Efficient Forestation in the Brazilian Amazon: Evidence from a Dynamic Model

June 15th

—

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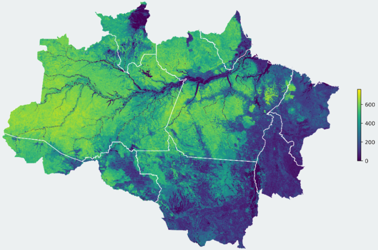
13th Conference on The Economics of Energy and Climate

Forest conservation is key to tackling global warming

Carbon stock



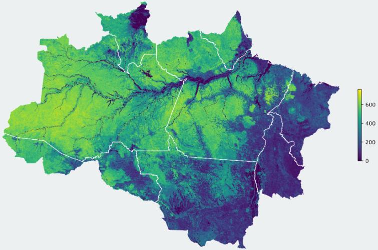
Limit rising global temperature hinges on a drastic reduction of CO_2 emissions over the next decades (IPCC 2018)

Reducing deforestation in tropical ecosystems has huge potential for reducing emissions (Stern, 2007; Bastin et al., 2019)

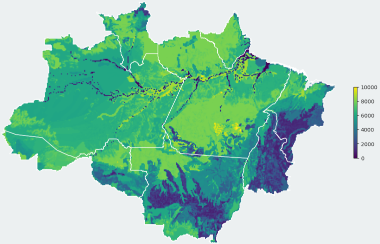
- Brazilian Amazon in 2000 = 200+ billion tons of CO_2
- Since then, land use changes released 16.7 billion tons of CO_2 in the atmosphere

Social cost vs. private benefit from deforestation

Carbon stock



Pasture suitability



The main driver of deforestation is extensive cattle ranching

- >80% of deforested area converted to pasture
- Most of remaining area converted to crops, e.g. soy

This paper

What is the carbon-efficient forestation in the Brazilian Amazon?

Dynamic discrete choice model where farmers choose land use: forest, pasture, crops

- Estimated with granular (30m) level panel for the Brazilian Amazon 2008-2017
- We estimate farmers' perceived value of the carbon stored in the forest
- **Efficient forestation**: farmers fully internalize the social cost of carbon (computed by the EPA)
- Policy counterfactuals based on the carbon content of the land, and taxes on cattle and crops

Literature

Cropland responses to prices and the economic environment

(Chomitz and Gray, 1999; Lubowski et al., 2006; Fezzi and Bateman, 2011; Scott, 2013; Souza-Rodrigues, 2019; Sant'Anna, 2021; Heilmayr et al., 2020; Hsiao, 2020)

Land use decisions using static general equilibrium models

(Costinot et al, 2016; Donaldson and Hornbeck, 2016; Pellegrina, 2020; Sotelo, 2020; Domínguez-Iino, 2020)

Large literature studying policies to fight deforestation (treatment effect framework)

(Alix-Garcia et al, 2015; Jayachandran et al, 2017; Assunção et. al., 2019; Burgess et. al., 2019; Barbier et al, 2020)

Carbon abatement cost of land use policies

(Jack, 2013; Jayachandran et al, 2017; Gillingham and Stock, 2018)

