for land appropriations** in the Amazon (Fearnside 2017).

Empirical Specification

Empirical Specification I

We depart from a simple panel regression specification:

$$y_{i,t} = \beta c_{i,t} + \mathbf{X}'_{i,t-s} \gamma + \mu_t + u_{i,t},$$

where

- ▶ $y_{i,t}$ denotes **forest loss** in municipality i at time t ,
- ▶ $c_{i,t}$ is a measure of **cattle expansion** (e.g. change in pasture area, cattle head),

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- ▶ $\mathbf{X}_{i,t-s}$ holds (suitably lagged) control variables,
- ▶ μ_t and time-fixed effects, and
- ▶ $u_{i,t} \sim \mathcal{N}(0, \sigma_y^2)$ is the error term.

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Entangled effects

However, β is not *identified*, i.e. as $c_{i,t}$ captures multiple drivers of the cattle expansion

Empirical Specification II

To *identify the causal effect* of cattle expansion, we use a shift-share instrument:¹

$$\begin{aligned}y_{i,t} &= \beta \hat{c}_{i,t} + \mathbf{X}'_{i,t-s} \gamma + \mu_t + u_{i,t} \\ c_{i,t} &= \mathbf{X}_{i,t-s} \alpha + \omega B_{i,t} + \mu_t^b + \varepsilon_{i,t}\end{aligned}$$

1. Also called ‘Bartik’; see Borusyak, Hull, and Jaravel 2022, for more details.

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- We instrument the measure of cattle expansion $c_{i,t}$ with

$$B_{i,t} = \sum_m z_{i,m,t=0} g_{m,t},$$

- constructed as interaction of **shifts** $g_{m,t}$ with **shares** $z_{i,m,t=0}$ for export market m

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Identification

We rely on *exogeneity of the shifts* for identification, and exploit *shares for relevance*

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Construction of the instrument [▸ Details](#)

We construct our shift-share (or *Bartik*) instrument $B_{i,t}$ as

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- ▶ Distance to slaughterhouse locations, interacted with municipality i 's initial cattle stocks as **share** $z_{i,m,t=0}$ to measure exposure to beef industry
 - ▶ Transport costs are crucial factor for the profitability of agriculture (Souza-Rodrigues 2019), and slaughterhouses are an intermediate destination (Vale et al. 2022)

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 - ▶ Transport costs are crucial factor for the profitability of agriculture (Souza-Rodrigues 2019), and slaughterhouses are an intermediate destination (Vale et al. 2022)
- ▶ Changes in international beef consumption as **shifts** $g_{m,t}$, where we consider
 - (i) changes in **all export destinations** weighted by exports at the municipality level
 - (ii) changes in **Chinese beef consumption** for periods lacking export information

Shift-Share Instrument Components

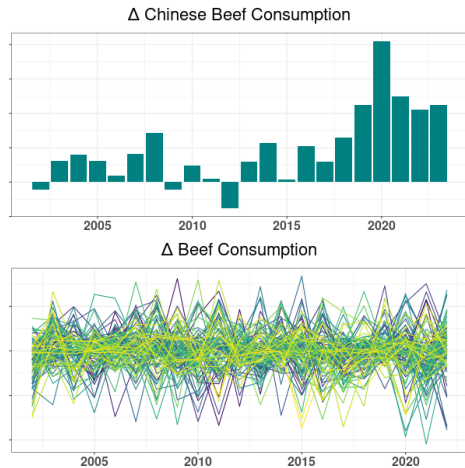
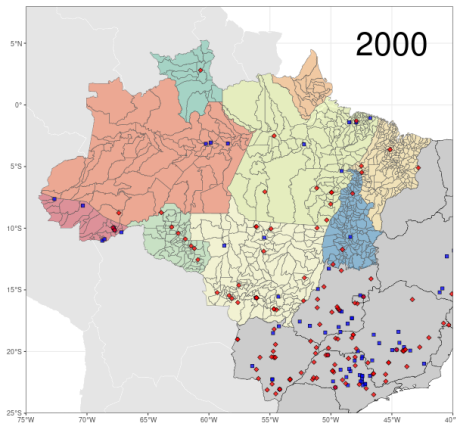


Chart: Slaughterhouse locations in 2000 and changes in aggregate beef consumption.

