ECON G6905

Topics in Trade

Jonathan Dingel

Fall 2025, Week 12

COLUMBIA UNIVERSITY

IN THE CITY OF NEW YORK

Today: Spatial environmental economics

We've already seen environmental features play various roles in this course. For example, first-nature "locational fundamentals" are often environmental features: deep-water harbors lower trade costs, and waterfront views are amenities that anchor neighborhood sorting by income.

Three themes for today's whirlwind tour of spatial environmental economics

- Valuing environmental amenities
- Environmental policy and comparative advantage
- Spatial margins of adjustment

Hedonic pricing of air pollution

- Classic application of spatial equilibrium: value environmental amenities
- Does the US government regulate air too much/little? Cost-benefit analysis requires estimates of each, and there isn't a (direct) market for clean air
- Chay and Greenstone (2005) study the capitalization of total suspended particulates (TSPs) air pollution into housing values
- Price of house i depends on its characteristics, $P_i = P(Z)$. What's $\frac{\partial P_i(Z)}{\partial z_n}$?
- If some elements of Z are unobserved and covary with $z_n =$ TSPs, difficult to estimate the hedonic price schedule
- E.g., areas with higher levels of TSPs tend to be more urbanized and have higher per capita incomes, population densities, and crime rates
- Smith and Huang (1995): 1/4 of estimates have perverse *positive* correlation between housing prices and pollution levels
- I'll focus on the OVB problem; see article for heterogeneous WTP

Clean Air Act regulation of TSPs

- Clean Air Act Amendments of 1970 requires the Environmental Protection Agency to annually assign each county to either nonattainment or attainment status for each of five pollutants if above either:
  - Threshold 1: the annual geometric mean concentration exceeds 75 μg/m^3
  - Threshold 2: the second-highest daily concentration exceeds 260 μg/m^3
- In their nonattainment counties, states are required to develop plant-specific regulations for every major source of pollution
- Local rules mandate investments in state-of-the-art pollution abatement equipment
- Chay and Greenstone (2005) focus on TSPs because limited data for other regulated pollutants in early 1970s

CAAAs reduced TSPs quite a bit

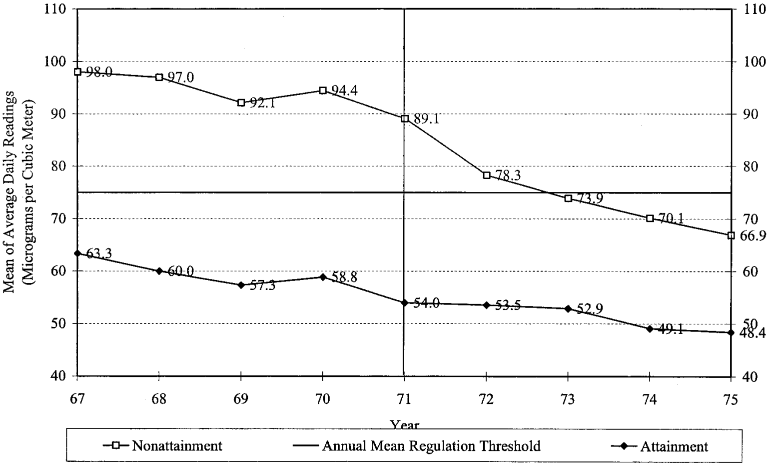


FIG. 2.—1967–75 trends in TSPs concentrations, by 1972 attainment status. The data points are derived from the 228 counties that were continuously monitored in this period. The 116 attainment counties had a 1970 population of approximately 25.8 million people, whereas about 63.4 million people lived in the 112 nonattainment counties in the same year. Each data point is the unweighted mean across all counties in the relevant regulatory category.

Nonattainment counties have TSP decreases and house-price increases

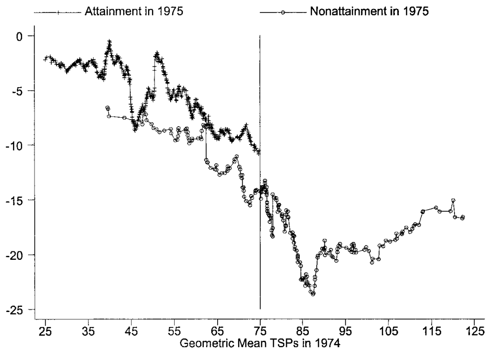


FIG. 4.—1970–80 change in mean TSPs by 1975 nonattainment status and the geometric mean of TSPs in 1974.

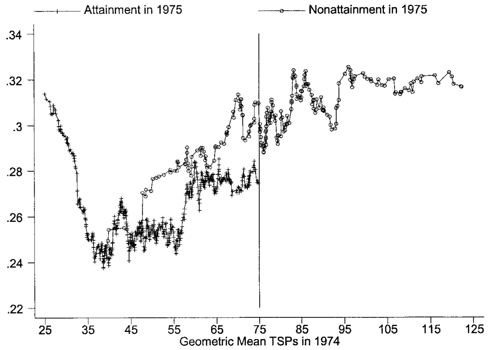


FIG. 5.—1970–80 change in log housing values by 1975 nonattainment status and the geometric mean of TSPs in 1974.

- Annual threshold is vertical bar at 75 μg/m^3
- Daily threshold violated by nonattainment counties to left of vertical bar

Cross-sectional and first-difference regressions suffer OVB

Cross-Sectional and First-Difference Estimates of the Effect of TSPs Pollution on Log Housing Values

	(1)	(2)	(3)	(4)
	A. 1970 Cross Section			
Mean TSPs (1/100)	.032	−.062	−.040	−.024
	(.038)	(.018)	(.017)	(.017)
R^2	.00	.79	.84	.85
Sample size	988	987	987	987
	B. 1980 Cross Section			
Mean TSPs (1/100)	.093	.096	.076	.027
	(.066)	(.031)	(.030)	(.028)
R^2	.00	.82	.89	.89
Sample size	988	984	984	984
	C. 1970–80 (First Differences)			
Mean TSPs (1/100)	.102	.024	.004	−.006
	(.032)	(.020)	(.016)	(.014)
R^2	.02	.55	.65	.73
Sample size	988	983	983	983
County Data Book covariates	no	yes	yes	yes
Flexible form of county covariates	no	no	yes	yes
Region fixed effects	no	no	no	yes

2SLS estimates using mid-decade nonattainment IVs

Instrumental Variables Estimates of the Effect of 1970–80 Changes in TSPs Pollution on Changes in Log Housing Values

	(1)	(2)	(3)	(4)
	A. TSPs Nonattainment in 1975 or 1976			
Mean TSPs (1/100)	−.362	−.213	−.266	−.202
	(.152)	(.096)	(.104)	(.090)
Sample size	988	983	983	983
	B. TSPs Nonattainment in 1975			
Mean TSPs (1/100)	−.350	−.204	−.228	−.129
	(.150)	(.099)	(.102)	(.084)
Sample size	975	968	968	968
	C. TSPs Nonattainment in 1970, 1971, or 1972			
Mean TSPs (1/100)	.072	−.032	−.050	−.073
	(.058)	(.042)	(.041)	(.035)
Sample size	988	983	983	983
County Data Book covariates	no	yes	yes	yes
Flexible form of county covariates	no	no	yes	yes
Region fixed effects	no	no	no	yes