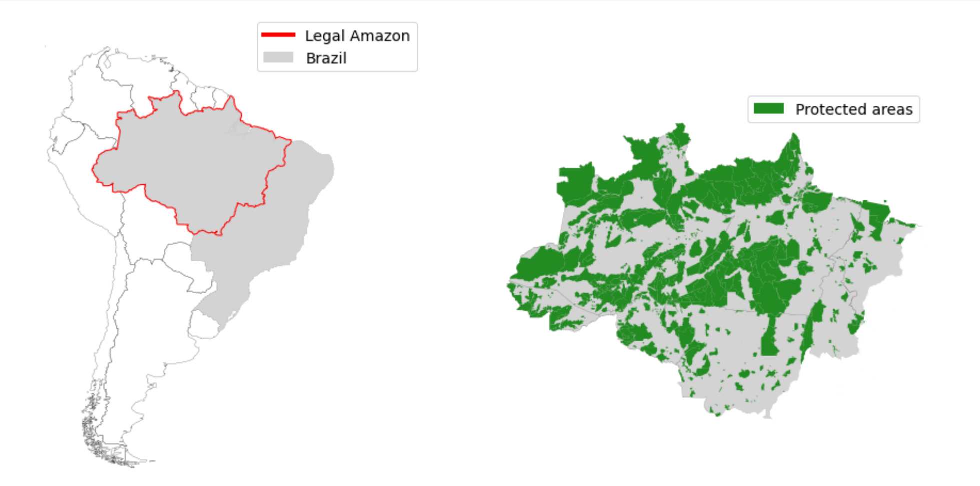
Plan for today

1. Background
2. Model
3. Empirical Analogues & Data
4. Estimation
5. Counterfactuals
   - Efficient Forestation
   - Policy Counterfactuals
6. Caveats & Extensions

1/ Background

Background

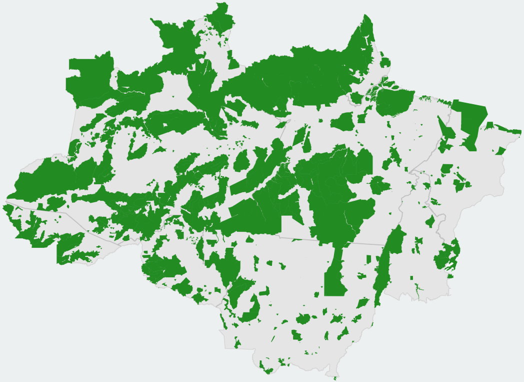
Legal Amazon and Protected Areas



89% of deforestation happens outside Protected Areas

Background

Legal Amazon – Protected Areas (in green)



Land use in the Legal Amazon (%)

	Share in 2008	Transitions from 2008 (row) to 2017 (column)		
		Forest	Crop	Pasture
	(1)	(2)	(3)	(4)
Forest	72	92.0	0.8	6.5
Crop	2	3.0	89.0	7.4
Pasture	21	13.0	5.4	81.0

- **The predominant agricultural activity in this region is cattle grazing**

Background

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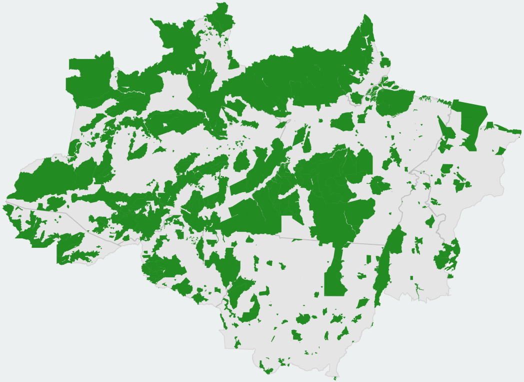

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Pasture	21	13.0	5.4	81.0

- **Forest regeneration is relatively common** (Gandour, 2019)

2/ Model

Model: Set up

Dynamic model with discrete time t= 1,2,3. . . .

A rational agent in time t decides land use $j \in \{\text{forest, crop, pasture}\}$ in field i

- Fields are grouped in locations m
- In our application, a field is a 30m pixel and a location is a 1km grid.

