Man Eats Forest
Impacts of Cattle Ranching on Amazon Deforestation

Nikolas Kuschnig & **Lukas Vashold***
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*Vienna University of Economics and Business
Department of Economics & Institute for Ecological Economics
lukas.vashold@wu.ac.at

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)
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  - footprint analyses lack causal interpretability
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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

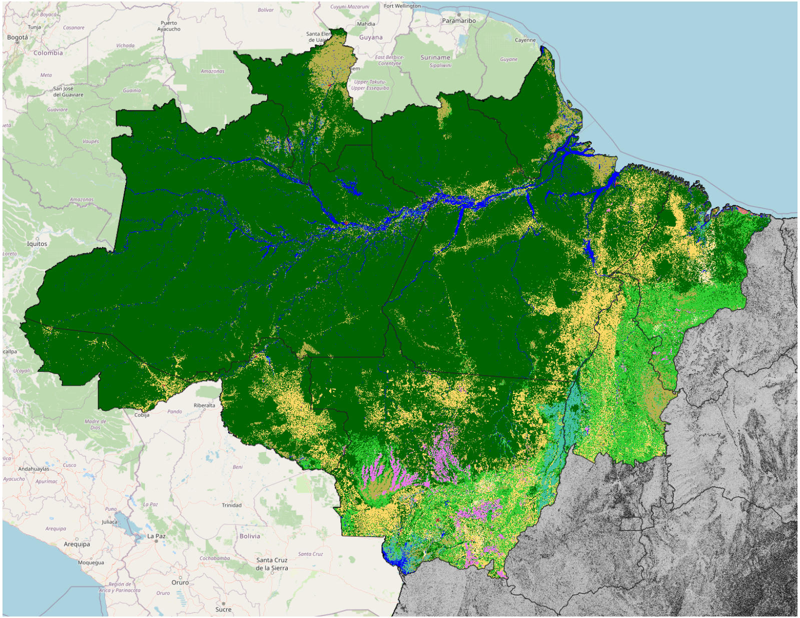
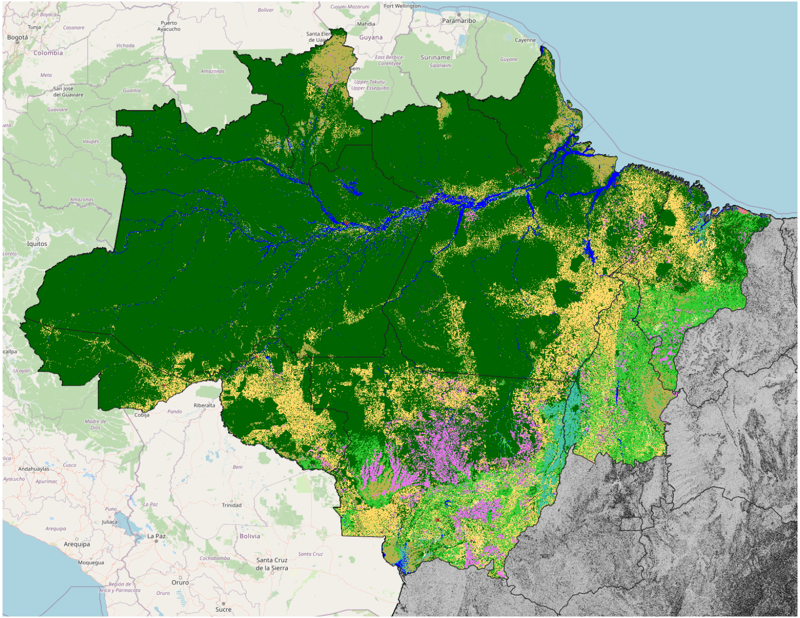


Chart: Land cover, including **forest**, **pasture**, and **croplands**, in the Legal Amazon in 2000.