See Chay and Greenstone (2005) Table 2 column 3 on Panel C IV problems

Valuations

- A welfare analysis of the non-marginal reductions in TSPs induced by the mid-decade TSPs regulations requires estimation of the MWTP *function*
- "A popular, but likely invalid, assumption is that preferences are homogeneous and linear with respect to air quality, so that the MWTP for clean air is constant"
- Mean housing values increased by roughly \$2,400 in nonattainment counties. With $\sim$19 million houses in these counties, the WTP is $\sim$\$45 billion.
- Per Rosen-Roback model, cannot only look at housing prices: WTP for lower TSPs shows up in housing-price differences *and* wage differences
- 2SLS regression with log income as outcome yields precise zero

"East-Side Story": Air pollution and persistent neighborhood sorting

Heblich, Trew, Zylberberg (2021) on 70 largest metropolitan areas in England

- "The heavy reliance on coal 1850–1960 generated unprecedented concentrations of sulphur dioxide in the atmosphere, which scarred cities"
- "Pollution from historical factories accounted for about 15% of the variation in neighborhood composition in 1881."
- "There is no evidence of excess deprivation in neighborhoods downwind from industrial chimneys before the rise of industrial coal in 1817."
- "Industrial coal pollution effectively stopped in the 1970s, but the path dependence in neighborhood sorting is still felt today."
- "The persistence of neighborhood sorting is tied not only to relocation frictions but also to its interaction with preferences for neighborhood composition."

This is akin to Lee and Lin (2018) with a temporary disamenity. Also relates to debates about poor people's higher exposure to environmental disamenities

Rising coal consumption amidst urbanization

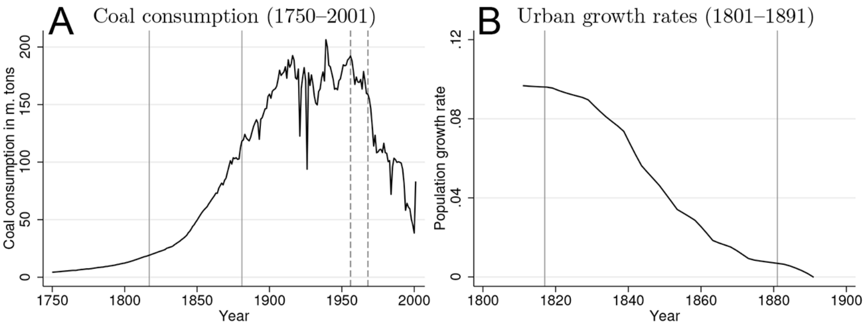
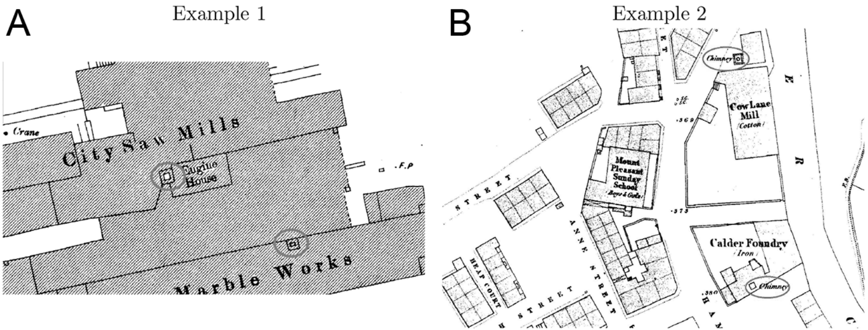


FIG. 1.—Coal consumption and migration during the Industrial Revolution. *A*, Increase and decrease in coal consumption over the period 1750–2000, based on the work of Warde (2007), who reports coal consumption in petajoule. To convert numbers from petajoule to tons, we use a conversion factor of 1 : 34,140. The solid vertical lines indicate the years 1817 and 1881, while the dashed vertical lines mark the introduction of the 1956 and 1968 Clean Air Acts. *B*, Average decadal population growth rate for the period 1801–91 in cities in our sample.

Locating chimneys and their coal usage



- Ordnance Survey maps show roads, railway, rivers, canals, the outline of each building and their use, and chimneys
- Georeference $\geq 5,000$ chimneys and use associated building description, assigned to one of 11 industrial categories by textual analysis (keyword matching)
- Compute coal use per chimney from coal use per worker, total employment, and count of chimneys

Modeling local air pollution

- Atmospheric dispersion modeling system (ADMS) incorporates the impact of temperature and humidity and accounts for complex terrain and changes in surface roughness.
- Winds blow mostly from the west/southwest (less predictable in Northern England)
- Residential sources: assume domestic chimneys are uniformly distributed within city at a very low altitude

Estimated pollution correlates with 1915 deposits across Manchester neighborhoods

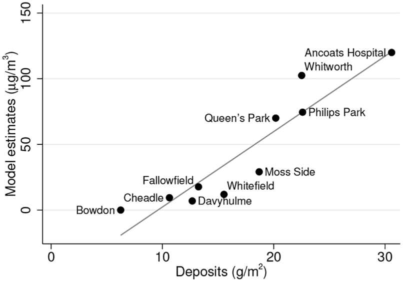


FIG. 5.—Air-pollution measures (external validity) across neighborhoods of Manchester, based on the First Annual Report of the Sanitary Committee on the Work of the Air Pollution Advisory Board, 1915. The graph charts the relationship between deposits, as collected by the Air Pollution Advisory Board (1915), and our measure of SO_2 concentration ($\mu g/m^3$).

More polluted places have more dark moths, who benefit from soot as camouflage

Polluted neighborhoods have less skilled residents

Regress skill share Y_{it} of LSOA i in parish p in city c on historical pollution P_i

$$Y_{it} = \alpha + \beta P_i + \gamma X_i + \nu Y_p + \delta_c + \varepsilon_{it}$$

X_i contains topographic, geographic, and disamenity controls

TABLE 2

Pollution and Shares of Low-Skilled Workers in 1881

	(1)	(2)	(3)	(4)	(5)	(6)
Pollution	.0440	.0428	.0409	.0378	.0354	.0338
	(.0071)	(.0073)	(.0068)	(.0066)	(.0067)	(.0069)
	[.1738]	[.1690]	[.1614]	[.1491]	[.1398]	[.1332]
Observations	5,538	5,538	5,538	5,538	5,538	5,538
Fixed effects (city)	No	Yes	Yes	Yes	Yes	Yes
Controls:						
Population	No	No	Yes	Yes	Yes	Yes
Topography	No	No	No	Yes	Yes	Yes
Amenities	No	No	No	No	Yes	Yes
Latitude/longitude	No	No	No	No	No	Yes

Note.—Standard errors are reported in parentheses and clustered at the parish level. Standardized effects are reported in brackets. Each cell is the result of a separate regression. The unit of observation is a lower layer super output area (LSOA). The set of population controls include the parish-level shares of farmers, managers, and blue-collar workers in 1817; the logarithm of the average property tax at the parish level in 1815; and total population in 1881. The set of topography controls include the average, maximum, and minimum elevations for the LSOA and the (inverse) distance to waterways as of 1827. The set of amenities controls include the (inverse) distance to the city hall, (inverse) distance to parks, share of LSOA within the city borders in 1880, LSOA area, (inverse) distance to the closest heavy industry, and (inverse) distance to the closest light industry. Latitude/longitude are for the LSOA centroid.