Flow profit of field i put to use j in period t:

$$\pi_j(w_{mt}, \varepsilon_{imjt}) = r_j(w_{mt}; \alpha) + \varepsilon_{imjt}.$$

Assumption 1. Market variables (e.g., prices) follow Markov process $F_{w_{m,t+1}|w_{mt},\varepsilon_{imjt},j} = F_{w_{m,t+1}|w_{mt}}$

Assumption 2. Field level unobservables ε_{imjt} have i.i.d type-I extreme value distribution

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Dynamics. Land conversion *sunk* cost $\Phi(j,k)$: e.g., $\Phi(\text{pasture,forest})$

Model: Value function and CCPs

Agent's value function:

$$V(k, w_{mt}, \varepsilon_{imt}) = \max_{j \in J} \{ \underbrace{\Phi(j, k) + r_j(w_{mt}; \alpha) + \rho E\left[E_\varepsilon [V(j, w_{mt+1}, \varepsilon_{imjt+1})] | w_{mt} \right]}_{v(j|k, w_{mt})} + \varepsilon_{imjt} \}$$

The type-I extreme value distribution for ε_{imjt} yields the logit Conditional Choice Probability (CCP):

$$p(j|k, w_{mt}) = \frac{\exp(v(j|k, w_{mt}))}{\sum_{j' \in J} \exp(v(j'|k, w_{mt}))}$$

Model: Regression equation

Use finite dependence property to “get rid” of continuation values and write a regression equation (Scott, 2013; Kalouptsidi, Scott and Souza-Rodrigues, 2021):

$$\log\left(\frac{p(j|k,w_{mt})}{p(k|k,w_{mt})}\right)-\rho\log\left(\frac{p(j|k,w_{m,t+1})}{p(j|j,w_{m,t+1})}\right)=(1-\rho)\Phi(j,k)+r_j(w_{mt};\alpha)-r_k(w_{mt};\alpha)$$
$$+\eta_j^V(w_{mt})-\eta_k^V(w_{mt})$$

where $\eta_j^V(w_{mt})$ denote an expectation error, i.e.:

$$\eta_j^V(w_{mt})=\rho(E\left[E_\varepsilon[V(j,w_{mt+1},\varepsilon_{imt+1})]|w_{mt}\right]-E_\varepsilon[V(j,w_{mt+1},\varepsilon_{imt+1})])$$

Model: Flow of returns

Crop:

$$r_{\text{crop}}(w_{mt};\alpha) = \bar{\alpha}_{\text{crop}} + \alpha_{\text{crop}}\left[\sum_{c\in\mathcal{C}} s_{cm}\left(p_{ct} - z_{mc}\right) y_{mc}\right] + \xi_{\text{crop},m,t}.$$

- Weighted sum of returns for different crops (corn and soybeans):
  - s_{cm} – share of crop c in location m
  - p_{ct} – price of crop c in period t
  - z_{cm} – transportation cost to get production from location m to the port
  - y_{cm} – potential yield for crop c in location m

- α_{crop} allows us to monetize the carbon perceived value
- $\xi_{\text{crop},m,t}$ accommodates a location fixed-effect

Model: Flow of returns

Crop:

$$r_{\text{crop}}\left(w_{mt};\alpha\right)=\bar{\alpha}_{\text{crop}}+\alpha_{\text{crop}}\left[\sum_{c\in\mathcal{C}}s_{cm}\left(p_{ct}-z_{mc}\right)y_{mc}\right]+\xi_{\text{crop},m,t}.$$

Pasture: flexible specification

$$r_{\text{pasture}}\left(w_{mt};\alpha\right)=\bar{\alpha}_j+\alpha^1_{j,t}y_{m,j}+\alpha^2_j d_m y_{m,j}+\xi_{j,m,t},\quad j=\text{pasture}$$

- $\alpha^1_{j,t}$ – coefficient of pasture suitability depends on time
- α^2_j – interaction of pasture suitability with road distance to ports

Model: Flow of returns

Crop:

$$r_{\text{crop}}(w_{mt};\alpha) = \bar{\alpha}_{\text{crop}} + \alpha_{\text{crop}}\left[\sum_{c\in\mathcal{C}} s_{cm}\left(p_{ct} - z_{mc}\right) y_{mc}\right] + \xi_{\text{crop},m,t}.$$

