Trade, Trees, and Health

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Motivation: trade and mortality

- Trade improves growth (Grossman and Helpman, 1990), productivity (Alcalá and Ciccone, 2004), and institutional quality (Levchenko, 2007).
- However, trade also leads to death due to environmental damage (Zhang et al., 2017).
- Incorporating the mortality impacts of trade has important welfare and distributional implications.

The existing literature on trade and mortality mostly focuses on:

- Production relocation
- Industrial emissions
- Local effects near polluters

Motivation: trade and mortality (con't)

Another channel through which trade causes death lies in natural capital depletion:

- Trade $\rightarrow$ agricultural expansion $\rightarrow$ deforestation $\rightarrow$ pollution $\rightarrow$ death

Why important?

- Trade-induced deforestation is a long-standing concern.
- Forests serve as effective filters for air pollution.
- Deforestation-induced pollution can spread to non-local areas.

Motivation: forest

- Natural capital accounting:
  - The UN launched statistical frameworks for rules to track changes in ecosystems and their services in March 2021.
  - The European Commission adopted an amendment proposal for Regulation EU 691/2011 on European environmental economic accounts in July 2022.
  - The White House published guidance to include environmental and ecosystem benefits in cost analysis on Feb 28, 2024.
- Our paper studies one natural capital: the value of forests

Why we care about forests?

- Ecosystem and biodiversity
- Carbon and oxygen cycling
- Global and micro climate
- Pollution and natural disasters
- Amenity value

This paper

We present a framework to estimate and integrate the empirical links between agricultural exports, forest losses, and health consequences:

1) Use a shift-share instrument to estimate the causal effects of agricultural exports on local deforestation.
2) Construct an aero-connectivity matrix that traces the trajectories of air currents over time and space.
3) Exploit month-over-month variability in wind linkages to estimate the causal effect of upwind deforestation on increases in air pollutants and premature deaths in downwind areas.

Preview of findings

- In Brazil, from 1997 to 2017, each 1,000 BRL increase in exports per capita reduces forest cover by 0.137 percentage points.
- Over 576,000 premature deaths in downwind areas due to trade-induced deforestation.
- \$0.14 loss in statistical life value per \$1 agricultural exports.

Literature Background

Research framework

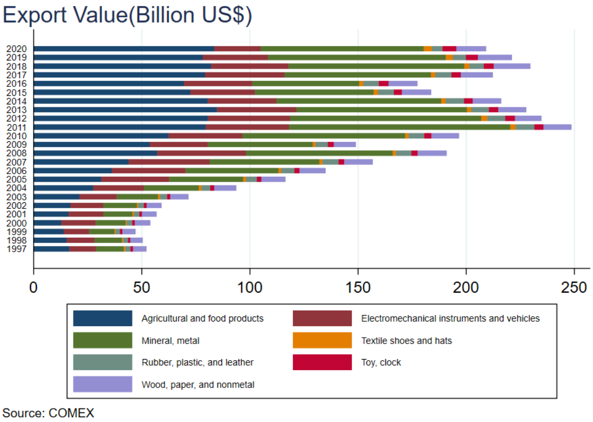
- Our objective: estimate the external health effects of trade-induced deforestation
- For each city i, external health effects:

$$Health\ Effects\ of\ i = \sum_r \underbrace{\frac{\partial Forest_i}{\partial Trade_i}}_{Section\ 3} \cdot \underbrace{\left(\frac{\partial Health_r}{\partial Forest_i} \middle| \overbrace{Wind_{i\to r}}^{Section\ 5.1}\right)}_{Section\ 5.2}$$

- $Forest_i$ and $Trade_i$: how much city i's deforestation is due to trade shocks to that city
- r: receiver city
- $Wind_{i\to r}$: how much city i affects city r's environmental condition due to wind flow

Data: Export

- COMEX Stat
- HS4 product, municipality, month, 1997-2019



▸ Summ Stat

Land use

- MapBiomas
- Annual land use subcategory for each 30m pixel

1) Forest
   - Forest formation, savanna formation, mangrove, sandy costal plain vegetation
2) Non-forest natural formation
3) Farming
   - Pasture, agriculture, forest plantation, mosaic of uses
     - Agriculture: temporary crop, perennial crop
     - Temporary: soybean, sugar cane, rice, cotton, other temporary crops
     - Perennial: coffee, citrus, other perennial crop
4) Non-vegetated area
5) Water
6) Others

Pollution and weather

Air quality:

- IEMA (the Instituto de Energia e Meio Ambiente)
- 380 stations, 2015-2022
- PM2.5, PM10, O3, NO2, SO2, CO at hour-station level
- Robustness: PM2.5 from Van Donkelaar et al. (2021), AOD from MODIS