Predicting air pollution using 1827 waterways

Steam engines need water for cooling

TABLE 3
POLLUTION AND SHARES OF LOW-SKILLED WORKERS IN 1881—INSTRUMENTAL VARIABLES SPECIFICATION

	(1)	(2)	(3)	(4)
	A. First Stage: Pollution			
Pollution (waterways)	.2904	.2020	.3100	.1834
	(.0331)	(.0347)	(.0403)	(.0384)
	B. Second Stage: Share of Low-Skilled Workers			
Pollution	.1286	.0937	.1143	.0695
	(.0199)	(.0296)	(.0201)	(.0359)
	[.5076]	[.3695]	[.4511]	[.2743]
Observations	4,830	4,830	4,557	4,557
F-statistic	77.16	33.91	59.22	22.81
OLS coefficient	.0408	.0216	.0392	.0209
Sample	Canal > 250 m	Canal > 250 m	Canal > 500 m	Canal > 500 m
Fixed effects (city)	Yes	Yes	Yes	Yes
Extended controls	No	Yes	No	Yes

Historical air pollution, modern neighborhood composition

TABLE 5
POLLUTION AND SHARES OF LOW-SKILLED WORKERS IN 1971–2011—INSTRUMENTAL VARIABLES SPECIFICATION

	1971	1981	1991	2001	2011
Pollution	.0300	.0406	.0342	.0462	.0495
	(.0164)	(.0198)	(.0257)	(.0193)	(.0214)
	[.2358]	[.2895]	[.1823]	[.2839]	[.2830]
Observations	4,829	4,830	4,830	4,830	4,830
F-statistic (first stage)	33.91	33.91	33.91	33.91	33.91
Fixed effects (city)	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes

NOTE.—Standard errors are reported in parentheses and clustered at the parish level (as defined in 1881). Standardized effects are in brackets. Each cell is the result of a separate regression. The unit of observation is a lower layer super output area (LSOA). The set of extended controls include all controls in col. 6 of table 2. As in cols. 1 and 2 of table 3, the instrument is the predicted pollution generated by a uniform allocation of pollution sources along waterways (as of 1827), and we exclude LSOA within 250 m of a waterway.

Pre-coal placebo test and modern outcomes

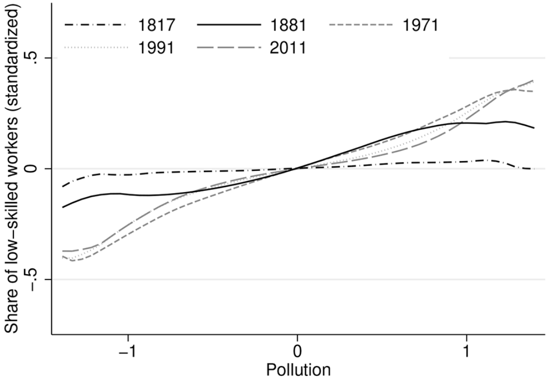


FIG. 10.—Pollution (x-axis) across neighborhoods and shares of low-skilled workers (y-axis) in 1817, 1881, 1971, 1991, and 2011. This figure represents the locally weighted regressions on all observations between the (standardized) shares of low-skilled workers and our (standardized) measure of past pollution. We consider the residuals of all measures once cleaned by city fixed effects as well as topography and population controls.

Model of dynamics

- "To interpret the persistence of past pollution, we develop a dynamic model of neighborhood choice with two types of households–low-skilled and high-skilled–that differ only in their income
- Each period, $1-\theta$ of households may move: migration reveals preferences over neighborhood characteristics
- If $\theta = 0$, it's equivalent to a static model
- With $\theta > 0$, demand depends on the past and future expected allocation of households
- Authors use historical pollution as an instrument for current neighborhood composition and its subsequent evolution

Scale, composition, and technique

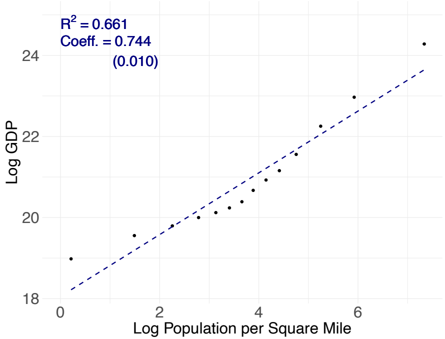
Consider environmental policy and comparative advantage. Since Grossman and Krueger (1993), economists have often decomposed variation in industrial pollution into

- the *scale* of output
- the *composition* of output across industries
- the *techniques* for producing a given good within an industry

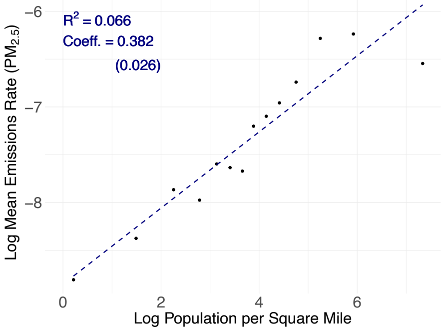
This decomposition can be applied to changes over time or variation across places

Denser counties: greater scale, dirtier industries, cleaner techniques

(a) Scale



(b) Composition

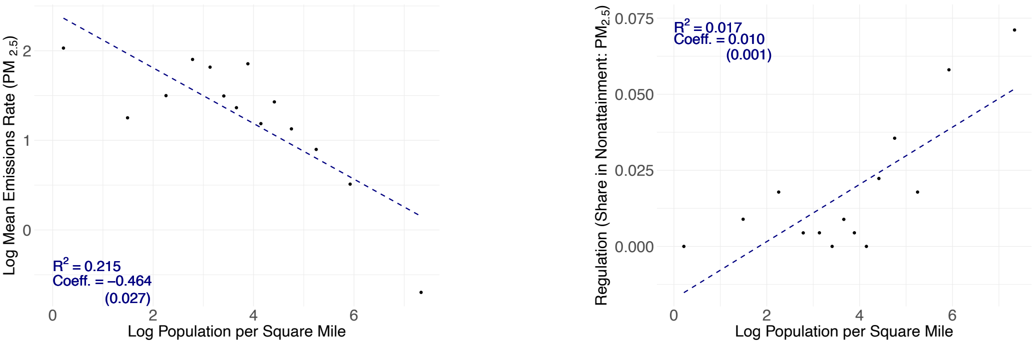


Balboni and Shapiro (2025), Figure 3

- Denser counties have higher GDP per capita and more people
- Denser counties have manufacturing and utilities rather than agriculture

Denser counties: greater scale, dirtier industries, cleaner techniques

(c) Technique (d) Regulation



Balboni and Shapiro (2025), Figure 3

- Denser counties use cleaner production techniques
- Denser counties are subject to more stringent regulation

Are cities greener? Smaller environmental footprint per person?