Pasture:

$$r_{\text{pasture}}(w_{mt};\alpha) = \bar{\alpha}_j + \alpha^1_{j,t} y_{m,j} + \alpha^2_j d_m y_{m,j} + \xi_{j,m,t}, \quad j = \text{pasture}$$

Forest: depends only on carbon stored in the vegetation

$$r_{\text{forest}}(w_{mt};\alpha) = 0 + \alpha_{\text{forest}} h_m + \xi_{\text{forest},m,t},$$

- h_m – potential stock of carbon

3/ Empirical Analogues & Data

Empirical Analogues & Data: Transition Probabilities

$$\log\left(\frac{p(j|k, w_{mt})}{p(k|k, w_{mt})}\right) - \rho \log\left(\frac{p(j|k, w_{m,t+1})}{p(j|j, w_{m,t+1})}\right) = (1-\rho)\Phi(j,k) + r_j(w_{mt};\alpha) - r_k(w_{mt};\alpha) + \text{error}$$

Land use in the Amazon: Mapbiomas (LANDSAT data)

- Classifies land use at 30-meters pixels: Forest, Pasture, Crop
- 2008-2017, after major policy change (Assunção et al, 2015; Burgess et al, 2019)
- We aggregate 30-m pixels i into 1-km locations m
- We set $\rho = 0.9$

Empirical Analogues & Data: Field Characteristics

crop: $\bar{\alpha}_{\text{crop}} + \alpha_{\text{crop}} \left[\sum_{c \in \mathcal{C}} s_{cm} \left(p_{ct} - z_{mc} \right) y_{mc} \right]$

pasture: $\alpha^1_{j,t} y_{m,j} \;+\; \alpha^2_j d_m y_{m,j} \;+\; \bar{\alpha}_j$

forest: $\alpha_{\text{forest}} h_m$

Share of crop production: IBGE

- Agricultural Census 2006
- Crops ($\mathcal{C}$): soybeans and corn

Prices across time: ESALQ

- Prices at major trade hubs in Brazil

Soil suitability: FAO GAEZ

- High input, rain fed

Empirical Analogues & Data: Field Characteristics

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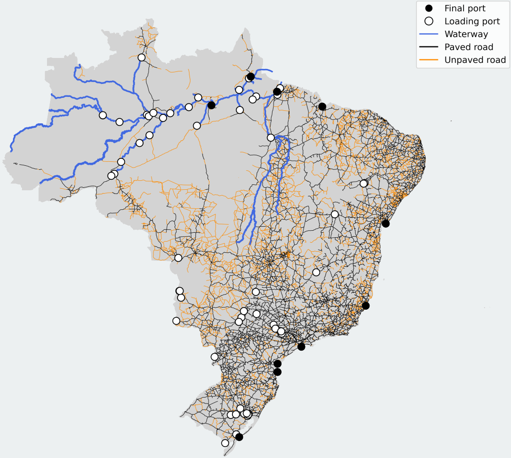
$$\text{forest: } \alpha_{\text{forest}} h_m$$

[trans cost det.]

- Transportation costs



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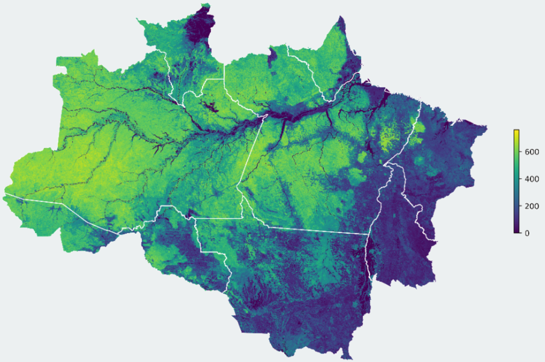
forest: $\alpha_{\text{forest}} h_m$

- Carbon Stock: Woods Hole Research Center.