Sources: Vale et al. 2022; FAO 2023

Data & Sources

Main sample covers 808 municipalities in the Legal Amazon from 2003 until 2022:

- ▶ Land cover and land use change statistics (MapBiomas 2023)
- ▶ Socioeconomic and agricultural data (IBGE 2022)
- ▶ Environmental fines (IBAMA 2022)
- ▶ Protected areas (UNEP-WCMC and IUCN 2022)
- ▶ Agricultural price indices constructed in the style of Assunção, Gandour, and Rocha 2015
- ▶ Meteorological indicators (Beguería, Vicente-Serrano, and Angulo-Martínez 2010)
- ▶ Slaughterhouse locations (Vale et al. 2022)
- ▶ Municipality-level beef exports (Ermgassen et al. 2020)
- ▶ International beef consumption (FAO 2023)

Results

Results

	2003–2022	2011–2022
Forest~	OLS	OLS
Cattle	-0.103 (0.03)	-0.109 (0.03)
Pasture	-0.895 (0.03)	-0.832 (0.04)
Covariates	Full	
Year FEs	Yes	
$N \times T$	16,160	9,696
F stat (Cattle)		
F stat (Pasture)		

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results

	2003–2022		2011–2022
Forest~	OLS	IV-CHN	OLS
Cattle	-0.103 (0.03)	-0.429 (0.14)	-0.109 (0.03)
Pasture	-0.895 (0.03)	-0.971 (0.03)	-0.832 (0.04)
Covariates	Full	...	
Year FEs	Yes	...	
$N \times T$	16,160	16,160	9,696
F stat (Cattle)		301.6	
F stat (Pasture)		796.1	

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results

Forest~	2003–2022		2011–2022		
	OLS	IV-CHN	OLS	IV-CHN	IV-EXP
Cattle	-0.103 (0.03)	-0.429 (0.14)	-0.109 (0.03)	-0.456 (0.13)	-0.381 (0.10)
Pasture	-0.895 (0.03)	-0.971 (0.03)	-0.832 (0.04)	-0.971 (0.03)	-0.914 (0.03)
Covariates	Full	...			
Year FEs	Yes	...			
$N \times T$	16,160	16,160	9,696	...	
F stat (Cattle)		301.6		414.1	56.8
F stat (Pasture)		796.1		816.4	111.9

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, biome heterogeneity

Biome	Amazon		Cerrado	
Dep.	Forest~ OLS	IV	Forest~	<i>incl. Savanna~</i>
Cattle	-0.108 (0.03)	-0.530 (0.15)		
Covariates	Full	...		

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, biome heterogeneity

Biome	Amazon		Cerrado	
Dep.	Forest~ OLS	IV	Forest~ OLS	<i>incl. Savanna~</i> IV
Cattle	-0.108 (0.03)	-0.530 (0.15)	-0.003 (.002)	-0.014 (0.02)
Covariates	Full	...		
Year FEs	Yes	...		
$N \times T$	10,060	...	21,240	...
				53.3

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, biome heterogeneity

Biome	Amazon		Cerrado			
Dep.	Forest~		Forest~		<i>incl. Savanna~</i>	
	OLS	IV	OLS	IV	OLS	IV
Cattle	-0.108 (0.03)	-0.530 (0.15)	-0.003 (.002)	-0.014 (0.02)	-0.028 (.001)	-0.342 (0.16)
Covariates	Full	...				
Year FEs	Yes	...				
$N \times T$	10,060	...	21,240	...		
F stat		188.7		53.3		53.3

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, regime heterogeneity

	Lula		Rousseff	Temer	Bolsonaro
Forest~	OLS	IV			
Cattle	-0.097 (0.03)	-0.479 (0.08)			
Covariates	Full	...			
<i>F</i> stat (Cattle)		150.1			