Holian and Kahn (2015): "a standardized household creates less greenhouse gas emissions from transportation in those metropolitan areas with a larger downtown share of college graduates" and "public transit ridership has increased more in those metropolitan areas where a larger share of downtown adult residents are college graduates"

Kahn and Walsh (Handbook 2015): "the social costs of suburbanization literature is really focused on a second-best world in which households and firms are spreading out without facing the social costs of their actions"

Holian and Kahn (2015): "homeowner communities in suburban areas are more likely to vote against such regulation, while homeowners in the center city area are more likely to favor carbon pricing."

Shapiro (2025): institutional comparative advantage in clean industries

Strong institutions provide comparative advantage in clean industries, improving a country's environmental quality

- industries that depend on institutions are clean
- strong institutions increase relative exports in clean industries
- industry's complexity explains clean goods' dependence on institutions
- cross-country differences in industry composition explain meaningful share of variation in emissions
- quantitative GE model says improving one country's institutions reduces its pollution through cross-country industrial reallocation

Some context: Institutional sources of comparative advantage

Costinot (2009) [Recall log-supermodularity ▸ Recall]:

- Ricardian model has $q(\omega, \sigma, \gamma) = h(\omega)a(\sigma, \gamma)$
- If $a(\sigma, \gamma)$ is LSM, then aggregate output $Q(\sigma, \gamma)$ is LSM
- "This first result …is at the heart, for example, of the recent literature on institutions and trade; see, for example, Acemoglu, Antras, and Helpman (2007), Costinot (2007), Cuñat and Melitz (2006), Levchenko (2007), Matsuyama (2005), Nunn (2007), and Vogel (2007). At a formal level, these papers all share the same fundamental objective: providing microtheoretical foundations for the log-supermodularity of factor productivity with respect to countries' "institutional quality" and sectors' "institutional dependence," whatever those characteristics may be."

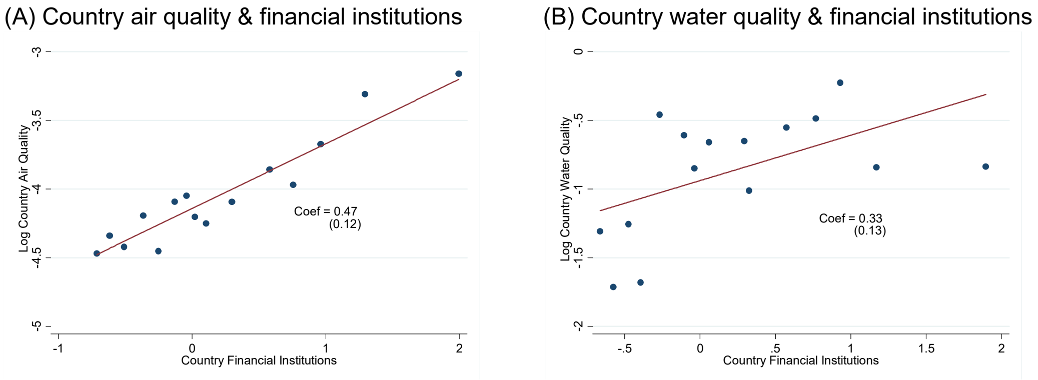
Chor (*JIE* 2010): "I find strong evidence for the importance of factor endowments, financial development, legal institutions, and labor market regimes as sources of comparative advantage, even when all interaction terms are run in one regression."

Measuring institutions, institutional dependence, and cleanliness

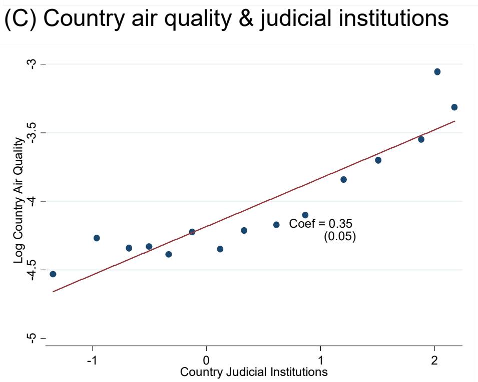
- Institutions: Financial depth (private credit/GDP), rule of law (World Bank index), labor market freedom (Heritage Foundation index)
- Institutional dependence: asset intangibility (Rajan & Zingales 1998, Manova 2013), differentiated inputs (Rauch 1999, Nunn 2007), std dev within-firm sales growth
- Factor endowments: capital per worker and human capital index (PWT)
- Factor intensities: capital and labor shares
- Country's environmental regulation: first PCA of 8 measures
- Industry's clean index: one minus PCA of tons of air/water emissions per dollar output (EPA + Census of Manufactures)
- Tariffs: CEPII's Market Access Map

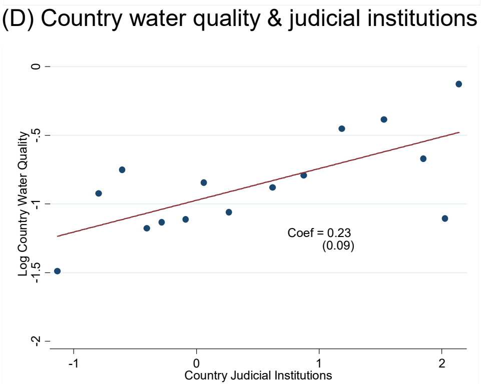
All variables are normalized, so a unit change is one standard deviation

Motivating correlation: Cleaner countries have better institutions



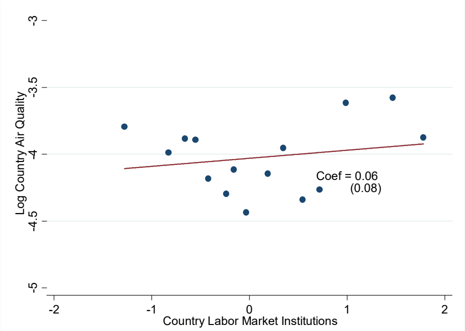
Motivating correlation: Cleaner countries have better institutions



