How Does Trade Openness Affect Real Income Volatility?

Evidence from India's Famine Era

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Volatility and Livelihoods

- Climatic shocks (which affect productivity) make rural, aricultural economies extremely volatile places in which to live.
  - Incomes fall
  - Prices of important consumption goods rise
  - $\Rightarrow$ Real incomes affected.
- Recent work has highlighted some dire consequences of these shocks
  - Output, consumption, investment fall
  - Mortality rises (dramatically in some cases)
- Open question: What can be done to dampen real income volatility?

Volatility and Trade Openness

- Our question: Does openness to trade exacerbate or dampen real income volatility?
- Theory of how trade openness affects the volatility of real incomes is ambiguous
  - Prices: stablilize
  - Nominal incomes: more volatile (Newbery-Stiglitz (1981) and specialization of production)
  - Real incomes: unclear
- Existing empirical evidence inconclusive.

Approach of This Paper

- Focus on case of extreme volatility: Famines in colonial-era India
  - 15-30 million famine deaths between 1875 and 1919 (when population $\sim$ 150 million)
- Observable source of volatility: Rainfall
  - Indian agriculture was "a gamble in monsoons"
- Dramatic change in openness to trade: Arrival of Railroads

Preview of Results

- Exploit methodology that explores how railroads changed the equilibrium 'responsiveness' of various outcome variables to rainfall (ie productivity) shocks.
- Results from number of outcomes follow pattern suggested by simple model:
  - Prices: less responsive.
  - Nominal incomes: more responsive.
  - Real incomes: less responsive.
  - Mortality rate: less responsive (virtually disappears).
  - 'Famine' index: less responsive (virtually disappears).

Outline

Background: Rainfall, Famine and Railroads

Theoretical Framework

Method and Results

- Price responsiveness
- Nominal income responsiveness
- Real income responsiveness
- Mortality responsiveness
- “Famine” index responsiveness

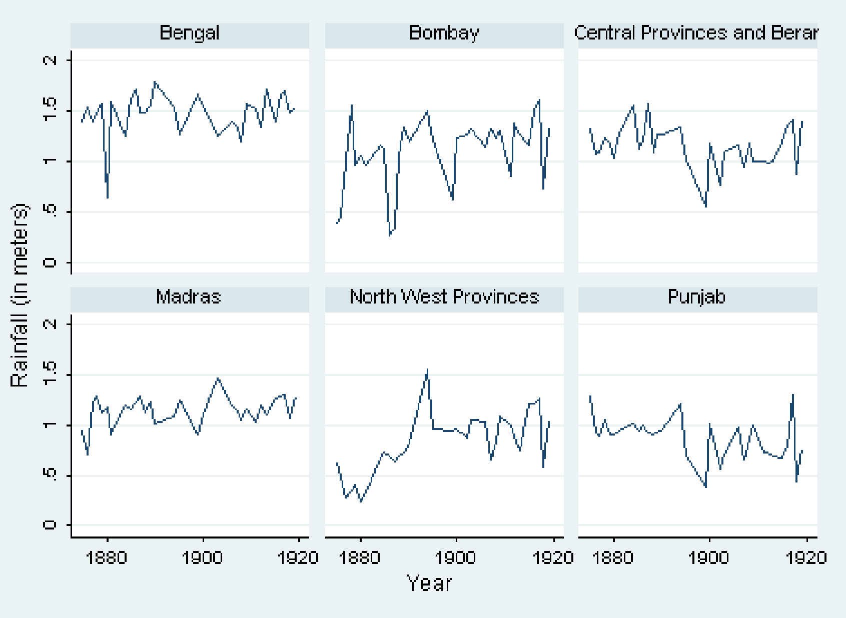
Conclusion

Outline

The Colonial Indian Economy

- Primarily agricultural:
  - 66 % of GDP in 1900 (Heston 1983)
- Agriculture was primarily rain-fed: 14 % irrigation in 1900
- Rainfall was extremely volatile

Volatility of Rainfall



Famines in Colonial India

- No consistent official definition of ‘famine’ applied
- But generally characterized by:
  - Crop failure
  - Knowles (1924): “agricultural lockouts, where both food supplies and agricultural employment, on which the bulk of the rural population depends, plummet”
  - High food prices
  - Excess death

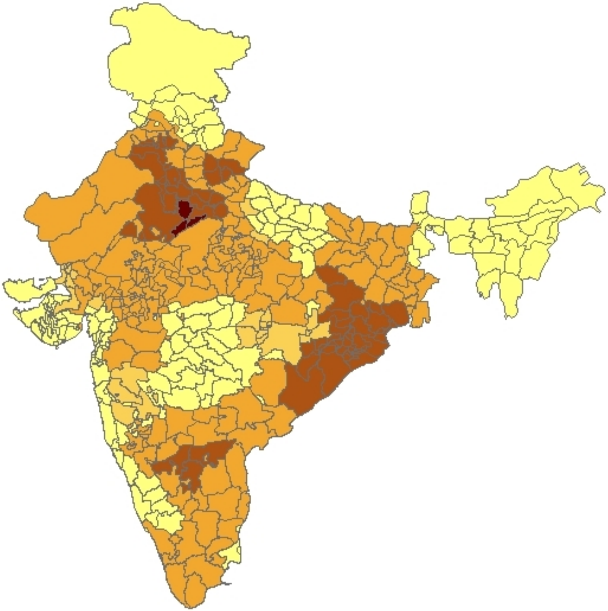
An Index of Famine Severity

- Srivastava (1968) catalogs all ‘famines and food scarcities’ between 1861 and 1919
  - Deliberately stopped there, as no famines after that until 1942