4/ Estimation

Estimation Results

Main estimates:

- Dividing $\hat{\alpha}_{\text{forest}}$ by $\hat{\alpha}_{\text{crop}}$, bring to present value using a 5% interest rate:
- **Perceived CO_2 present value of $7.26/ton**
- This is the privately perceived carbon value

Model Parameter	Estimate
α_{crop}	0.000386
	(0.00001)
α_{forest}	0.000580
	(0.00002)

Standard errors computed with a spatial block bootstrap on a 25km by 25km grid

5/ Counterfactuals

Counterfactuals: Overview

1. Go back to the value function to compute conditional choice probabilities (CCP) for each location
    - **Assumption:** no uncertainty about market state variables, w_{mt}
    - This gives a transition matrix for each location
2. Compute steady-state distribution of each location m
    - I.e., the invariant distribution of the CCP
3. Aggregate to get steady-state land use

How far are we from efficient forestation?

The efficient forest cover is the one in which agents fully internalize the social cost of carbon

- Social cost of carbon in 2030 (EPA): $50/ton of CO2
- **Efficient SS**: 90.3% of the forest and 99.5% of carbon are preserved.

Steady state forest cover:

Efficient forest cover (perceived carbon value $50/ton) − Business-as-usual forest cover (perceived carbon value $7.26/ton) = 1,075,000 km^2

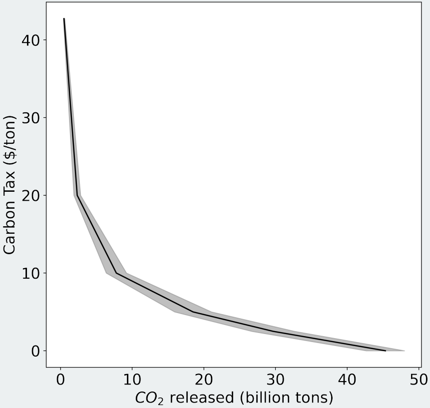
CO2 released from the forest in the steady state:

Efficient CO2 emission (perceived carbon value $50/ton) − Business-as-usual CO2 emission (perceived carbon value $7.26/ton) = -44 billion ton

Preserving the forest through carbon tax

How could a carbon tax based on the carbon content of the land shape farmers' choices?

CO_2 emission (tons)



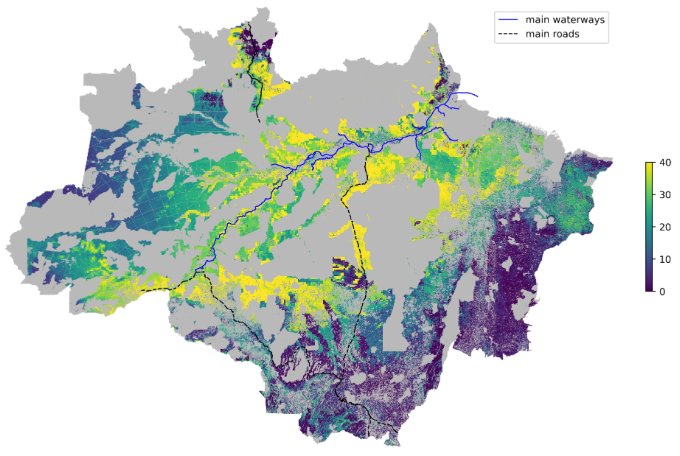
The effect of perceived higher carbon value is convex:

- $2.5/ton carbon tax would preserve 34% of the efficient carbon stock (-15 $GtCO_2$)
- $10/ton carbon tax would preserve 84% of the efficient carbon stock (-37 $GtCO_2$)

[forest cover]

Where is inefficient deforestation more likely to take place?

Excess emissions per location in business-as-usual relative to efficient scenario
(Carbon stock efficient - Carbon stock BAU)



Targeted carbon tax

- Large scale policy interventions may involve large sums with little "additionality"
- Can we think of a targeted carbon tax, that is, that would apply only to the inefficient emissions top x% locations?