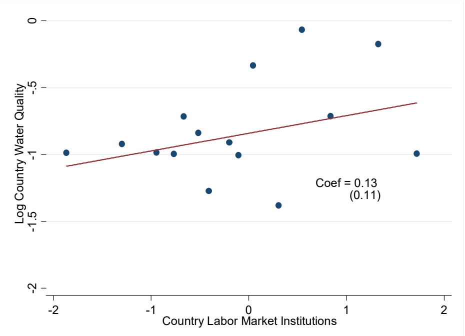


Motivating correlation: Cleaner countries have better institutions

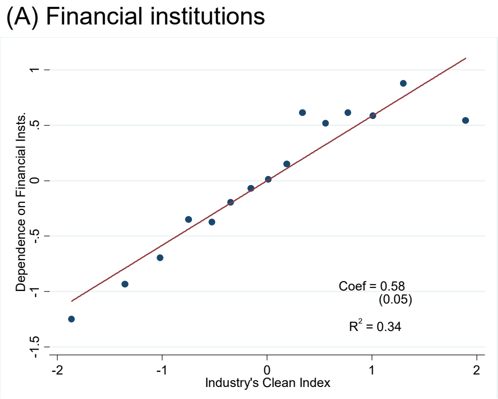
(E) Country air quality & labor market institutions

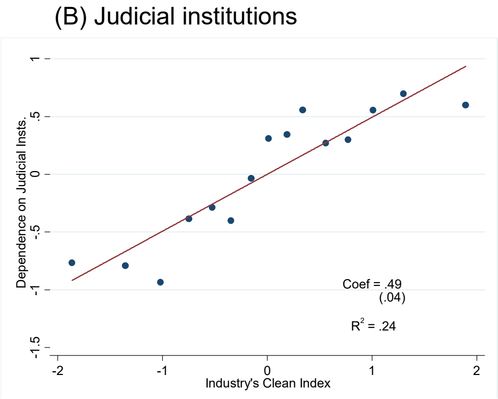


(F) Country water quality & labor market institutions

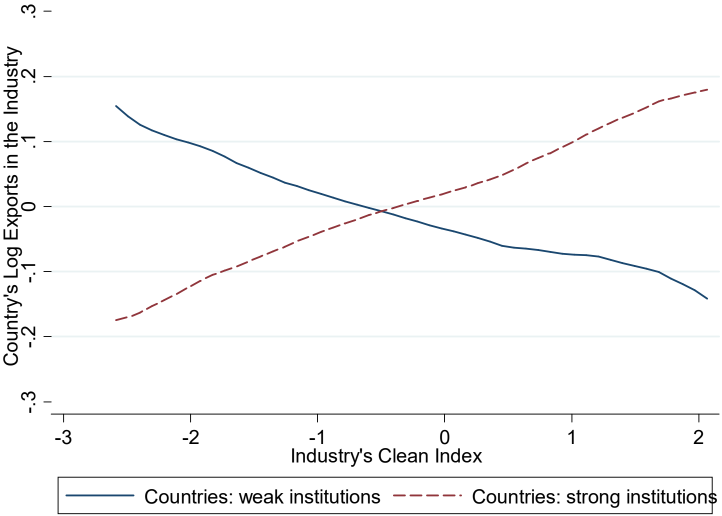


Industries that depend more on institutions are cleaner





Countries with strong institutions export more in clean industries



Gravity regression: Sources of comparative advantage

Standard gravity model from a multi-sector Ricardian model:

$$X_{ijs} = \xi \frac{T_{is} \left(c_{is}\phi_{ijs}\right)^{-\theta_s}}{P_{js}^{-\theta_s}} X_{js}$$

Estimating equation for a cross section of trade flows:

$$\ln X_{ijs} = \alpha \underbrace{E_i \times I_s}_{\text{institutions}} + \sum_f \beta_f \underbrace{E_i^f \times I_s^f}_{\text{factor inputs}} + \pi \underbrace{R_i \times Z_s}_{\text{regulation}} + \gamma \ln \underbrace{(1 + t_{ijs})}_{\text{a.v. tariffs}} + \zeta_{js} + \eta_{ij} + \epsilon_{ijs}$$

Replace institutional dependence I_s by industry's clean index Z_s

$$\ln X_{ijs} = \alpha^C E_i Z_s + \sum_f \beta_f^C E_i^f I_s^f + \pi^C R_i Z_s + \gamma^C \ln (1 + t_{ijs}) + \zeta_{js}^C + \eta_{ij}^C + \epsilon_{ijs}^C$$

Stronger environmental regulations reduce dirty exports

Table 2—Sources of Comparative Advantage

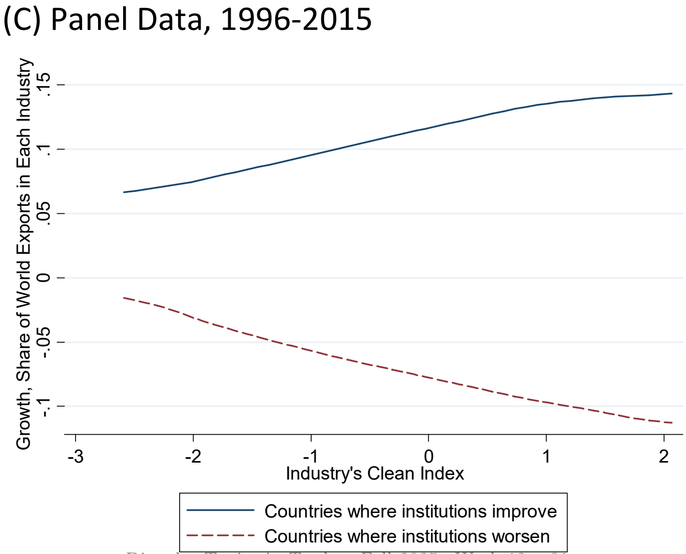
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Comparative advantage in all industries										
Country endowment × industry intensity:										
Institutions: financ.	0.057***	—	—	—	—	—	—	—	0.036**	—
	(0.012)	—	—	—	—	—	—	—	(0.015)	—
Institutions: judicial	—	0.054***	—	—	—	—	—	—	0.025**	—
	—	(0.010)	—	—	—	—	—	—	(0.010)	—
Institutions: labor	—	—	0.006	—	—	—	—	—	0.004	—
	—	—	(0.004)	—	—	—	—	—	(0.004)	—
Institutions: index	—	—	—	0.057***	—	—	—	—	—	0.038***
	—	—	—	(0.007)	—	—	—	—	—	(0.008)
Environmental reg.	—	—	—	—	0.048***	—	—	—	0.017*	0.022**
	—	—	—	—	(0.009)	—	—	—	(0.010)	(0.009)
Factor capital/lab.	—	—	—	—	—	-0.025	—	—	0.186**	0.172*
	—	—	—	—	—	(0.096)	—	—	(0.089)	(0.098)
Factor: skills	—	—	—	—	—	—	0.348***	—	0.282***	0.285***
	—	—	—	—	—	—	(0.036)	—	(0.035)	(0.033)
Log(1+tariffs)	—	—	—	—	—	—	—	-0.085***	-0.084***	-0.085***
	—	—	—	—	—	—	—	(0.009)	(0.009)	(0.009)