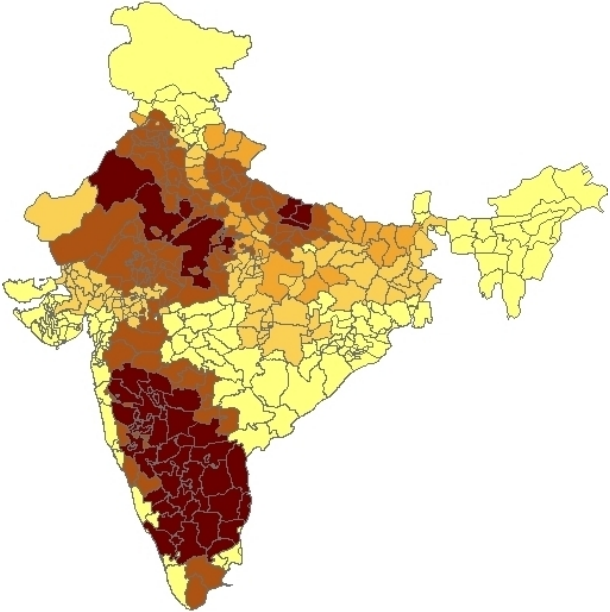
- Each event was described (and some mapped) consistently, and in considerable detail

- We use these descriptions to code each district and year according to:
  - $F_{dt} = 0$: no mention in Srivastava (1968)
  - $F_{dt} = 1$: described as “mild food scarcity”
  - $F_{dt} = 2$: “famine”, but “not severe”
  - $F_{dt} = 3$: “severe famine”