Legal Amazon in 2022



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Background, Deforestation in Brazil

Reasons for high levels and resurgence include:

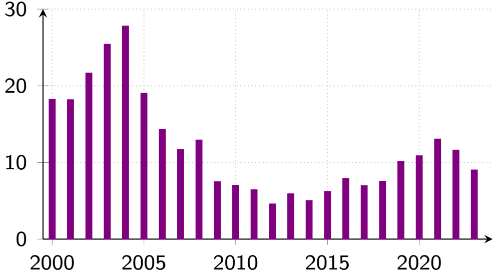

Chart: Deforestation in the Brazilian Amazon (in 1,000 km^2).

a. Cusack et al. 2021; Pendrill et al. 2022.
b. Reydon, Fernandes, and Telles 2020.
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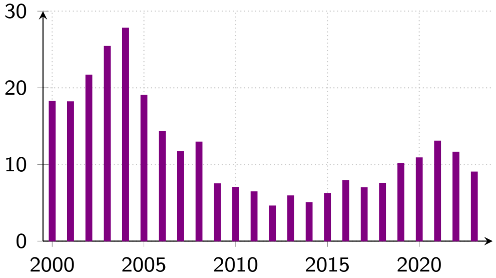
- strong and rising **demand for agricultural products**, especially **beef products**[a]
  - can be met with *intensification*, or deforestation at the *extensive margin*.



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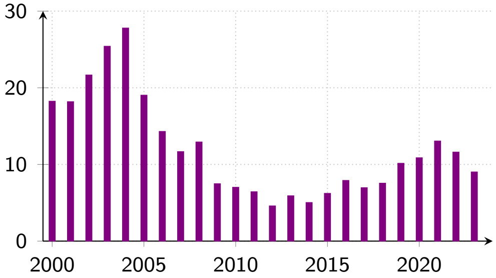
- weak *land governance* enabling speculative **land appropriation**[b]
    - forest is cut, agricultural activities are feigned, and ownership is claimed.



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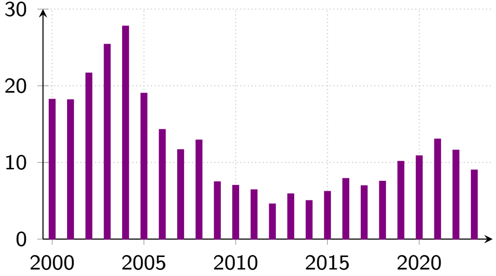
- *policy interventions* being **not resilient** with respect to political influence[c]



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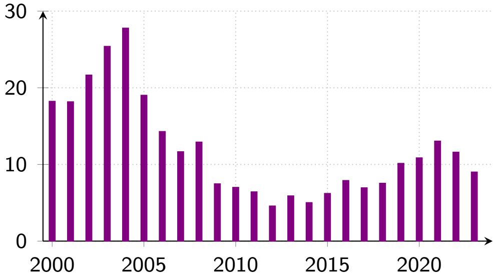

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- ...is moving deeper into the Amazon (Vale et al. 2022) and is the **proximate cause of ~90-95% of deforestation** there (Haddad et al. 2024),
- ...is linked to deforestation that accounts for a **fifth of global land use emissions** from the tropics, ~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 (first-difference) panel regression specification:

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

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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- $\boldsymbol{X}_{i,t-s}$ holds (suitably lagged) control variables,
- μ_t are time-fixed effects, and
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Entangled effects

However, β is not *identified*, i.a. 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]

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

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c_{i,t} &= \boldsymbol{X}_{i,t-s}\boldsymbol{\alpha} + \omega B_{i,t} + \mu_t^b + \varepsilon_{i,t}
\end{aligned}
$$

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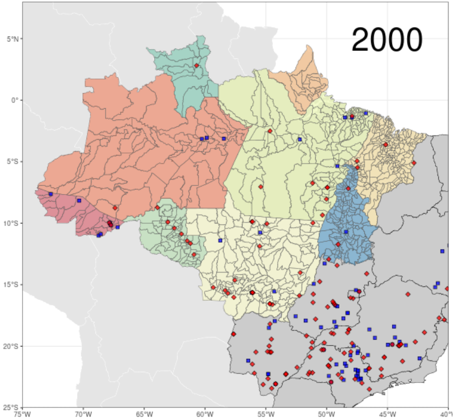
  - Transport costs are crucial factor for the profitability of agriculture (Souza-Rodrigues 2019), and slaughterhouses are an intermediate destination (Vale et al. 2022)
- Changes in international beef consumption as **shifts** $g_{m,t}$, where we consider
  - (i) changes in **all export destinations**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