Stronger institutions increase relative exports in cleaner industries

Panel B: Comparative advantage in clean industries

Country endowment × clean industry index:										
Institutions: financ.	0.051***	—	—	—	—	–	–	–	0.035**	—
	(0.010)	—	—	—	—	–	–	–	(0.015)	—
Institutions: judicial	—	0.054***	—	—	—	–	–	–	0.008	—
	—	(0.010)	—	—	—	–	–	–	(0.031)	—
Institutions: labor	—	—	0.018**	—	—	–	–	–	0.006	—
	—	—	(0.008)	—	—	–	–	–	(0.008)	—
Institutions: index	—	—	—	0.054***	—	–	–	–	—	0.038***
	—	—	—	(0.007)	—	–	–	–	—	(0.012)
Environmental reg.	—	—	—	—	0.048***	–	–	–	0.008	0.008
	—	—	—	—	(0.009)	–	–	–	(0.028)	(0.014)
Country endowment × industry intensity:										
Factors capital/lab.	—	—	—	—	–	-0.025	–	–	0.112	0.115
	—	—	—	—	–	(0.096)	–	–	(0.086)	(0.094)
Factors: skills	—	—	—	—	–	–	0.348***	–	0.307***	0.302***
	—	—	—	—	–	–	(0.036)	–	(0.034)	(0.034)
Log(1+tariffs)	—	—	—	—	–	–	–	-0.085***	-0.084***	-0.085***
	—	—	—	—	–	–	–	(0.009)	(0.009)	(0.009)

Improving institutions and faster export growth in clean industries



Industry's complexity explains clean goods' dependence on institutions

"Polluting industries, often described as 'heavy industry', use large, long-lived, tangible assets like machines and boilers to process and convert dense raw materials into finished products."

- Large, expensive machines are tangible collateral for loans
- Dirty industries disproportionately use raw materials that are relatively homogeneous and traded through open markets (e.g., fewer patent lawsuits)

Table 3—Which Industry Characteristics Explain the Importance of Institutions for Clean Industries?

	Association with clean index	Dependence of clean industries on institutions:			Comparative advantage of clean industries
		Financial	Judicial	Labor	
	(1)	(2)	(3)	(4)	(5)
Baseline	—	0.58***	0.49***	0.18***	0.041***
	—	(0.05)	(0.04)	(0.05)	(0.010)
Energy share	-0.37***	0.50***	0.42***	0.16***	0.042***
	(0.12)	(0.05)	(0.04)	(0.05)	(0.010)
Raw materials share	-0.36***	0.49***	0.33***	0.17***	0.031***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.009)
Upstreamness	-0.33***	0.49***	0.41***	0.20***	0.049***
	(0.05)	(0.05)	(0.04)	(0.05)	(0.010)

Industry composition explains some of the variation in emissions

Mean country has total pollution emissions 72% lower than US; gross output 89% lower

Table 4—Decomposition: Scale, Composition, and Technique, US as Reference

	All (1)	CO (2)	NO_x (3)	$PM_{2.5}$ (4)	SO_x (5)	VOCs (6)
1. Scale, composition, and technique	-0.72	-0.75	-0.83	-0.45	-0.67	-0.89
	(0.70)	(0.67)	(0.35)	(1.53)	(0.87)	(0.19)
2. Scale	-0.89	—	—	—	—	—
	(0.19)	—	—	—	—	—
3. Composition	1.75	1.20	2.11	2.75	2.11	0.55
	(1.23)	(1.21)	(1.46)	(1.98)	(2.23)	(0.55)
4. Technique	-0.02	0.10	-0.36	0.25	0.20	-0.32
	(0.59)	(0.76)	(0.44)	(1.07)	(1.19)	(0.31)
5. |Composition|	1.76	1.24	2.11	2.77	2.11	0.59
	(1.21)	(1.17)	(1.45)	(1.95)	(2.23)	(0.51)
6. |Technique|	0.47	0.51	0.49	0.74	0.88	0.38
	(0.36)	(0.57)	(0.28)	(0.81)	(0.82)	(0.22)

Notes: calculations use full Exiobase data. Scale, composition, and technique are all proportional difference relative to US. Row 2 uses production but not pollution data, so it is identical across pollutants. Emission rates are winsorized at 99.9th percentile. Calculations cover all industries. CO is carbon monoxide, NO_x is nitrogen oxides, $PM_{2.5}$ is particulate matter smaller than 2.5 micrometers, SO_x is sulfur oxides, and VOCs are volatile organic compounds.

Climate change: Changing locational fundamentals and reallocation

- Climate change can alter productivity, marginal utility of consumption/leisure, disutility of work, capital depreciation rates, hazard rate of destructive disasters, etc
- Many studies use variation in weather to estimate climate damage functions
- Spatial pattern of climate changes is complicated: "The models predict greater temperature change in the polar regions than near the equator. This change in gradient can drive changes in circulation. The results may be warmer in some places and colder in others, wetter in some places and drier in others…" (Schelling 1992)
- Even a uniform rise in temperatures would have heterogeneous consequences: a warmer Yukon Territory is likely more attractive
- I will emphasize spatial margins of adjustments to climate change

Temperature damages to US crops (Schlenker and Roberts 2009)

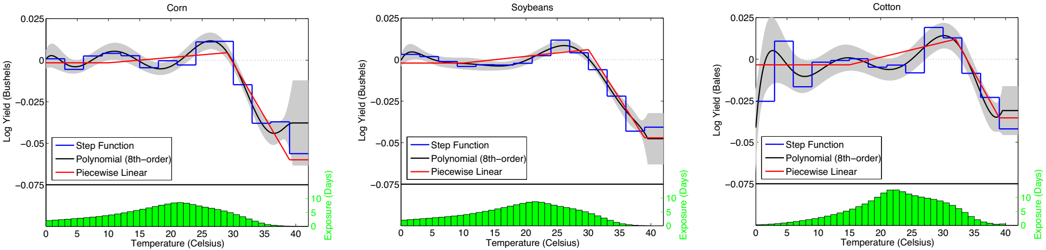


Fig. 1. Nonlinear relation between temperature and yields. Graphs at the top of each frame display changes in log yield if the crop is exposed for one day to a particular 1° C temperature interval where we sum the fraction of a day during which temperatures fall within each interval. The 95% confidence band, after adjusting for spatial correlation, is added as gray area for the polynomial regression. Curves are centered so that the exposure-weighted impact is zero. Histograms at the bottom of each frame display the average temperature exposure among all counties in the data.

"Our data are comprised of new fine-scale weather outcomes merged together with a large panel of crop yields that spans most U.S. counties from 1950 to 2005. The new weather data include the length of time each crop is exposed to each one-degree Celsisus temperature interval in each day, summed across all days of the growing season, all estimated for the specific locations within each county where crops are grown. The new fine-scale weather data facilitate estimation of a flexible model that can detect nonlinearities and breakpoints in the effect of temperature on yield."