Weather:

- ERA5
- Daily U-wind, V-wind, temperature, precipitation for each 0.25° pixel
- Robustness: BDMEP (Banco de Dados meteorológicos para Ensino e Pesquisa).
- 5611 weather stations, daily temperature, precipitation and wind

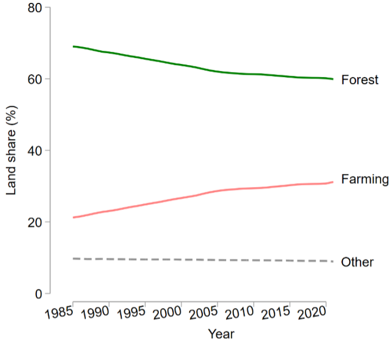
Mortality

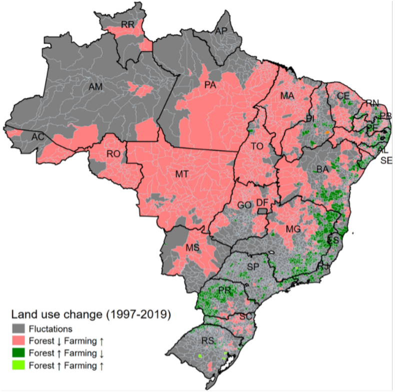
Mortality microdata:

- Mortality Information System (Sistema de Informações sobre Mortalidade, SIM)
- Death record level, municipality of residence, date of death, reason of death based on ICD-10

Step #1: Trade and deforestation

Agricultural land expansion and deforestation:





Notes: This figure shows temporal and geographic trends in the substitution between agricultural land and forests. “Fluctuations” correspond to areas with less than 3 percent changes in forest or farmland coverage over the study period.

Research design

$$\Delta LandCover_{iy} = \beta \Delta Export_{iy} + \lambda W_{iy} + \varepsilon_{iy}$$

- $\Delta LandCover_{iy}$: three-year change rate in a certain type of land cover in region i year y
  - e.g. For forest:

$$\Delta LandCover_{i,forest,y} = \frac{Forest_{i,y} - Forest_{i,y-3}}{Land_{i,y-3}}$$

- We aggregate the municipality-level data to micro-region-level for temporal consistency
- $\Delta Export_{iy}$: regional export growth per capita:

$$\Delta Export_{iy} = \frac{Export_{i,y} - Export_{i,y-3}}{Pop_{i,y-3}}$$

- Robust using 1,6 year lags

IV for $\Delta Export_{iy}$

The shift-share instrument:

$$\Delta Bartik_{i,y} = \sum_j \frac{Export_{ij,y_0}}{Export_{i,y_0}} \left(\frac{X_{j,y}^{ROW} - X_{j,y-3}^{ROW}}{\frac{X_{j,y}^{ROW} + X_{j,y-3}^{ROW}}{2}} \right)$$

- $X_{j,y}^{ROW}$: other major importing/exporting countries of agricultural products imports/exports in product j and year y.
- $Export_{ij,y_0}/Export_{i,y_0}$: the share of product j in region i's historical export
- Alternative IV: Replace $X_{j,y}^{ROW}$ with $X_{j,y}^{-i}$
  $X_{j,y}^{-i}$: national exports in product j and year y by excluding the state in which region i is located.

Identifying assumption

- Two assumptions in recent literature: conditionally exogenous *shares* (Goldsmith-Pinkham et al., 2020) or random *shocks* (Borusyak et al., 2022).
- We assume agriculture export shocks are arguably exogenous:
  1) For major agriculture exporters, overall agricultural export growth is not driven by a few products. ▸ Link1
  2) The number of products is high. ▸ Link2
  3) Export shares are not too concentrated in a few products. ▸ Link3

Results: Export and land use, forest, 2SLS

Each 1,000 BRL increase in export per capita reduces forest cover by 0.137 pp.

	Forest	Forest formation	Savanna formation	Mangrove	Sandy coastal plain vegetation
$\Delta Export$	-0.137***	-0.076**	-0.060*	0.000*	-0.000
	(0.03)	(0.03)	(0.04)	(0.00)	(0.00)
Observations	19,053	19,053	19,053	19,053	19,053
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	3yrs	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