Shift-Share Instrument Components



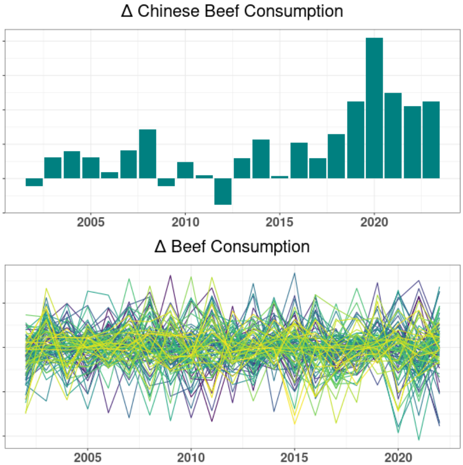


Chart: Slaughterhouse locations in 2000 and changes in aggregate beef consumption.
Sources: Vale et al. 2022; FAO 2023

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

Forest∼	2003–2022	2011–2022
	OLS	OLS
Cattle	**-0.103**	**-0.109**
	(0.03)	(0.03)
Pasture	**-0.895**	**-0.832**
	(0.03)	(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**	**-0.429**	**-0.109**
	(0.03)	(0.14)	(0.03)
Pasture	**-0.895**	**-0.971**	**-0.832**
	(0.03)	(0.03)	(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 OLS	2003–2022 IV-CHN	2011–2022 OLS	2011–2022 IV-CHN	2011–2022 IV-EXP
Cattle	**-0.103**	**-0.429**	**-0.109**	**-0.456**	**-0.381**
	(0.03)	(0.14)	(0.03)	(0.13)	(0.10)
Pasture	**-0.895**	**-0.971**	**-0.832**	**-0.971**	**-0.914**
	(0.03)	(0.03)	(0.04)	(0.03)	(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	
	Forest~		Forest~	*incl. Savanna*~
	OLS	IV		
Cattle	**-0.108**	**-0.530**		
	(0.03)	(0.15)		
Covariates	Full	...		
Year FEs	Yes	...		
$N \times T$	10,060	...		
F stat		188.7		

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

Results, biome heterogeneity

Biome	Amazon		Cerrado		
	Forest$\sim$		Forest$\sim$		*incl. Savanna*$\sim$
	OLS	IV	OLS	IV	
Cattle	**-0.108**	**-0.530**	-0.003	-0.014	
	(0.03)	(0.15)	(.002)	(0.02)	
Covariates	Full	...			
Year FEs	Yes	...			
$N \times T$	10,060	...	21,240	...	
F stat		188.7		53.3	

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Results, biome heterogeneity

Biome	Amazon		Cerrado			
	Forest∼		Forest∼		*incl. Savanna*∼	
	OLS	IV	OLS	IV	OLS	IV
Cattle	**-0.108**	**-0.530**	-0.003	-0.014	**-0.028**	**-0.342**
	(0.03)	(0.15)	(.002)	(0.02)	(.001)	(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**	**-0.479**			
	(0.03)	(0.08)			
Covariates	Full	...			
Year FEs	Yes	...			
$N \times T$	6,464	6,464			
F stat		150.1			

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

Results, regime heterogeneity

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

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Results, regime heterogeneity

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

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	Lula		Rousseff		Temer		Bolsonaro	
Forest∼	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Cattle	**-0.097**	**-0.479**	**-0.046**	-0.121	**-0.086**	**-0.575**	**-0.159**	**-0.517**
	(0.03)	(0.08)	(0.01)	(0.06)	(0.03)	(0.15)	(0.04)	(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		150.1		38.8		65.7		261.2

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

Results, intensification

	All biomes		Legal Amazon	Amazon biome
Forest$\sim$	OLS	IV		
Cattle per pasture	**0.054**	**0.276**		
	(0.02)	(0.10)		
Covariates	Full	...		
Year FEs	Yes	...		
$N \times T$	31,480	...		
F stat		782.6		

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

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	All biomes		Legal Amazon		Amazon biome
Forest$\sim$	OLS	IV	OLS	IV	
Cattle per pasture	**0.054**	**0.276**	**0.104**	**0.503**	
	(0.02)	(0.10)	(0.03)	(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

	All biomes		Legal Amazon		Amazon biome	
Forest$\sim$	OLS	IV	OLS	IV	OLS	IV
Cattle per pasture	**0.054**	**0.276**	**0.104**	**0.503**	**0.108**	**0.530**
	(0.02)	(0.10)	(0.03)	(0.18)	(0.03)	(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**	**-0.311**		
	(0.06)	(0.07)		
Soy (ton)	**-0.033**	**-0.064**		
	(0.01)	(0.02)		
Covariates	Full	...		
Year FEs	Yes	...		
$N \times T$	16,160	...		
F stat (Soy, ha)		252.2		
F 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**	**-0.311**	**-0.066**	**-0.295**	
	(0.06)	(0.07)	(0.02)	(0.08)	
Soy (ton)	**-0.033**	**-0.064**	**-0.005**	**-0.060**	
	(0.01)	(0.02)	(0.01)	(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**	**-0.311**	**-0.066**	**-0.295**	**-0.198**	**-0.493**
	(0.06)	(0.07)	(0.02)	(0.08)	(0.05)	(0.10)
Soy (ton)	**-0.033**	**-0.064**	**-0.005**	**-0.060**	**-0.020**	**-0.098**
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(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:

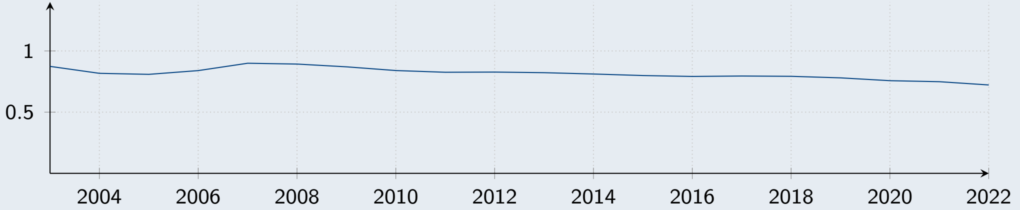
- Varying **share** definitions
  - Different computations of distance to slaughterhouses
  - Omitting slaughterhouse location information
  - Updating shares over time
- **Sample** variations
  - All municipalities in Amazon, Cerrado, and Pantanal
  - Only municipalities with deforestation and 10% initial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

Conclusion

Discussion, effect size

- *Stocking rates* suggest that **each cow** requires ~**0.8 hectare** of grazing area[2]

Pasture area per cattle head



2. Arantes et al. 2018.
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Discussion, effect size

- *Stocking rates* suggest that **each cow** requires ∼**0.8 hectare** of grazing area[2]
- Reported **forest-to-pasture** transition rate of ∼**0.66 hectare** per cattle[3]

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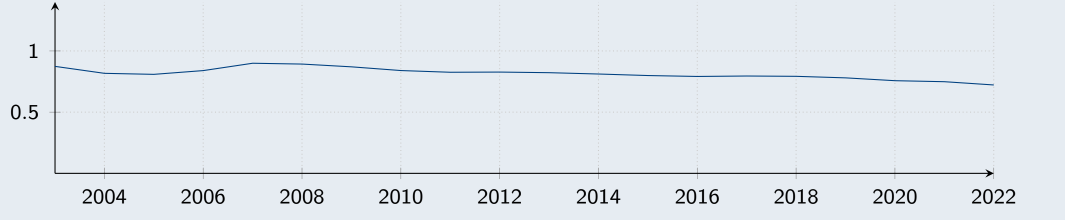

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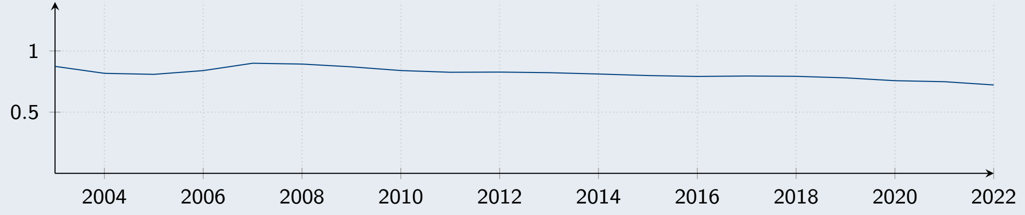

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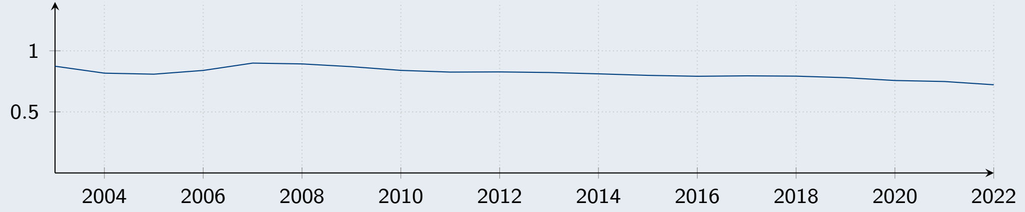
- Naive estimates suggest almost **decoupling** of cattle and land
- Our **instrumented estimates** are closer to those suggested by footprint analyses
  - but still amount to only **63–75%** of them
  - large share of observed deforestation **unexplained**