Temperature damages to US crops (Schlenker and Roberts 2009)

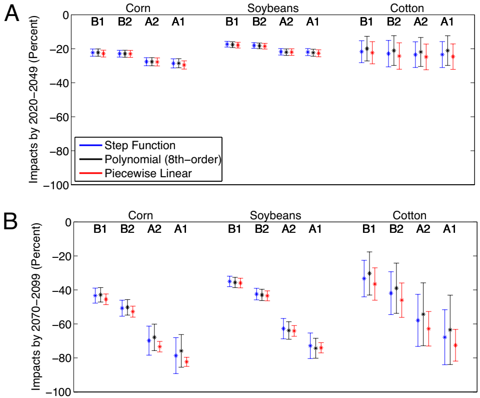


Fig. 2. Predicted climate-change impacts on crop yields under the Hadley III climate model. Graphs display predicted percentage changes in crop yields under four emissions scenarios. Frame A displays predicted impacts in the medium term (2020–2049) and frame B shows the long term (2070–2099). A star indicates the point estimates, and whiskers show the 95% confidence interval after adjusting for spatial correlation. The color corresponds to the regression models in Fig. 1.

"Holding Current Growing Regions Fixed, Area-Weighted Average Yields Are Predicted to Decrease by 30–46% Before the End of the Century Under the Slowest Hadley III Warming Scenario (B1), and Decline by 63–82% Under the Most Rapid Warming Scenario (A1FI)."

Statistical extrapolation is not a sensible economic forecast

- The statistical model of crop c in place i at time t

$$\text{yields}_{cit} = f_c(X_{it}, T_{it})$$

  is not an economic model; it is closer to production-function estimation with omitted inputs (X_{it} contains county FEs, time trends, and precipitation)
- A naive extrapolation like $\text{yields}^{\text{forecast}}_{ci,2099} = f_c(X_{i\bar{t}}, T^{\text{forecast}}_{i,2099})$ that feeds in 2099 temperatures and fixes endogenous/control variables X at their time $\bar{t}$ values is not a counterfactual scenario in an economic model
- Output is produced by decision makers who can
  - invest in heat-resistant crop varieties
  - switch to planting other crops
  - move to other places

Spatial margins of adjustment to climate change

Desmet, Rossi-Hansberg (2015):

“Temperature varies by parallel from 0° Celsius in the North Pole to 28° Celsius in the Equator. . . most land in the world is essentially economically unused and empty. . . any substantial cost of climate change must be associated with the frictions involved in moving production and people from their current sites to the regions that will be suitable for production in the future”

Kahn (2014):

“The menu of choices offered by a system of cities reduces our exposure to climate change risk. . . Nations featuring multiple cities with low migration barriers between these cities are uniquely suited to adapt to most of the emerging challenges associated with climate change. . . The themes of competition, choice, innovation and experimentation are the basis for my optimism concerning our collective ability as urbanites to withstand this emerging threat.”

Schelling (AER 1992):

“Almost everybody who attends this lecture in New Orleans will have undergone a greater change in the past few days than is expected to occur in any fixed locality during the coming century.”

See also Obolensky, Tabellini & Taylor (2024) on climate mismatch

Costinot, Donaldson, Smith (2016)

- If climate-change damages are spatially uneven, how might global agricultural trade respond?
- Food and Agriculture Organization's Global Agro-Ecological Zones (GAEZ) data set uses agronomic models of yields and high-resolution data on soil, topography, and climatic conditions to predict crop-by-crop yields for 1.7 million grid cells.
- Competitive model of trade between countries with heterogeneous "fields"
- Two elasticities of substitution and one productivity dispersion parameter drive responses
- Counterfactual scenarios show crop switching damps climate-change damages by about two-thirds, while adjustments to trade flows have little consequence

These exercises rely heavily on the GAEZ productivities for un-produced outputs

Climate damages could raise gains from trade (relative to autarky)

Simple example:

- Imagine symmetric $2 \times 2 \times 2$ economy: North and South islands have East and West fields with identical yields for wheat and rice
- Equilibrium: relative price is one, West field grows wheat, East field grows rice, no net trade
- Climate change: South's wheat yields fall, North's rice yields fall
- In autarky, large losses; with free trade, no loss at all because damage created comparative advantage and countries switch to fully specialized production

Preferences

The representative agent in country i has quasi-linear preferences over outside good and a composite of all crops C_i:

$$U_i = C_i^0 + \beta_i \ln C_i$$

C_i aggregates crops indexed by k (elasticity κ) and crop varieties indexed by origin j (elasticity σ)

$$C_i = \left[\sum_{k \in \mathcal{K}} (\beta_i^k)^{1/\kappa} (C_i^k)^{(\kappa-1)/\kappa}\right]^{\kappa/(\kappa-1)}$$

$$C_i^k = \left[\sum_{j \in \mathcal{I}} (\beta_{ji}^k)^{1/\sigma} (C_{ji}^k)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}$$

Production technologies

- A_i^0 is labor productivity in freely traded outside good
- Crop k is Leontief combination of L hectares of land and N laborers in parcel ω of field f with TFP $A_i^{fk}(\omega)$ and labor intensity $\nu_i^f(\omega)$

$$Q_i^{fk}(\omega) = A_i^{fk}(\omega) \min\{L_i^{fk}(\omega), N_i^{fk}(\omega)/\nu_i^f(\omega)\}$$

  $A_i^{fk}(\omega)$ and $\nu_i^f(\omega)$ are iid Frechet distributed with location parameters A_i^{fk} (from GAEZ data) and shape parameter θ
- Competitive markets with iceberg trade costs

$$p_{ij}^k = \tau_{ij}^k p_i^k$$

Competitive equilibrium

No surprises here. Utility maximization:

$$C_{ji}^k = \beta_i \frac{\beta_i^k (P_i^k)^{1-\kappa}}{\sum_{l \in \mathcal{K}} \beta_i^l (P_i^l)^{1-\kappa}} \frac{\beta_{ji}^k (\tau_{ji}^k p_j^k)^{-\sigma}}{\sum_{n \in \mathcal{I}} \beta_{ni}^k (\tau_{ni}^k p_n^k)^{1-\sigma}} \quad \text{for all } i, j \in \mathcal{I}, k \in \mathcal{K}$$

Probability parcel ω of field f in country i allocated to crop k:

$$\pi_i^{fk} = \frac{(p_i^k A_i^{fk})^\theta}{(\alpha_i)^\theta + \sum_{l \in \mathcal{K}} (p_i^l A_i^{fl})^\theta} \quad \text{for all } f \in \mathcal{F}_i, i \in \mathcal{I}, \text{ and } k \in \mathcal{K}$$

Output is sum across fields (of area s_i^f) using selection-corrected productivities

$$Q_i^k = \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk} \left[\frac{(p_i^k A_i^{fk})^\theta}{(\alpha_i)^\theta + \sum_{l \in \mathcal{K}} (p_i^l A_i^{fl})^\theta} \right]^{(\theta-1)/\theta} \quad \text{for all } i \in \mathcal{I} \text{ and } k \in \mathcal{K}$$