First stage

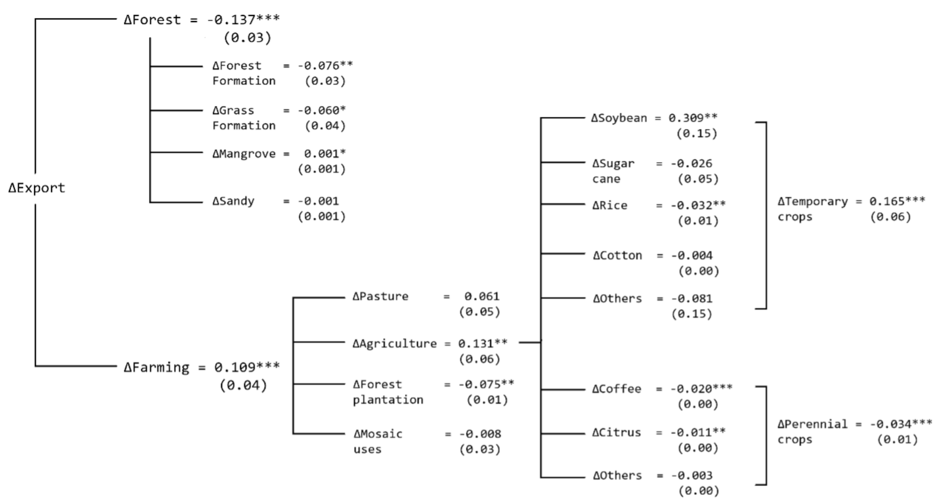
Export and land use, farm land, 2SLS

Each 1,000 BRL increase in export per capita increases farm land cover by 0.109 pp.

	Farming	Pasture	Agriculture	Forest plantation	Mosaic of uses
$\Delta Export$	0.109***	0.061	0.131**	-0.075***	-0.008
	(0.04)	(0.05)	(0.06)	(0.01)	(0.03)
Observations	19,053	19,053	19,053	19,053	19,053
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	3yrs	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

Export and land use



Step #2: Air flow modeling

- Goal: estimate downwind environmental and health effects
- Matrix: monthly flow intensities between all micro-region pairs
- We simulate wind streamlines from each micro-region emitter
- At a given emitter centroid on a given day, we compute the next position of wind using actual wind speed and direction.
- We look for the next position on the following day, then the day after,..., for 14 days. We find the new pollution location on day 0 at emitter coordinates $E(lon_0, lat_0)$, day 1 $E(lon_1, lat_1)$,..., day 14 at $E(lon_{14}, lat_{14})$.
- On day t, affected areas are in the downwind area of $E(lon_t, lat_t)$. Pollution intensity is zero in crosswind and upwind areas, and decreases with distance to $E(lon_t, lat_t)$.
- Remaining pollution at new emitting centers $E(lon_t, lat_t)$ decreases with t.

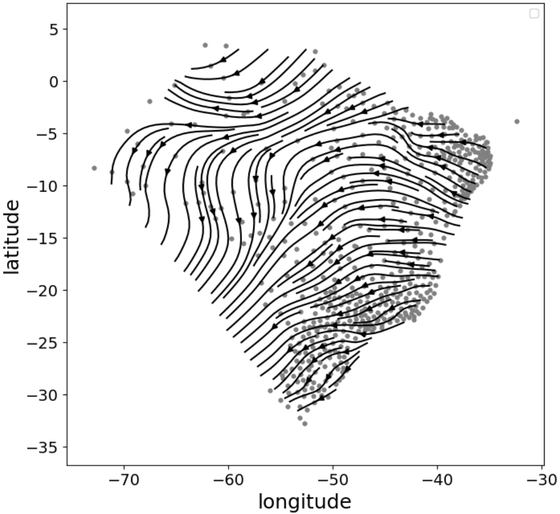
Air flow modeling (con't)

Flow coefficient f_{ijt} from emitter i to receiver j on day t:

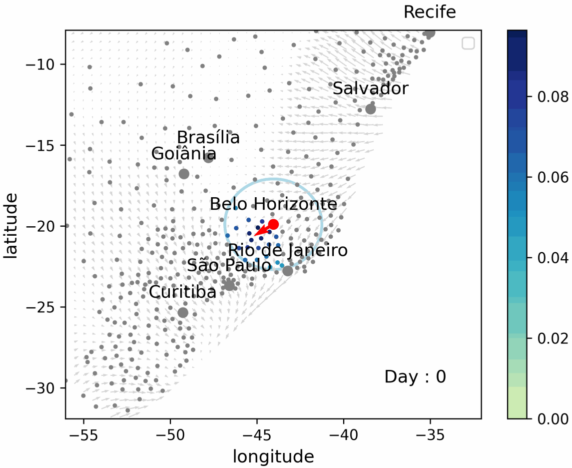
$$f = exp(-\alpha r - \beta s - \gamma d)$$

- r: distance between emitter i and receiver j
- d: distance between new center $E(lon_t, lat_t)$ and receiver j
- s: scalar product between the current direction vector and the vector between $E(lon_t, lat_t)$ and receiver j
- α, β, γ are positive parameters:
    - $exp(-\alpha r)$: flow decreases over steps due to dispersion
    - $exp(-\beta s)$: we assign a higher flow to receivers that are close to the downwind direction at $E(lon_t, lat_t)$
    - $exp(-\gamma d)$: we assign a higher flow to receivers close to $E(lon_t, lat_t)$
    - $(\alpha, \beta, \gamma) = (0.7, 0.5, 0.2)$ were empirically determined to balance spatially continuous areas affected by current trajectory and the directionality of flow in each step.