Pasture area per cattle head



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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

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Table: Land use in m^2 for nutritional needs.[4]

	beef	cheese	eggs	nuts	**potatoes**
2,000 kcal	239.0	45.4	8.7	4.2	2.4
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- Few interventions **disincentivize** the demand for **GHG-intensive products**
  - **Domestically**, recent tax restructuring could have been more targeted[5]
  - **Internationally**, a global uniform GHG tax would strongly affect meat products[6]

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

- lukas.vashold@wu.ac.at
- www.vashold.eu

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Appendix

Evolution of the beef industry in Brazil, 1966–2016

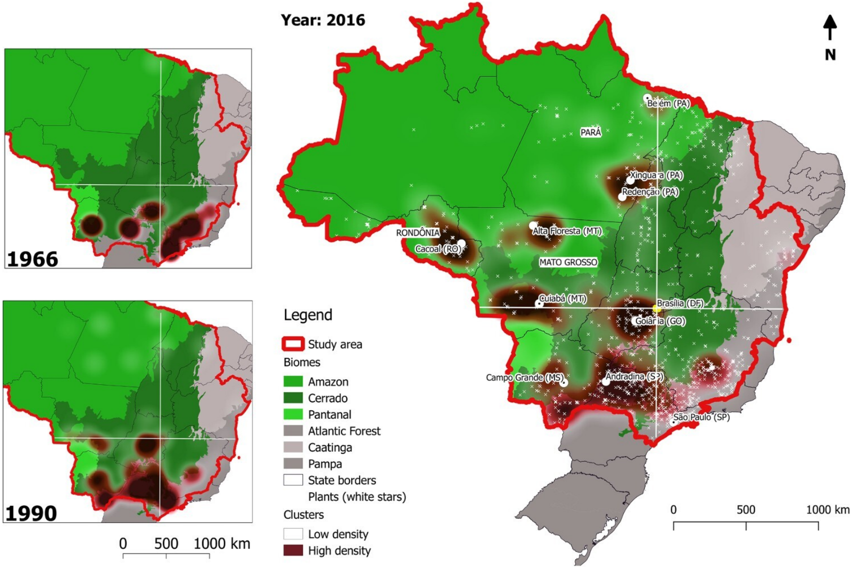

Chart: The beef industry in Brazil experienced a clear northward expansion into the Amazon biome, especially so in recent decades (taken from Vale et al. 2022).

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

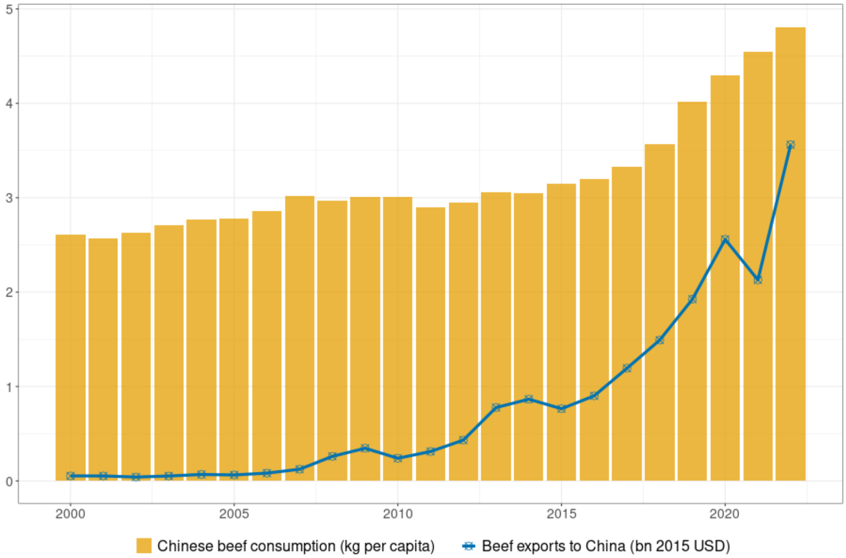

Chart: Chinese per capita beef consumption and Brazilian exports of beef products to China. Sources: FAO 2023 & UN Comtrade 2022

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,[7]
  - but is unlikely to affect Amazon deforestation in other ways.

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

7. UN Comtrade 2022; FAO 2023.

Construction of export-weighted instrument ◂ Return

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 $g_{m,t}$.