Markets clear:

$$Q_i^k = \sum_{j \in \mathcal{I}} \tau_{ij}^k C_{ij}^k \quad \text{for all } i \in \mathcal{I} \text{ and } k \in \mathcal{K}$$

Data

- 50 countries (90% of world crop value) and 10 crops (71%)

Rice	17.3%	White potato	5.6%
Maize	11.4%	Sugarcane	4.7%
Wheat	10.7%	Banana	3.4%
Tomato	5.9%	Cotton	3.2%
Soybean	5.6%	Oil palm	3.2%

- GAEZ provides pre- (1961-1990) and post-CC (2071-2100) field-level productivities (scenario: high inputs, rain-fed water supply)
- FAO: Output quantity, land use, and prices in 2009 by crop-country (ki) pair
- Comtrade: Bilateral crop-level trade values X_{ij}^k in 2009

Estimation: Demand system

- Estimate $\sigma = 5.4$ using average GAEZ yield Z_i^k as IV for p_i^k

$$\ln\left(X_{ij}^k / X_j^k\right) = M_j^k + (1-\sigma)\ln p_i^k + \underbrace{\ln[\beta_{ij}^k (\tau_{ij}^k)^{1-\sigma}]}_{\equiv\, \epsilon_{ij}^k}$$

(no $X_{ij}^k = 0$ observations; no τ_{ij} covariates; cannot reject that $\sigma^k = \sigma\ \forall k$)

- Estimate $\kappa = 2.8$ using CES demand and Z_j^k as IV for P_j^k

$$\ln\left(X_j^k / X_j\right) = M_j + (1-\kappa)\ln \underbrace{\left[\sum_{i\in\mathcal{I}} \beta_{ij}^k \left(\tau_{ij}^k p_i^k\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}}_{=P_j^k} + \epsilon_j^k$$

- Quasi-linear preferences make demand shifter $\beta_j = X_j$

Estimation: Productivity heterogeneity (θ, α_i)

- Given θ, choose labor cost shifter α_i to match land allocated to crops

$$L_i(\theta, \alpha_i) = \sum_{k \in \mathcal{K}} \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk} \left[\pi_i^{fk}\right]^{(\theta-1)/\theta}$$

- Estimate θ to minimize distance between Q_i^k in model and data

$$Q_i^k(\theta, \alpha_i) = \sum_{f \in \mathcal{F}_i} s_i^f A_i^{fk} \underbrace{\left[\frac{(p_i^k A_i^{fk})^\theta}{(\alpha_i)^\theta + \sum_{l \in \mathcal{K}} (p_i^l A_i^{fl})^\theta}\right]}_{=\pi_i^{fk}}^{(\theta-1)/\theta}$$

- Estimate α_i and $\theta = 2.46$ by constrained non-linear least squares

$$\min_{\theta, \{\alpha_i\}} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} \left[\ln Q_i^k(\theta, \alpha_i) - \ln Q_i^k\right]^2 \text{ s.t. } L_i(\theta, \alpha_i) = L_i \ \forall i \in \mathcal{I}$$

- This assumes measurement error in outputs, not productivities
- See paper on model fit

Counterfactual scenarios: Productivity change

First-order approximation of productivity changes: $\Delta A_i = \sum_{k \in K} \sum_{f \in \mathcal{F}_i} \rho_i^{fk} \Delta A_i^{fk}$

- The approximation ignores terms of trade effects
- $\rho_i^{fk} \equiv p_i^k Q_i^{fk} / Y_i$ denotes the initial fk share of country i's GDP
- $\rho_i^{fk} = \rho_i^k \times \phi_i^{fk}$ with revenue $\rho_i^k \equiv p_i^k Q_i^k / Y_i$ and output $\phi_i^{fk} \equiv Q_i^{fk} / Q_i^k$ shares
- Logit math yields $\phi_i^{fk} = \frac{(A_i^{fk})^\theta [\alpha_i^\theta + \sum_{l \in K} (p_i^l A_i^{fl})^\theta]^{(1-\theta)/\theta}}{\sum_{g \in \mathcal{F}_i} (A_i^{gk})^\theta [\alpha_i^\theta + \sum_{l \in K} (p_i^l A_i^{gl})^\theta]^{(1-\theta)/\theta}}$, which can be computed using GAEZ productivity, price data, and estimated α_i and θ
- Indonesia, the median country, has $\Delta A_i = -1.3\%$
- For world, climate change is -0.34% decrease in GDP

Full model using A_i' instead of A_i:

- welfare loss of 0.26% of world GDP

Counterfactual scenarios: Trade versus reallocation

No production adjustment: fix π_i^{fk} at baseline shares

- $(Q_i^k)' = \sum_{f \in \mathcal{F}_i} s_i^f (A_i^{fk})' \left[\pi_i^{fk}\right]^{(\theta-1)/\theta}$
- World welfare loss of -0.78% of GDP is triple the baseline scenario
- Farmers' ability to substitute crops when comparative advantage shifts may substantially mitigate the ill effects of climate change.

No trade adjustment: fix crop export shares at baseline

- Require exports of crop k by country i to stay constant fraction of output

$$\sum_{j \neq i} \tau_{ij}^k (C_{ij}^k)' / (Q_i^k)' = \sum_{j \neq i} \tau_{ij}^k C_{ij}^k / Q_i^k \;\forall ik$$

- Impose quantity restrictions by equivalent wedges δ_i^k (trade taxes)

$$(p_{ij}^k)' = \delta_i^k \tau_{ij}^k (p_i^k)' \;\forall i \neq j \in \mathcal{I}, \forall k \in \mathcal{K}$$

- World welfare loss of 0.27% is virtually same as in case of full adjustment

Summary

- Spatial-equilibrium logic lets us value local environmental benefits
- Local air pollution interacts with spatial sorting by skill
- Comparative advantage is important for environmental policy and climate adaptation
- Spatial margins are one important dimension of adaptation to climate change

Recall: Log-supermodularity

A function $g : \mathbb{R}^n \to \mathbb{R}^+$ is *log-supermodular* if $\forall x, x' \in \mathbb{R}^n$

$$g\left(\max\left(x, x'\right)\right) \cdot g\left(\min\left(x, x'\right)\right) \geq g(x) \cdot g(x')$$

where max and min are component-wise operators.

- $g(x)$ is LSM in (x_i, x_j) if $g(x_i, x_j; x_{-i,-j})$ is LSM
- $g(x)$ is LSM $\iff g(x)$ is LSM in (x_i, x_j) $\forall i, j$
- $g > 0$ and g is $C^2 \Rightarrow \frac{\partial^2 \ln g}{\partial x_i \partial x_j} \geq 0 \iff g(x)$ is LSM in (x_i, x_j)

Some handy properties:

- LSM is preserved by multiplication and integration
- An argmax of a LSM objective is increasing in other variables