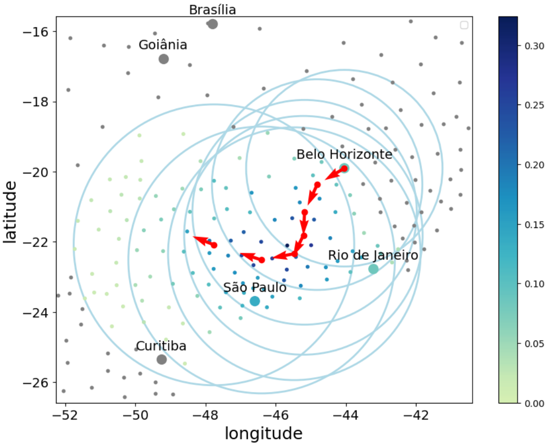
Visualization (1/4): Streamlines



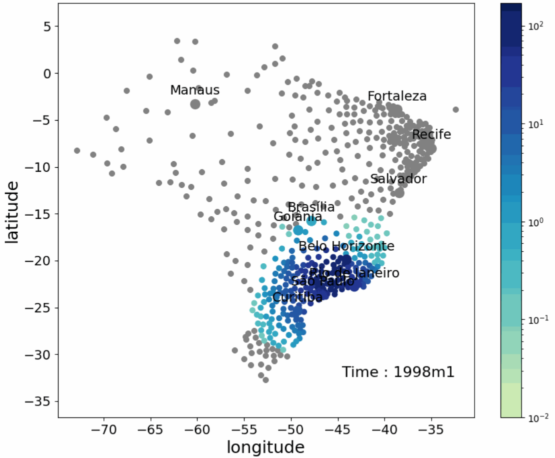
Visualization (2/4):
A sample trajectory from Belo Horizonte



Visualization (3/4):
Affected areas from this sample trajectory



Visualization (4/4):
Aggregated receiver scores from Belo Horizonte



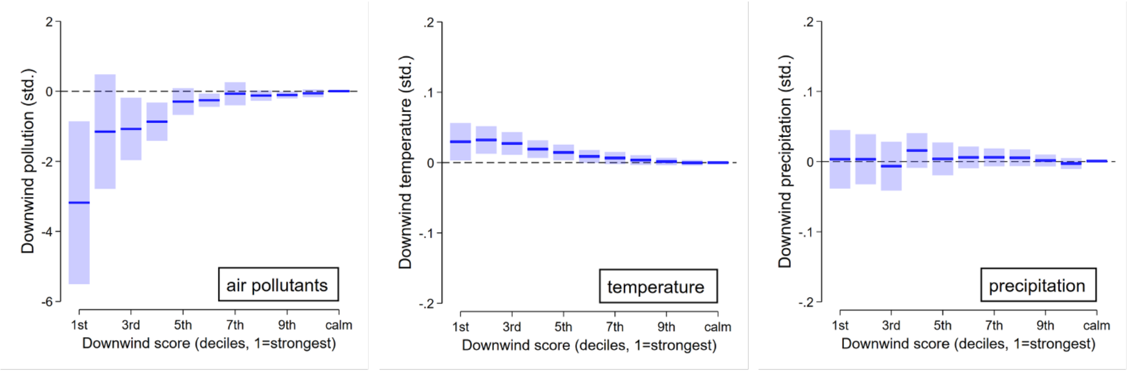
Step #3: Upwind forest and downwind outcomes

$$Y_{r,m,y} = \beta_1 Forest_{i,y} \times Wind_{i \to r,m,y} + \beta_2 Forest_{i,y} + \beta_3 Wind_{i \to r,m,y}$$
$$+\alpha_{i,r,m} + \tau_y + \varepsilon_{r,m,y}$$

- $Y_{r,m,y}$: receiver micro-region r's outcome in year y month m
  - Air pollution, temperature and precipitation, mortality
- $Forest_{i,y}$: emitter micro-region i's forest area, standardized to mean zero sd one
- $Wind_{i \to r,m,y}$: downwind score from i to r in year y month m
- $\alpha_{i,r,m}$: emitter-by-receiver-by-month FEs
- β_1: how the relationship between emitter's forest and receiver's outcome vary by downwind intensity