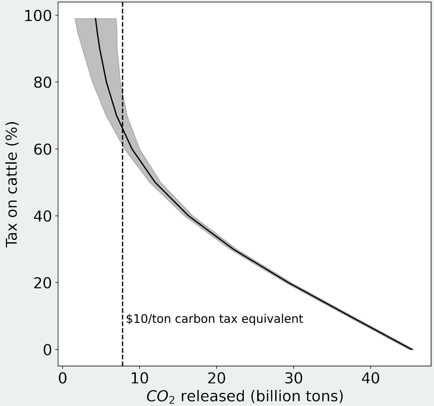
Carbon tax ($/ton)	Percentile (%)					
	1	2	5	10	25	100
2.5	-0.5	-1.0	-2.2	-4.2	-8.9	-15
5.0	-0.8	-1.6	-3.7	-7.0	-14.8	-26
10.0	-1.1	-2.1	-4.8	-9.1	-19.7	-37
20.0	-1.1	-2.2	-5.1	-9.7	-21.4	-42

- Targeting only the top 25% of locations with most inefficient emissions at $10 would already close $\sim$ 45% of the emissions gap

Preserving the forest through taxes on cattle ranching

How could taxes on cattle ranching and crops shape farmers' choices?

CO_2 emission (tons)



Taxing returns of cattle also effective:

- a 20% tax on cattle would preserve 36% of the efficient carbon stock (-16 $GtCO_2$)
- a 65% tax on cattle would preserve 84% of the efficient carbon stock (-37 $GtCO_2$)
- Taxing **crops** produces virtually no changes in emissions

[forest cover]

6/ Caveats & Extensions

Caveats & Extensions

We do not consider **loss in biodiversity and other externalities**

- This makes the optimal forest gap even larger once those are explicitly factored in

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We assess the role of **forest regeneration** [forest regen]

- Robustness assuming regenerated forest stays 30 years without any carbon stock
- Emission gap: -62 $GtCO_2$

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The Amazon would transition into a savanna ecosystem if deforested area reaches a **tipping point** ($\approx$ 40%) (Oyama and Nobre, 2003; Soares Filho, 2006/2010; Franklin Jr and Pindyck, 2018)

- In the business-as-usual scenario, the Amazon reaches 31% of deforested area

Caveats & Extensions

Main analysis ignores possible **equilibrium effects** from the policies considered

- Back-of-the-envelope international beef prices increase 1.9% in the efficient steady state
- Acreage offset would be 2.6% of the pasture area

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We estimate equilibrium choices under **current technologies** [double crop]

- Extension modeling the return of agriculture using the most productive technology available
- Emission gap: -37 $GtCO_2$

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Private **discount rates** [discount]

- We estimate the model with smaller private discount rates ($\rho = 0.95$)
- Emission gap: -54 $GtCO_2$

Conclusion

We compute the long-run carbon-efficient forest cover and stock of carbon in the Brazilian Amazon

- Dynamic discrete choice model of land use estimated with rich set of remote sensing data

In the long run, the business-as-usual scenario will generate the **inefficient**

- release of 44 billion tons of CO_2
- loss of over 1 million km^2 of forest cover

We show that **policies based on the carbon content of the land** can mitigate a substantial part of inefficient forest loss: land use response to these are very convex!

Taxes on cattle can help to close the gap, but crop taxes seem ineffective

THANK YOU! Marcelo Sant'Anna – marcelo.santanna@fgv.br

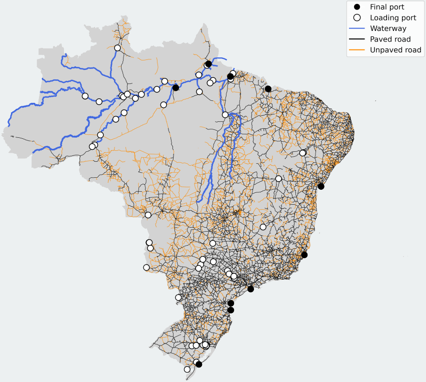
Transportation costs by land

Estimation of transportation cost model based on sample of origin-destination freight costs