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, regime heterogeneity

	Lula		Rousseff		Temer	Bolsonaro
Forest~	OLS	IV	OLS	IV		
Cattle	-0.097 (0.03)	-0.479 (0.08)	-0.046 (0.01)	-0.121 (0.06)		
Covariates	Full	...				
Year FEs	Yes	...				
$N \times T$	6,464	6,464	4,040	4,040		
F stat (Cattle)		150.1		38.8		

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Forest~	OLS	IV	OLS	IV	OLS	IV	
Cattle	-0.097 (0.03)	-0.479 (0.08)	-0.046 (0.01)	-0.121 (0.06)	-0.086 (0.03)	-0.575 (0.15)	
Covariates	Full	...					
Year FEs	Yes	...					
$N \times T$	6,464	6,464	4,040	4,040	2,424	2,424	
F stat (Cattle)		150.1		38.8		65.7	

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Forest~	Lula		Rousseff		Temer		Bolsonaro	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Cattle	-0.097 (0.03)	-0.479 (0.08)	-0.046 (0.01)	-0.121 (0.06)	-0.086 (0.03)	-0.575 (0.15)	-0.159 (0.04)	-0.517 (0.13)
Covariates	Full	...						
Year FEs	Yes	...						
$N \times T$	6,464	6,464	4,040	4,040	2,424	2,424	3,232	3,232
F stat (Cattle)		150.1		38.8		65.7		261.2

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, intensification

Forest~	All biomes		Legal Amazon	Amazon biome
	OLS	IV		
Cattle per pasture	0.054 (0.02)	0.276 (0.10)		
Covariates	Full	...		
<i>F</i> stat	782.6			

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Results, intensification

Forest~	All biomes		Legal Amazon		Amazon biome
	OLS	IV	OLS	IV	
Cattle per pasture	0.054 (0.02)	0.276 (0.10)	0.104 (0.03)	0.503 (0.18)	
Covariates	Full	...			
Year FEs	Yes	...			
$N \times T$	31,480	...	16,160	...	
F stat		782.6		397.3	

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, intensification

Forest~	All biomes		Legal Amazon		Amazon biome	
	OLS	IV	OLS	IV	OLS	IV
Cattle per pasture	0.054 (0.02)	0.276 (0.10)	0.104 (0.03)	0.503 (0.18)	0.108 (0.03)	0.530 (0.29)
Covariates	Full	...				
Year FEs	Yes	...				
$N \times T$	31,480	...	16,160	...	10,060	...
F stat		782.6		397.3		245.7

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, soy (preliminary)

	Forest~		Savanna~	Pasture~
	OLS	IV		
Soy (ha)	-0.291 (0.06)	-0.311 (0.07)		
Soy (ton)	-0.033 (0.01)	-0.064 (0.02)		
Covariates	Full	...		
<i>F</i> stat (Soy, ton)		169.9		

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, soy (preliminary)

	Forest~		Savanna~		Pasture~
	OLS	IV	OLS	IV	
Soy (ha)	-0.291 (0.06)	-0.311 (0.07)	-0.066 (0.02)	-0.295 (0.08)	
Soy (ton)	-0.033 (0.01)	-0.064 (0.02)	-0.005 (0.01)	-0.060 (0.02)	
Covariates	Full	...			
Year FEs	Yes	...			
$N \times T$	16,160	...			
F stat (Soy, ha)		252.2		252.2	
F stat (Soy, ton)		169.9		169.9	

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, soy (preliminary)

	Forest~		Savanna~		Pasture~	
	OLS	IV	OLS	IV	OLS	IV
Soy (ha)	-0.291 (0.06)	-0.311 (0.07)	-0.066 (0.02)	-0.295 (0.08)	-0.198 (0.05)	-0.493 (0.10)
Soy (ton)	-0.033 (0.01)	-0.064 (0.02)	-0.005 (0.01)	-0.060 (0.02)	-0.020 (0.01)	-0.098 (0.03)
Covariates	Full	...				
Year FEs	Yes	...				
$N \times T$	16,160	...				
F stat (Soy, ha)		252.2		252.2		252.2
F stat (Soy, ton)		169.9		169.9		169.9

Standard errors clustered at the municipality-level. Significant ($p < 0.01$) estimates in **bold**.