Results: Downwind pollution and weather

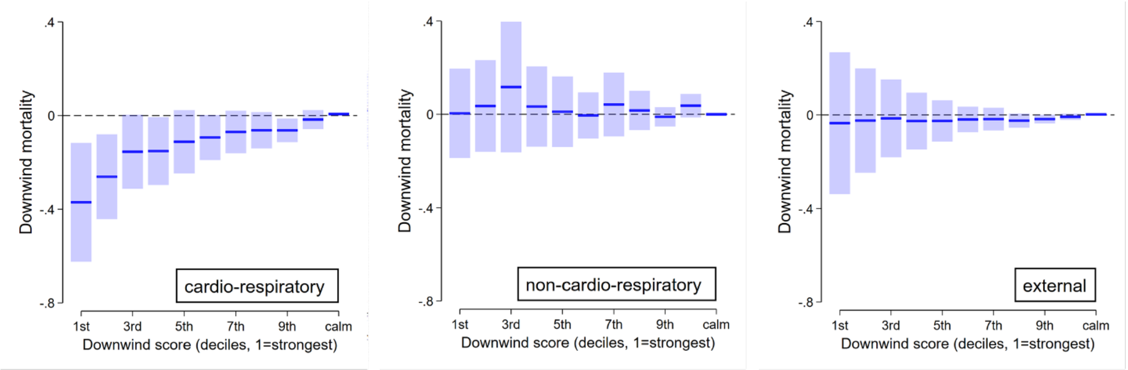
Upwind forest decreases downwind air pollution, and has little effects on downwind weather.



Notes: These figures show estimates on changes in downwind outcomes per 1 SD increase in upwind forest cover, separately by downwind exposure score bins. Each chart shows a separate regression following the exact same specification except for the outcome variable. Within each chart, horizontal step lines show point estimates, and range bars show 95 percent confidence intervals.

Downwind health

Upwind forest decreases downwind cardiorespiratory mortality, and has little effects on placebo mortality due to external causes ("accidents").



Excess death due to trade

$$
\begin{aligned}
&\text{Excess death due to } i\text{'s trade} \\
&= \sum_{r,m,y} (\beta_{\Delta Trade \to \Delta Forest} \cdot \Delta Trade_i) \cdot (-\beta^{i \to r,m,y}_{Forest \to CRmortality} \cdot Population_{r,y})
\end{aligned}
$$

- Total excess death due to micro-region i's export is the product of 1) and 2), summed across all receiver micro-regions and time

1) Trade-induced deforestation in i
2) excess deaths per unit of deforestation at a receiver micro-region r

1997-2017, all Brazil:

- 2.8 million ha loss of forest due to export growth
- 576,000 excess deaths
- For reference, annual death in Brazil is 1.28 million
- $\rightarrow$ Export growth increases death by 2.14%

Implications

Statistical life value loss:

- VSL = 0.7 million USD in Brazil (Ashenfelter and Greenstone, 2004; Narain and Sall, 2016)
- 576,000 excess deaths are equivalent to 404 billion USD
- \$0.14 loss in statistical life value per \$1 exports increase

Lower bound estimate of excess damage:

- Death in the same micro-region
- Long-term mortality effect
- Morbidity and productivity loss

Appendix

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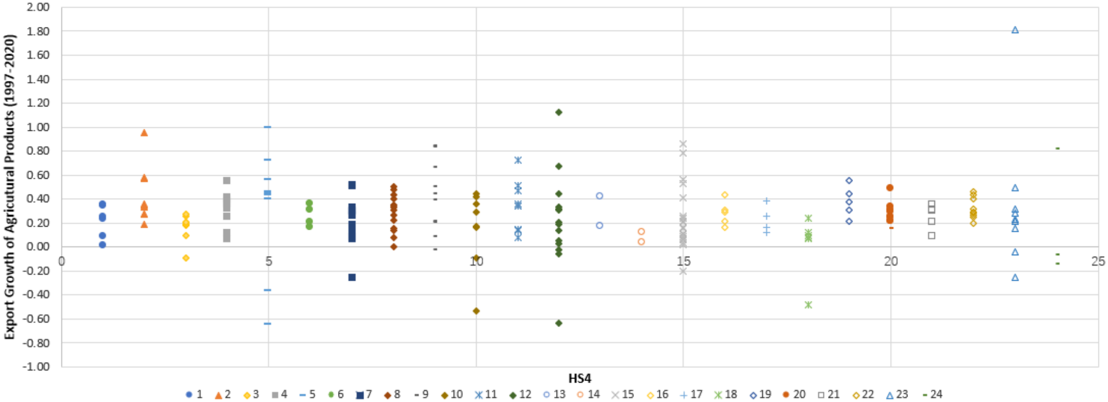
Random shocks 1