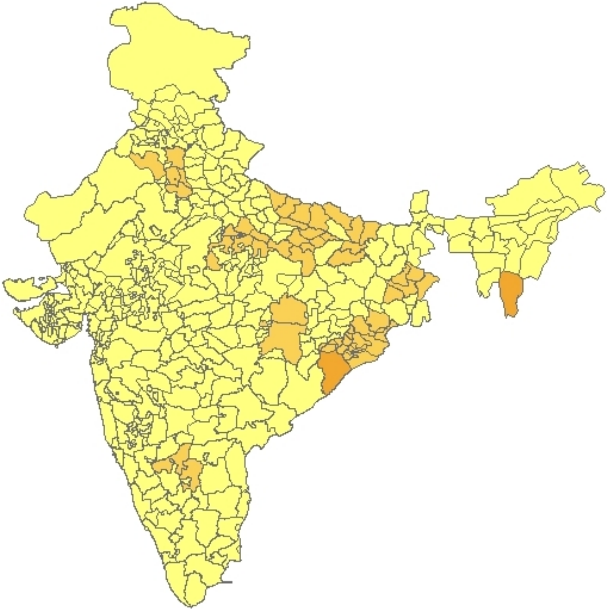
Famine Intensity: 1860-1869 Average



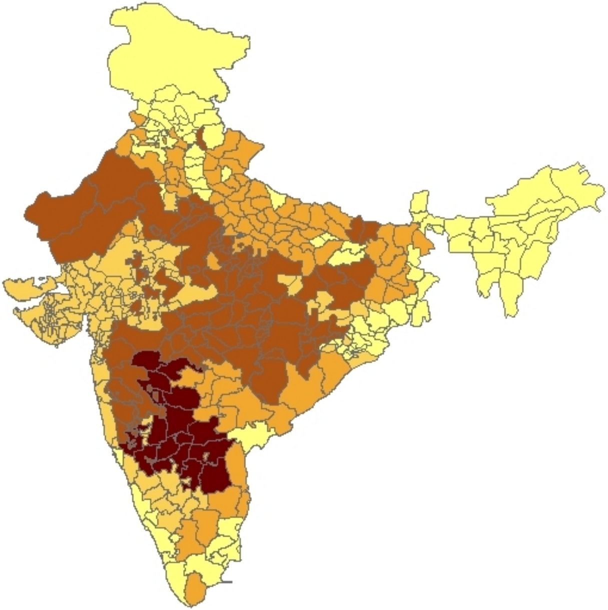
Famine Intensity: 1870-1879 Average



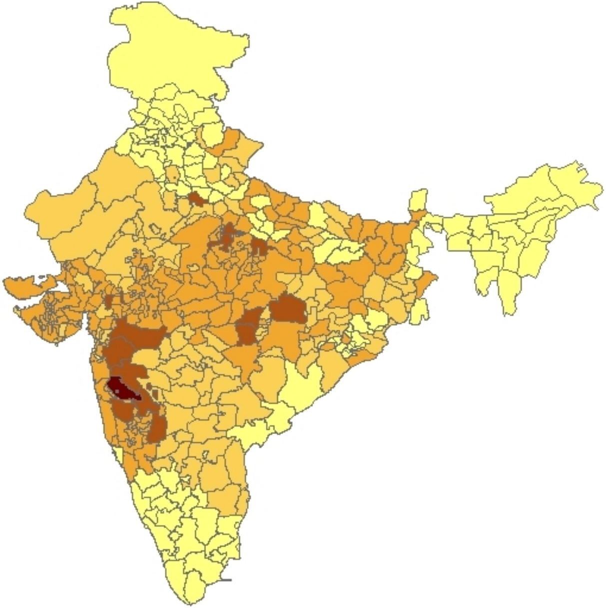
Famine Intensity: 1880-1889 Average



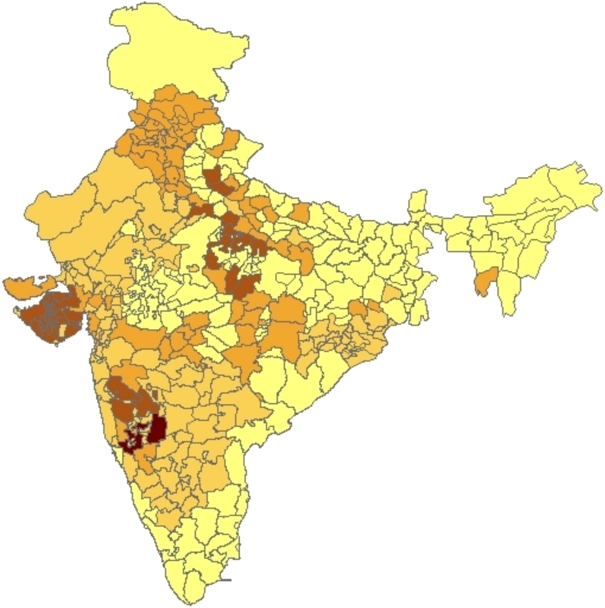
Famine Intensity: 1890-1899 Average



Famine Intensity: 1900-1909 Average



Famine Intensity: 1910-1919 Average

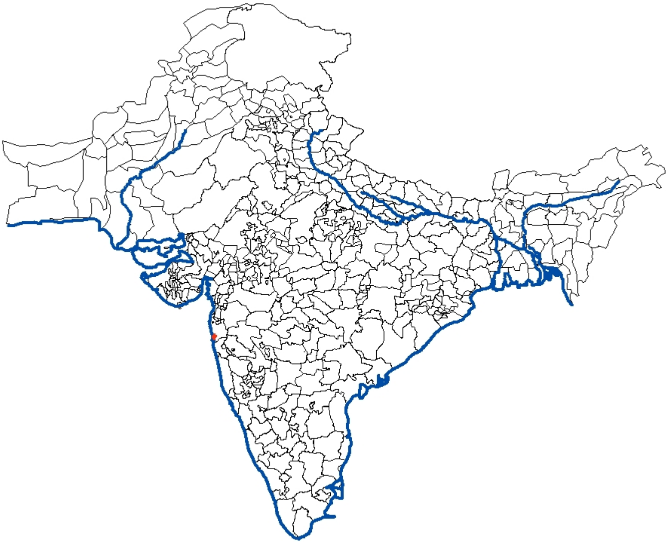


Transportation in Colonial India

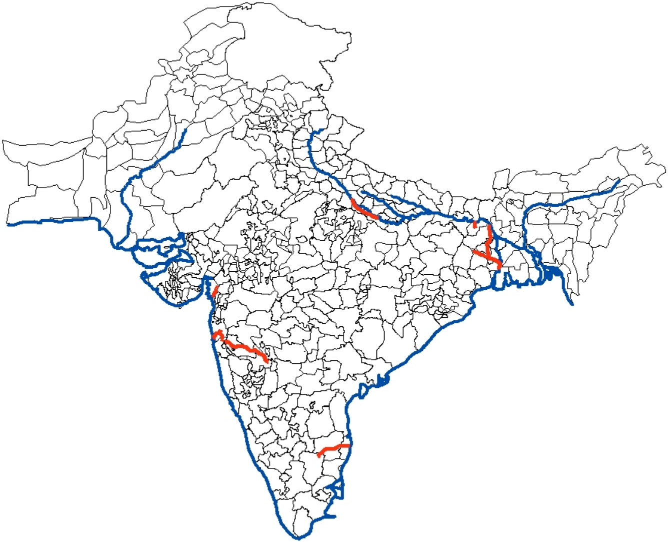
- Pre-rail transportation (Deloche 1994, 1995):
  - Roads: bullocks, 10-30 km per day (ie 2-3 months to port)
  - Rivers: seasonal, slow
  - Coasts: limited port access for steamships

- Railroad transportation:
  - Faster: 600 km per day
  - Safer: predictable, year-round, limited damage, limited piracy
  - Cheaper:
    - $\sim 4.5\times$ cheaper than roads
    - $\sim 3\times$ cheaper than rivers
    - $\sim 2\times$ cheaper than coast
  - Donaldson (2008): Aggregates these benefits together $\Rightarrow$ railroads 'shrunk distance' by a factor of 8 relative to roads.