Results, robustness

We assess the **sensitivity of results** along several dimensions:

- ▶ Varying share definitions
 - ▶ Different computations of distance to slaughterhouses
 - ▶ Omitting slaughterhouse location information
 - ▶ Updating shares over time
- ▶ Sample variations
 - ▶ All municipalities in Amazon, Cerrado, and Pantanal
 - ▶ Only municipalities with deforestation and 10% initial tree cover
- ▶ Specification variations
 - ▶ Including municipality FEs / time trends
 - ▶ Excluding year FEs
 - ▶ Lag order of treatment/instrument

Conclusion

Discussion, effect size

- *Stocking rates* suggest that **each cow** requires **roughly 0.8 hectare** of grazing area², reported **forest-to-pasture transition per cattle** in that range

Pasture area per cattle head



2. Arantes et al. 2018.

Discussion, effect size

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- ▶ Naive estimates suggest almost **decoupling** of cattle and land

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- ▶ *Stocking rates* suggest that **each cow** requires **roughly 0.8 hectare** of grazing area², reported **forest-to-pasture transition per cattle** in that range
- ▶ Naive estimates suggest almost **decoupling** of cattle and land
- ▶ Our **instrumented estimates** are closer to those suggested by footprint analyses
 - ▶ but still amount to only **63–75%** of them
 - ▶ large share of observed deforestation **unexplained**

Pasture area per cattle head



2. Arantes et al. 2018.

Discussion, implications

- ▶ The beef industry is considered a **driver of economic growth**
 - ▶ Monitoring *supply chains* complicated (Alix-Garcia and Gibbs 2017),
 - ▶ but recent initiatives (EUDR) could be role model for other markets

3. Haddad et al. 2024.

4. Godfray et al. 2018.

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Table: Land use in m² for nutritional needs.³

	beef	cheese	eggs	nuts	potatoes
2,000 kcal	239.0	45.4	8.7	4.2	2.4
100g protein	163.6	39.8	5.7	7.9	5.2

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- ▶ Few interventions **disincentivize** the demand for **GHG-intensive products**
 - ▶ **Domestically**, recent tax restructuring could have been more targeted⁴
 - ▶ **Globally**, uniform GHG tax would strongly affect meat products⁵

3. Poore and Nemecek 2018.

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For **more information**, download the slides or contact me at

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Appendix

Evolution of the beef industry in Brazil, 1966–2016

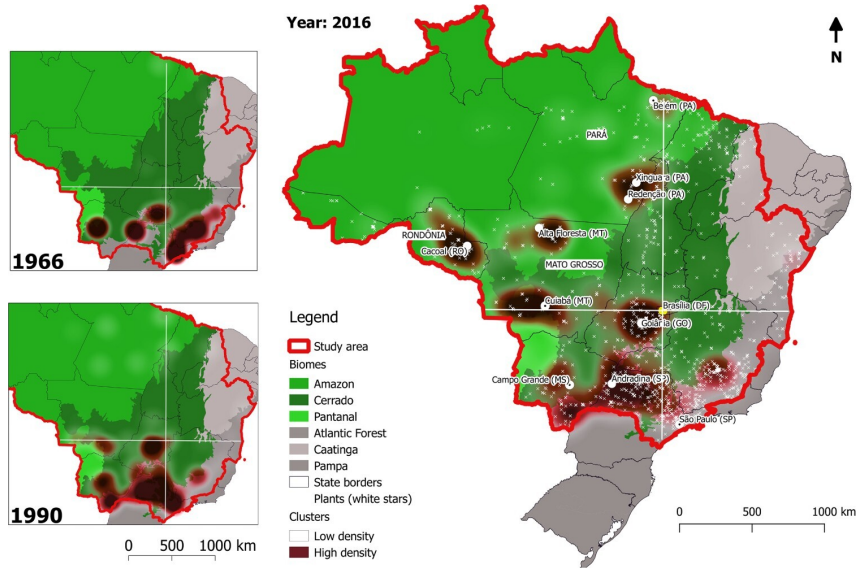


Chart: The beef industry in Brazil experienced a clear northward expansion into the Amazon biome, especially so in recent decades (taken from Vale et al. 2022).