1. Rasterize road network considering different relative pixel-crossing costs (θ)
2. For each origin-destination pair ℓ, k, compute road-quality adjusted distance $d_{\ell,k}(\theta)$
3. Estimate freight cost model by NLLS:

$$FC_{\ell,k} = \beta_0 + \beta_1 d_{\ell,k}(\theta) + \epsilon_{\ell,k}$$

4. Use estimated parameters to compute for each location m, transportation costs to ports



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Estimation: Overview

Structural regression equation:

$$Y_{j,k,m,t} = (1-\rho)\Phi(j,k) + r_j(w_{mt};\alpha) - r_k(w_{mt};\alpha) + \eta_j^V(w_{mt}) - \eta_k^V(w_{mt})$$

where $Y_{j,k,m,t}$ is the LHS transition probabilities expression

Want to allow for fixed location effects, that may correlate with time-varying crop returns.

1. First, take differences, and estimate the coefficient of crop, α_{crop}, and some parameters of pasture using a first difference regression using Anderson and Hsiao (1981)
2. Estimate the coefficient of forest, α_{forest}, and remaining parameters of pasture from the regression in levels.
3. Recover land conversion sunk costs.

[back] [ident.] [variation]

Identification: Endogeneity issue

$$\Delta Y_{j,k,m,t} = \alpha_{\text{crop}} X_{j,k,m,t} + (\alpha^1_{\text{pasture},t} - \alpha^1_{\text{pasture},t-1}) W_{j,k,m,t} + \Delta\zeta_{j,k,m,t},$$

$$X_{j,k,m,t} = \begin{cases} (\tilde{r}_{mt} - \tilde{r}_{m,t-1}) & \text{, if } j = \text{crop and } k \neq \text{crop}, \\ -(\tilde{r}_{mt} - \tilde{r}_{m,t-1}) & \text{, if } k = \text{crop and } j \neq \text{crop}, \\ 0 & \text{, otherwise.} \end{cases}$$

$$\Delta\zeta_{j,k,m,t} = \left[\eta^V_j(w_{mt}) - \eta^V_k(w_{mt})\right] - \left[\eta^V_j(w_{m,t-1}) - \eta^V_k(w_{m,t-1})\right] + \left[\xi_{jmt} - \xi_{kmt}\right] - \left[\xi_{jm,t-1} - \xi_{km,t-1}\right]$$

$\eta^V_j(w_{m,t-1})$ is a difference of expected and realized values, thus correlated with $\tilde{r}_{mt}$

$$\eta^V_j(w_{m,t-1}) = \rho(E\left[\bar{V}(j, w_{mt}) | w_{m,t-1}\right] - \bar{V}(j, w_{mt}))$$

[back]

Results: First stage

Regressor	Estimate (1)	Estimate (2)
$\tilde{r}_{i,t-2}$	0.04322***	0.04605***
	(2.19e-5)	(1.78e-5)
$W_{j,k,i,2011}$	-3.27e-2***	-4.78e-2***
	(1.60e-5)	(2.64e-5)
$W_{j,k,i,2012}$	-7.66e-4***	-3.46e-2***
	(1.59e-5)	(2.63e-5)
$W_{j,k,i,2013}$	2.90e-2***	5.38e-2***
	(1.61e-5)	(2.65e-5)
$W_{j,k,i,2014}$	1.76e-2***	4.02e-2***
	(1.61e-5)	(2.66e-5)
$W_{j,k,i,2015}$	1.03e-2***	2.58e-2***
	(1.60e-5)	(2.65e-5)
$W_{j,k,i,2016}$	-4.30e-2***	-6.06e-2***
	(1.60e-5)	(2.64e-5)
F-Stat	3,107,226	3,796,531

Number of observations 79,473,168.