- Within each HS 2-digit product, export growth rates vary a lot across 4-digit products



Return

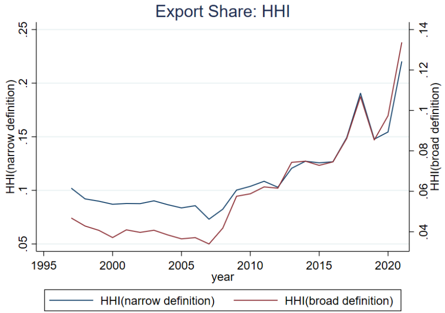
Random shocks 2

Classifications	No. of HS4 in 1997	No. of HS4 in 2018
Animal	40	43
Vegetable products	92	97
Foodstuffs	54	56
Skins, leather & furs	20	18
Wood & wood products	64	64
Metals	147	146
Sum	417	424

Return

Random shocks 3

- Export shares are not too concentrated in a few products.



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Sum	417	424

First stage results

2SLS First Stage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)	ΔExport per capita (1000 BRL)
IV1 other states	1.35***							
IV1 other states (drop 5 top export products)		4.90***						
IV2 other countries			1.21***					
IV2 other countries (drop 5 top export products)				3.34***				
IV3 major export countries					1.32***			
IV3 major export countries (drop 5 top export products)						3.84***		
IV4 import countries without Brazil							1.304611***	
IV4 import countries without Brazil (drop 5 top export products)								4.121932***
Observations	19,053	19,053	19,053	19,053	19,053	19,053	19,053	19,053
Cluster amc	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Weight: Agricultural employment

Return

Contribution to the literature

- Trade and health:
  - Most literature focuses on the role of production and industrial emissions (Shapiro and Walker, 2018; Copeland et al., 2022)
  - Our channel: deforestation
  - Related to ours: studies on trade and deforestation (Ferreira, 2004; Carreira et al., 2024), no health effects or non-local effects

- Wind as an instrument for air pollution:
  - Most literature uses dominant wind directions (e.g. Bombardini and Li, 2020; Gong et al., 2023)
  - Our improvements: multiple continuous steps with decayed concentration; affected areas not trajectory lines

Contribution to the literature (con't)

- Environmental and health effects of forests:
  - Effects on human health (Xing et al., 2023), micro climate (Araujo et al., 2023; Grosset et al., 2023)
  - Identifications come from tree planting programs (Xing et al., 2023; Grosset et al., 2023).
  - Afforestation vs. deforestation: older forests being better pollution filters and carbon sinks than new forests

Return

Trade, agriculture expansion, and deforestation

Why trade causes agricultural expansion?

- Increased demand and market access
- Technology transfer and investment

Why agricultural expansion causes deforestation?

- Timber as a product or input
- Clearing land
- Infrastructure development

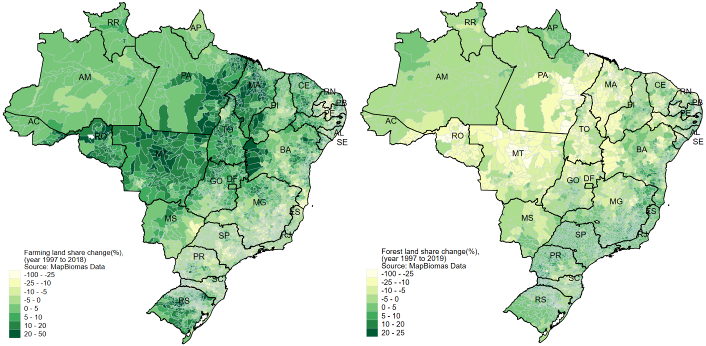
Forest and air pollution

- Filtration:
  Trees act as physical filters, capturing airborne particles. Bark and leaves serve as deposition sites for these particles.
- Absorption:
  Trees absorb polluting gases through their leaves, including NO_2, SO_2, and O_3.
- Microclimate:
  Trees reduce air temperature through shading and evapotranspiration. High temperature is conducive to O_3 formation.

Brazilian exporting dynamics

We conduct empirical analysis in Brazil:

- Rapid worldwide deforestation between 1990 and 2020
  - South America accounts for $\approx 49\%$
- Simultaneous rise in world trade of agricultural products since the 1990s.