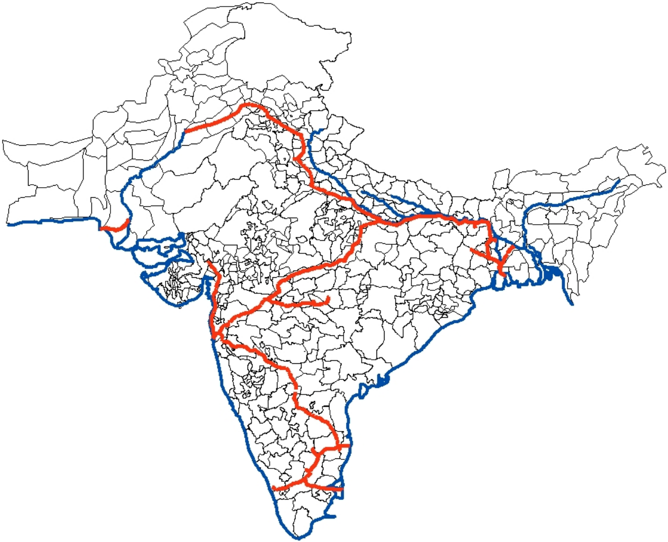
Railroad Network: 1853



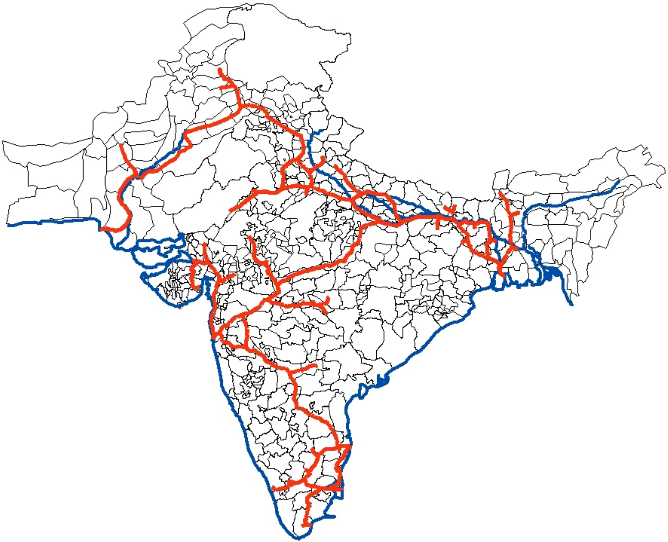
Railroad Network: 1860



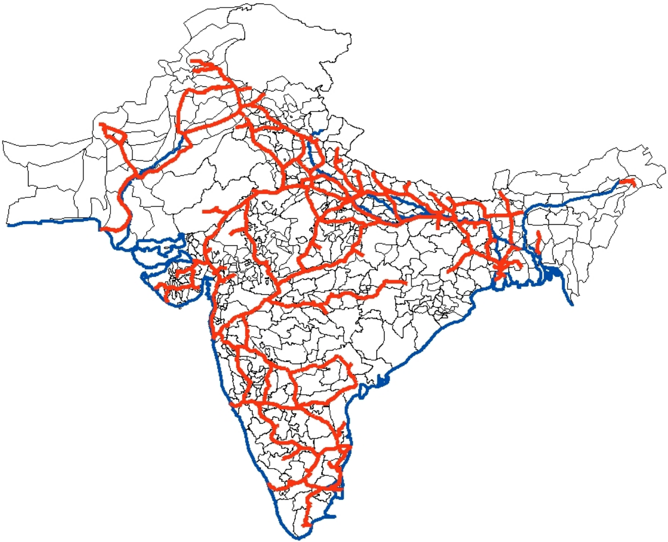
Railroad Network: 1870



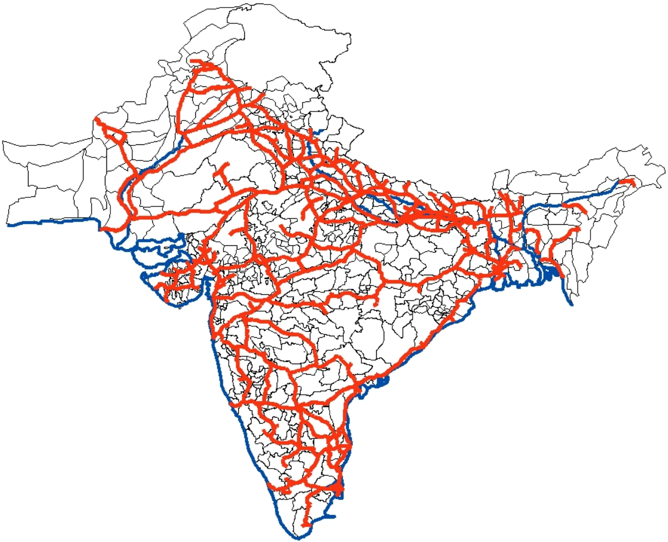
Railroad Network: 1880



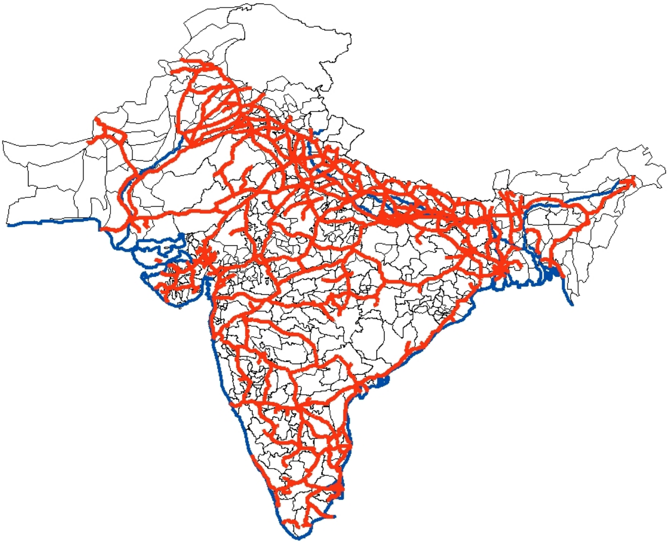
Railroad Network: 1890



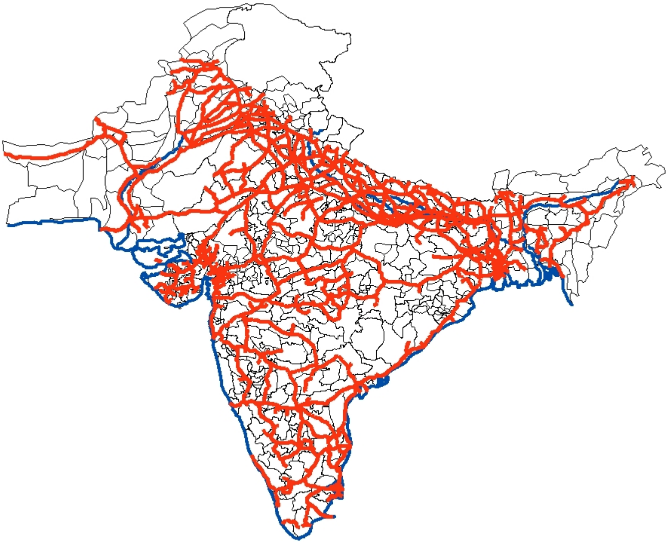
Railroad Network: 1900



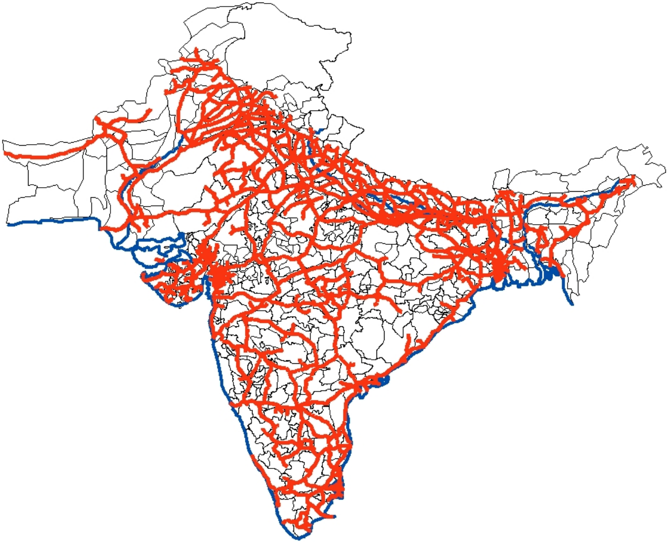
Railroad Network: 1910



Railroad Network: 1920



Railroad Network: 1930



Railroads and Famine Prevention

- Active debate at the time over whether railroads were good or bad for famine-prevention
  - 1880 Famine Commission influenced by Smith (1776): "...the drought [in "rice countries"] is, perhaps, scarce ever so universal as necessarily to occasion a famine, if the government would allow a free trade." $\Rightarrow$ Recommended a number of railroads to be constructed as 'famine lines'.
  - Gandhi (1938) and Nationalist Historians: "Railroads increased the frequency of famines, because, owing to the facility of means of locomotion, people sell out their grains, and it is sent to the dearest markets."

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Model Set-up

- Multi-sector version of Eaton and Kortum (2002)—general equilibrium with:
  - Many (≥ 2) regions
  - Many (≥ 2) goods
  - Trade costs $T \in [1, \infty)$
- K goods (e.g. rice, wheat):
  - indexed by k
  - each available in continuum of varieties (j)
- D regions (districts, foreign countries)
  - $o =$ origin
  - $d =$ destination
- Static model: study 'volatility' through comparative statics on exogenous variable that is stochastic in reality.