China's appetite for beef is (partly) satisfied by Brazilian cattle

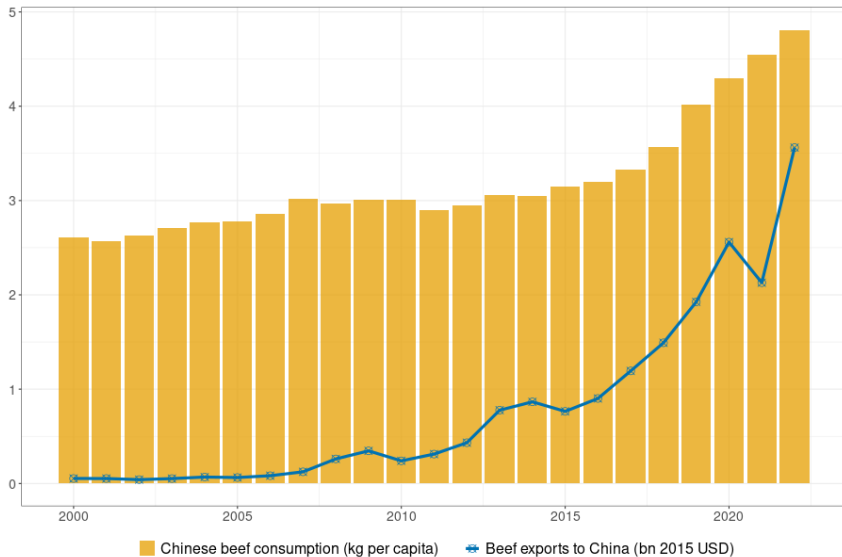


Chart: Chinese per capita beef consumption and Brazilian exports of beef products to China.
Sources: FAO 2023 & UN Comtrade 2022

Construction of the instrument [◀ Return](#)

We construct our Bartik (or *shift-share*) instrument $B_{i,t}$ using:

- ▶ Distance to slaughterhouse locations, interacted with municipality i 's proportion on overall pasture area/cattle head as **share** variable $z_{i,t=0}$.
 - ▶ Pasture *expansion is clustered* around relevant infrastructure
 - ▶ Transport costs are crucial factor for the profitability of agriculture (Souza-Rodrigues 2019), and slaughterhouses are an intermediate destination (Vale et al. 2022)

$$z_{i,t=0} = \exp\{-d_{i,t=0}\} \times \frac{1}{C_{t=0}} \sum_k c_{k,t=0},$$

- ▶ Changes in foreign (Chinese) beef consumption as **exogenous shift** variable g_t .
 - ▶ The demand is *relevant to* and partly satisfied with Brazilian beef,⁶
 - ▶ but is unlikely to affect Amazon deforestation in other ways.

$$g_t = \Delta \text{steak}_t^{CHN}.$$

6. UN Comtrade 2022; FAO 2023.

We construct also an instrument based on export-weighted shocks:

- ▶ Beef consumption changes in m export destinations:

$$B_{i,t} = \sum_m z_{i,m,t=0} g_{m,t-1}$$
$$z_{i,m,t=0} = z_{i,t=0} \times \frac{\text{exports}_{i,m,t=0}}{\text{exports}_{i,t=0}},$$

- ▶ where the share $z_{i,t=0}$ from before is interacted with export shares of destinations m .
- ▶ Export shares at the municipality level are taken from Ermgassen et al. 2020, only available for period 2010–2020.
- ▶ Growth in beef consumption of market m as **shift** variable $g_{m,t}$.