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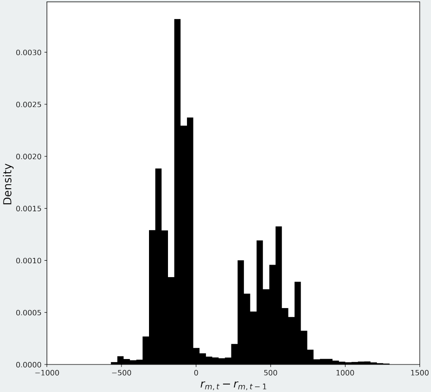
Identifying variation

Variation in crop return difference



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$$\tilde{r}_{mt} - \tilde{r}_{m,t-1} = \sum_{c \in \mathcal{C}} s_{cm} y_{mc} \left(p_{ct} - p_{c,t-1}\right)$$

- Prices are the only observed state variables that vary over time
- Thus, since we take differences in $\tilde{r}_{mt}$, variation in prices over time helps identifying α_{crop}.
- However, this is not the sole variation in $\tilde{r}_{mt}$
- y_{mc} and s_{cm} magnifies price variation, generating cross section variation in $X_{j,k,m,t}$

Recent tech: double cropping

Carbon tax	Δ Forest cover ($1,000 km^2$)	Δ CO_2 released (billion tons)
\$2.5	161	-8
\$5.0	304	-15
\$10.0	521	-25
\$20.0	750	-34
\$33.7	874	-37

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Forest regeneration

Carbon tax (US$/ton)	Carbon price (US$/ton)	Share of forest $<$ 30 yrs	$\Delta\ CO_2$ released (billlion tons)
0	7.26	0.51	
2.50	9.76	0.43	-13.35
5.00	12.26	0.35	-25.85
10.00	17.26	0.24	-42.42
20.00	27.26	0.14	-55.45
42.73	49.99	0.07	-62.41

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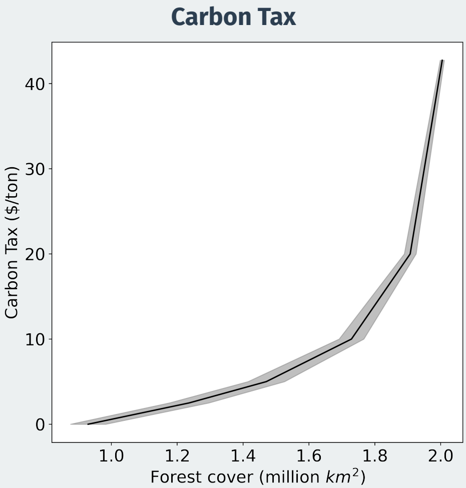
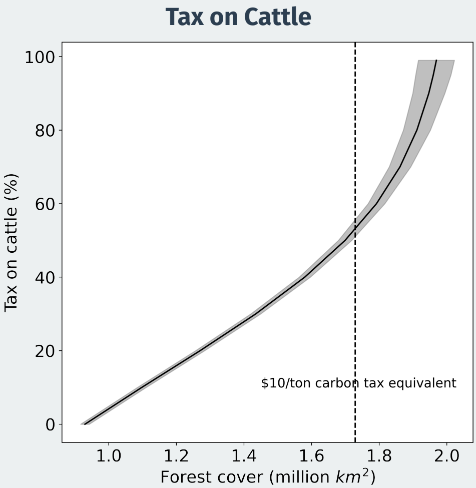
Discount rate $\rho = 0.95$

Carbon tax	Δ Forest cover $(1,000 km^2)$	Δ CO_2 released (billion tons)
$2.5	346	-18
$5.0	638	-32
$10.0	954	-46
$20.0	1156	-52
$44.28	1264	-54

[back]

Policy counterfactuals: forest cover (km^2)





[back carbon] [back cattle]