Model Environment

- Technology: $q_o^k(j) = L_o^k \; z_o^k(j) \qquad p_{oo}^k(j) = \frac{r_o}{z_o^k(j)}$

$$z_o^k(j) \sim F_o^k(z) = \exp(-A_o^k \, z^{-\theta_k})$$

Model Environment

- Technology: $q_o^k(j) = L_o^k \; z_o^k(j) \qquad p_{oo}^k(j) = \frac{r_o}{z_o^k(j)}$

$$z_o^k(j) \sim F_o^k(z) = \exp(-A_o^k \, z^{-\theta_k})$$

- Tastes: $U_o = \sum_{k=1}^{K} \left(\frac{\mu_k}{\varepsilon_k}\right) \ln \left(\int_0^1 (C_d^k(j))^{\varepsilon_k} dj \right)$

Model Environment

- Technology: $q_o^k(j) = L_o^k \; z_o^k(j)$ $\qquad p_{oo}^k(j) = \frac{r_o}{z_o^k(j)}$

$$z_o^k(j) \sim F_o^k(z) = \exp(-A_o^k \, z^{-\theta_k})$$

- Tastes: $U_o = \sum_{k=1}^K \left(\frac{\mu_k}{\varepsilon_k}\right) \ln \left(\int_0^1 (C_d^k(j))^{\varepsilon_k} dj\right)$

- Trading: iceberg trade costs $T_{od}^k \geq 1, \; T_{oo}^k = 1$

$$\Rightarrow p_{od}^k(j) = T_{od}^k \, p_{oo}^k(j)$$

Prediction 1: Railroads reduce price responsiveness

- Prices: $p_d^k = \lambda_1^k \left[\sum_{o=1}^{D} A_o^k \left(r_o T_{od}^k\right)^{-\theta_k}\right]^{-1/\theta_k}$

- Prediction 1: Price responsiveness $\left(\frac{dp}{dA}\right)$ and trade costs (T) around symmetric equilibrium (and 3 countries, 1 commodity):

$$\underbrace{\frac{d}{dT_{do}^k}\left|\frac{dp_d^k}{dA_d^k}\right| > 0}_{\text{less own responsiveness}} \qquad \underbrace{\frac{d}{dT_{do}^k}\left|\frac{dp_d^k}{dA_o^k}\right| < 0}_{\text{more 'connected' responsiveness}}$$

Prediction 2: Railroads increase nominal income responsiveness

- This follows from simple intuition in Newbery and Stiglitz (1981) or Rodrik (1997):
  - Nominal incomes: $P \times Q$.
  - Volatility in Q is technological and can't be altered.
  - Volatility in P is endogenous and depends on demand curve. But in conventional settings, P will move to offset Q.
  - So lack of price responsiveness acts as insurance, for nominal incomes.

Prediction 3: Railroads decrease real income responsiveness

- Taking p_o as the numeraire, and with $K = 1$, can write real income (welfare) as:

$$\ln r_o = \frac{1}{\theta} \ln A_o + \frac{1}{\theta} \ln \left[1 + \frac{1}{r_o L_o} \sum_{d \neq o} r_d L_d (T_{od})^{-1/\theta} p_d^{\theta} \right]$$

- Prediction 3: Around symmetric equilibrium (and 3 countries, 1 commodity):

$$\frac{d}{dT_{od}^{k}} \left| \frac{d\left(\frac{r_o}{\widetilde{P}_o}\right)}{dA_o} \right| > 0$$

Outline

Econometric Specification

- Estimate regressions of following form:

$$\begin{aligned} Y_{dt} = \alpha_d &+ \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} \\ &+ \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt} \end{aligned}$$

- We think of γ_3 as 'responsiveness'.
- Where:
  - Y_{dt} is a outcome variable of interest: prices, nominal incomes, real incomes, mortality rate, famine index.
  - $RAIL_{dt}$ is a dummy variable for railroad penetration.
  - $RAIN_{dt}$ is total amount of annual rainfall.

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Price Responsiveness

- Recall Prediction 1: $\frac{d}{dT^k_{dot}} \left| \frac{dp^k_{dt}}{dA^k_{dt}} \right| > 0$
- Suggests linear approximation:

$$\begin{aligned} \ln p^k_{dt} = & \beta^k_d + \beta^k_t + \beta_{dt} \\ & + \chi_1 RAIN^k_{dt} + \chi_2 RAIN^k_{dt} \times RAIL_{dt} + \varepsilon^k_{dt} \end{aligned}$$

- Data:
  - p^k_{dt} = avg retail price in 239 districts, for 17 crops, annually 1861-1930
  - $RAIN^K_{dt}$ = amount of rain over district-crop growing period
  - *Crop Calendar* and daily rain from 3614 gauges

Rain gauges

Price Responsiveness Results

$$\ln p_{dt}^{k} = \beta_{d}^{k} + \beta_{t}^{k} + \beta_{dt} + \chi_1 RAIN_{dt}^{k} + \chi_2 RAIN_{dt}^{k} \times RAIL_{dt} + \varepsilon_{dt}^{k}$$

Dependent variable: log price	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Local rainfall	-0.256 (0.102)**			
(Local rainfall) x (Railroad in district)				
Neighboring district rainfall				
(Neighboring district rainfall) x (Connected to neighbor by rail)				
Observations	73,000			
R-squared	0.89			

Note: Regressions include crop x year, district x year and district x crop fixed effects. OLS standard errors clustered at the district level.