Brazil's land use: farmland vs. forest (1997 vs. 2018)

Return

Data: Export, Summ Stat

Brazil's major export products 1997 vs. 2018:

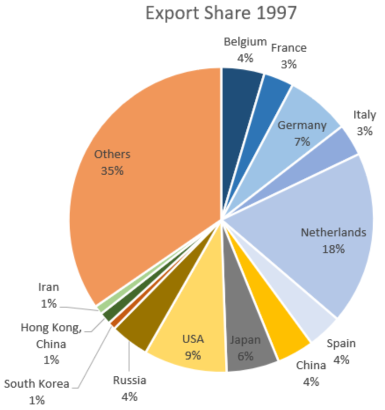
Top HS4 1997 Description	Export share(%)
Coffee	5.186
Soybean oilcake	5.063
Soybean	4.632
Cane or beet sugar	3.338
Unmanufactured tobacco	2.061
fruit juices and vegetable juices	1.997
Meat and edible offal	1.724
Soya-bean oil and its fractions	1.124
Cigars, cheroots, cigarillos and cigarettes	1.072
Extracts, essences and concentrates, of coffee, tea or maté	0.724
Other prepared or preserved meat	0.477
Coconuts, Brazil nuts and cashew nuts	0.346
Meat of bovine animals, frozen	0.279
Meat of swine, fresh, chilled or frozen	0.267
Vegetable materials and vegetable waste	0.209
Butter, fat and oil, from cocoa	0.161
Sugar confectionery	0.147
Crustaceans	0.136
Vegetable waxes (other than triglycerides)	0.122
Pepper of the genus Piper	0.112

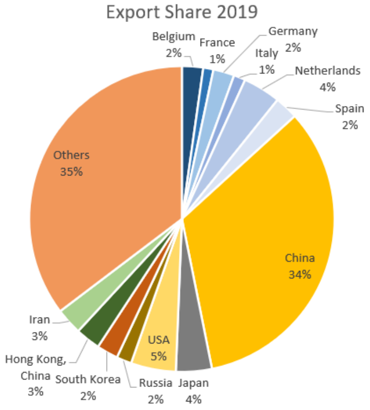
Top HS4 2018 Description	Export share(%)
Soybean	14.255
Soybean oilcake	2.857
Cane or beet sugar	2.814
Meat and edible offal	2.586
Meat of bovine animals, frozen	1.965
Coffee	1.885
Maize (corn)	1.722
fruit juices and vegetable juices	1.014
Unmanufactured tobacco	0.817
Meat of swine, fresh, chilled or frozen	0.462
Soya-bean oil and its fractions	0.442
Meat of bovine animals	0.388
Undenatured ethyl alcohol of an alcoholic strength by volume of 80 % vol or higher	0.386
Other prepared or preserved meat	0.382
Extracts, essences and concentrates, of coffee, tea or maté	0.255
Live bovine animals	0.229
Edible offal of bovine animals, swine, sheep, goats, horses, asses, mules or hinnies	0.207
Rice	0.201
Animal (not fish) guts, bladders, stomachs and parts	0.181
Food preparations not elsewhere specified or included	0.154

Notes: Share is the export value of a certain HS-4 product as a share of Brazil's total export

Data: Export, Summ Stat (con't)

Brazil's agriculture export by trade partner:





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Robustness 1: IV using ROW imports

	Forest				
		Forest formation	Savanna formation	Mangrove	Sandy coastal plain vegetation
$\Delta Export$	-0.112***	-0.091***	-0.021	0.000**	-0.001**
	(0.02)	(0.04)	(0.02)	(0.00)	(0.00)
	Farming				
		Pasture	Agriculture	Forest plantation	Mosaic of uses
$\Delta Export$	0.076***	0.109**	0.122*	-0.059***	-0.096**
	(0.02)	(0.05)	(0.07)	(0.01)	(0.04)
Observations	22,864	22,864	22,864	22,864	22,864
IV	ROW importing	ROW importing	ROW importing	ROW importing	ROW importing
Lag	3yrs	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

Robustness 2: alternative time differences

	Difference 1 year				
	Forest	Farming	Agriculture	Temporary crop	Soybean
$\Delta Export$	-0.090*	0.112***	-0.06	0.022	0.462
	(0.05)	(0.04)	(0.04)	(0.03)	(0.38)
Observations	79,979	79,979	79,979	79,979	79,979
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	1yr	1yr	1yr	1yr	1yr
	Difference 6 years				
	Forest	Farming	Agriculture	Temporary crop	Soybean
$\Delta Export$	-0.129**	0.227***	0.241*	0.298***	0.448***
	(0.05)	(0.07)	(0.11)	(0.11)	(0.17)
Observations	15,242	15,242	15,242	15,242	15,242
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	6yrs	6yrs	6yrs	6yrs	6yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