Price Responsiveness Results

$$\ln p_{dt}^{k} = \beta_d^k + \beta_t^k + \beta_{dt} + \chi_1 RAIN_{dt}^k + \chi_2 RAIN_{dt}^k \times RAIL_{dt} + \varepsilon_{dt}^k$$

Dependent variable: log price	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Local rainfall	-0.256	-0.428		
	(0.102)**	(0.184)***		
(Local rainfall) x (Railroad in district)		0.414		
		(0.195)**		
Neighboring district rainfall				
(Neighboring district rainfall) x (Connected to neighbor by rail)				
Observations	73,000	73,000		
R-squared	0.89	0.89		

Note: Regressions include crop x year, district x year and district x crop fixed effects. OLS standard errors clustered at the district level.

Price Responsiveness Results

$$\ln p_{dt}^{k} = \beta_d^k + \beta_t^k + \beta_{dt} + \chi_1 RAIN_{dt}^k + \chi_2 RAIN_{dt}^k \times RAIL_{dt} + \varepsilon_{dt}^k$$

Dependent variable: log price	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Local rainfall	-0.256	-0.428	-0.402	
	(0.102)**	(0.184)***	(0.125)***	
(Local rainfall) x (Railroad in district)		0.414	0.375	
		(0.195)**	(0.184)*	
Neighboring district rainfall			-0.021	
			(0.018)	
(Neighboring district rainfall) x			-0.082	
(Connected to neighbor by rail)			(0.036)**	
Observations	73,000	73,000	73,000	
R-squared	0.89	0.89	0.90	

Note: Regressions include crop x year, district x year and district x crop fixed effects. OLS standard errors clustered at the district level.

Price Responsiveness Results

$$\ln p_{dt}^k = \beta_d^k + \beta_t^k + \beta_{dt} + \chi_1 RAIN_{dt}^k + \chi_2 RAIN_{dt}^k \times RAIL_{dt} + \varepsilon_{dt}^k$$

Dependent variable: log price	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Local rainfall	-0.256	-0.428	-0.402	0.004
	(0.102)**	(0.184)***	(0.125)***	(0.035)
(Local rainfall) x (Railroad in district)		0.414	0.375	0.024
		(0.195)**	(0.184)*	(0.120)
Neighboring district rainfall			-0.021	
			(0.018)	
(Neighboring district rainfall) x			-0.082	Salt
(Connected to neighbor by rail)			(0.036)**	
Observations	73,000	73,000	73,000	8,489
R-squared	0.89	0.89	0.90	0.53

Note: Regressions include crop x year, district x year and district x crop fixed effects. OLS standard errors clustered at the district level.

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- Price responsiveness
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Conclusion

Nominal Income Responsiveness

- Recall Prediction 2: $\frac{d}{dT_{dot}} \left| \frac{dr_{dt}}{dA_{dt}} \right| < 0$
- Suggests linear approximation:

$$\begin{aligned} \ln r_{dt} = \alpha_d + & \quad \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} \\ + & \quad \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt} \end{aligned}$$

- Data:
  - $r_{ot} L_o = \sum_k p^k_{ot} q^k_{ot}$ (NB: $\neq \int p^k_{ot}(j) q^k_{ot}(j) dj$), 17 agricultural crops (ignores: taxes/transfers, intermediate inputs, income from other sectors, income inequality)
  - Annually for 239 districts, 1870-1930.

Results: Nom. Income Responsiveness

$\ln r_{dt} = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$

Dependent variable: log nominal agricultural income	OLS (1)
Railroad in district	0.241
	(0.114)*
Rainfall in district	1.410
	(0.632)***
(Railroad in district)*(Rainfall in district)	
Observations	14,340
R-squared	0.771

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

Results: Nom. Income Responsiveness

$\ln r_{dt} = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$

Dependent variable: log nominal agricultural income	OLS (1)	OLS (2)
Railroad in district	0.241	0.168
	(0.114)*	(0.082)**
Rainfall in district	1.410	0.532
	(0.632)***	(0.249)**
(Railroad in district)*(Rainfall in district)		0.901
		(0.444)**
Observations	14,340	14,340
R-squared	0.771	0.775

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

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Real Income Responsiveness

- Recall Prediction 3: $\frac{d}{dT_{dot}}\left|\frac{d\left(\frac{r_{dt}}{\widetilde{P}_{dt}}\right)}{dA_{dt}}\right| > 0$
- Suggests linear approximation:

$$\ln\left(\frac{r_{dt}}{\widetilde{P}_{dt}}\right) = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt}$$

- Data:
  - $\widetilde{P}_{ot}$ = (chain-weighted) Fisher ideal price index, 17 agricultural crops (ignores: other costs of living, gains from new varieties)
  - Annually for 239 districts, 1870-1930.