Robustness 3: Lula's presidency

Trade-induced deforestation is less severe during Lula's presidency, 2003-2011

	Forest	Farming	Agriculture	Temporary crop	Soybean
	Before 2011				
	Forest	Farming	Agriculture	Temporary crop	Soybean
$\Delta Export$	0.072	0.020	0.907	0.796	0.373
	(0.10)	(0.38)	(0.68)	(0.61)	(0.61)
Observations	11,431	11,431	11,431	11,431	11,431
	After 2011				
	Forest	Farming	Agriculture	Temporary crop	Soybean
$\Delta Export$	-0.084**	0.107**	0.094	0.134**	0.235
	(0.03)	(0.04)	(0.06)	(0.06)	(0.15)
Observations	7,622	7,622	7,622	7,622	7,622
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	3yrs	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

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Additional results: Export and land transition

	From forest			
	To farming	To agriculture	To temporary crop	To soybean
$\Delta Export$	0.116**	0.013***	0.009***	0.001***
	(0.05)	(0.00)	(0.00)	(0.00)
Observations	79,979	79,979	79,979	79,979
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

Export and agriculture investment

	Defensives cost	#Harvesting machines	#Planting machines	#Tractors
Δ*Export*	14.9**	0.58*	0.74***	0.22**
	(6.59)	(0.35)	(0.16)	(0.01)
Observations	3805	3805	3805	3805
IV	ROW exporting	ROW exporting	ROW exporting	ROW exporting
Lag	3yrs	3yrs	3yrs	3yrs

Notes: Regressions are weighted by agricultural employment. Standard errors are clustered at the micro-region level.

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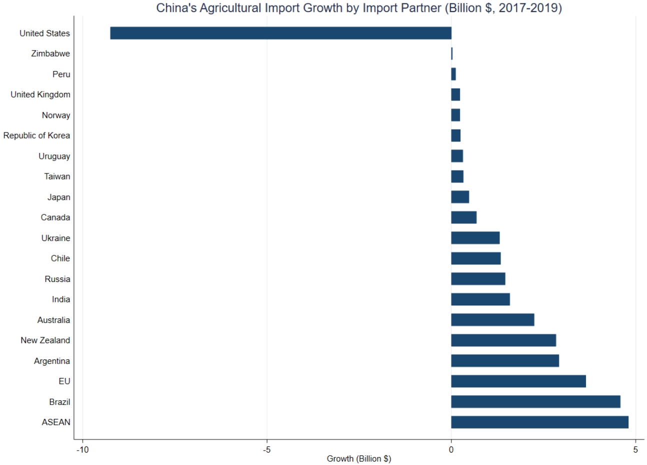
The US-China trade war

- Started in January 2018 with Trump setting tariffs and other trade barriers on China with the goal of forcing it to make changes to what the U.S. says are unfair trade practices and intellectual property theft.
- On all trading partners: global safeguard tariffs on solar panels and washing machines in January 2018; tariffs on steel and aluminum under national security grounds in March 2018
- Targeted at Chinese products since July 2018
- Consequences: Tit for tat
- In January 2020, US and China signed an agreement to halt further tariff escalations.

Trade war and China’s agricultural import



Data

Chinese tariffs (2017-2019):

- Most-favored nation (MFN) tariffs: HS 10-digit product, month
- Chinese retaliatory tariffs on the U.S. goods during the US-China trade war: China's State Council: HS 8-digit product, country, date
- We focus on the period 2017-2019: No further tariff escalations since January 2020

Trade data:

- Import value from China Customs: HS 8-digit, country, month

Brazil export to China and ROW

Empirical strategy

- Idea: US-China trade war $\implies$ China imports more agricultural goods from Brazil.
- Is deforestation an unintended consequence of the trade war?

$$\Delta Y_{it} = \beta \Delta Tariff_{it} + \lambda Z_{it} + \varepsilon_{it}$$

- ΔY_{it} is the month-to-month change in forest fire alerts and deforestation in region i in month t
- $\Delta Tariff_{it}$ is the month-to-month change in weighted tariffs faced by region i in month t

Results

- Outcome: daily fire spots
- Data from INPE's BDQueimadas. 1998-2020, daily fire coordinates
- A 1% increase in Chinese retaliatory tariff on the US leads to 0.0324% increase in fire areas.

	$\Delta\#Fire\ pixels/area$	$\Delta ln(\#Fire\ pixels + 1)$
$\Delta ln(Tariff)$	0.0324^{***}	25.19^{***}
	(0.004)	(2.52)
Observations	52,776	52,776
Year	Y	Y
State-month FEs	Y	Y

Notes: Standard errors are clustered at the micro-region level.

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