Results: Real Income Responsiveness

$$\ln\left(\frac{r_{dt}}{\widetilde{P}_{dt}}\right) = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$$

Dependent variable: log real agricultural income	OLS (1)
Railroad in district	0.186
	(0.085)**
Rainfall in district	1.248
	(0.430)***
(Railroad in district)*(Rainfall in district)	
Observations	14,340
R-squared	0.767

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

Results: Real Income Responsiveness

$$\ln\left(\frac{r_{dt}}{\widetilde{P}_{dt}}\right) = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$$

Dependent variable: log real agricultural income	OLS (1)	OLS (2)
Railroad in district	0.186	0.252
	(0.085)**	(0.132)*
Rainfall in district	1.248	2.434
	(0.430)***	(0.741)***
(Railroad in district)*(Rainfall in district)		-1.184
		(0.482)**
Observations	14,340	14,340
R-squared	0.767	0.770

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

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Mortality Responsiveness

- Mortality as consumption proxy:
  - Ideally would like to track consumption, to see how strongly real income volatility passes through into consumption volatility.
  - Unfortunately consumption is unobserved here.
  - However, in this low-income and low-health environment, the mortality rate may proxy for living standards (ie consumption).

- Data on mortality rate:
  - M_{ot} = Crude death rate.
  - Mandatory vital event registration began in 1865. Registration was probably incomplete—Dyson (1991) uses census data to argue that registration was 70-90% complete (depending on the province).
  - Annually for 239 districts, 1870-1930.

Results: Mortality Responsiveness

$\ln M_{dt} = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$

Dependent variable: log mortality rate	OLS (1)
Railroad in district	-0.080
	(0.061)
Rainfall in district	-0.064
	(0.032)**
(Railroad in district)*(Rainfall in district)	
Observations	13,512
R-squared	0.642

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

Results: Mortality Responsiveness

$\ln M_{dt} = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}$

Dependent variable: log mortality rate	OLS (1)	OLS (2)
Railroad in district	-0.080	-0.143
	(0.061)	(0.078)*
Rainfall in district	-0.064	-0.145
	(0.032)**	(0.062)***
(Railroad in district)*(Rainfall in district)		0.123
		(0.059)**
Observations	13,512	13,512
R-squared	0.642	0.647

Note: Regressions include district and year fixed effects, and control for neighboring region railroad effects. OLS standard errors clustered at the district level.

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“Famine” Index Responsiveness

- Previous results on mortality rate covered full continuum of mortality fluctuations.
- Focus here on extreme events that were explicitly referred to as “famines”.
- Estimate latent variable model using ordered logit:

$$\begin{aligned} F^*_{dt} = \alpha_d + & \quad \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} \\ + & \quad \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt} \end{aligned}$$

- Data on famine index:
  - F_{ot} = Index based on Srivastava (1968) classifications.
  - Annually for 239 districts, 1861-1919.

Results: "Famine" Index

Dep. var.: Famine intensity index	(1)	(2)	(3)
Railroad in district	0.194		
	(0.374)		
Rainfall in district [year t]	-0.855***		
	(0.208)		

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.

Results: “Famine” Index

Dep. var.: Famine intensity index	(1)	(2)	(3)
Railroad in district	0.194	-1.625***	
	(0.374)	(0.572)	
Rainfall in district [year t]	-0.855***	-2.218***	
	(0.208)	(0.532)	
(Railroad in district)		1.858***	
x (Rainfall in district, year t)		(0.541)	

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.

Results: "Famine" Index

Dep. var.: Famine intensity index	(1)	(2)	(3)
Railroad in district	0.194	-1.625***	0.309
	(0.374)	(0.572)	(0.390)
Rainfall in district [year t]	-0.855***	-2.218***	-0.860***
	(0.208)	(0.532)	(0.204)
(Railroad in district)		1.858***	
x (Rainfall in district, year t)		(0.541)	
Rainfall in district [year t-1]			-0.699***
			(0.215)

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.

Results: “Famine” Index

Dep. var.: Famine intensity index	(4)	(5)
Railroad in district	-2.178***	
	(0.690)	
Rainfall in district [year t]	-2.316***	
	(0.518)	
(Railroad in district)	1.848***	
x (Rainfall in district, year t)	(0.521)	
Rainfall in district [year t-1]	-1.171***	
	(0.395)	
(Railroad in district)	0.692*	
x (Rainfall in district, year t - 1)	(0.404)	

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.

Results: "Famine" Index

Dep. var.: Famine intensity index	(4)	(5)
Railroad in district	-2.178***	-2.136***
	(0.690)	(0.754)
Rainfall in district [year t]	-2.316***	-17.35
	(0.518)	(20.40)
(Railroad in district)	1.848***	1.729***
x (Rainfall in district, year t)	(0.521)	(0.565)
Rainfall in district [year t-1]	-1.171***	9.316
	(0.395)	(21.51)
(Railroad in district)	0.692*	0.758*
x (Rainfall in district, year t - 1)	(0.404)	(0.458)

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district. Column (5) includes rainfall (in t) -times-trend and rainfall (in t-1)-times-trend interactions

Interpretation

- Results demonstrate role of railroads in strongly dampening equilibrium volatility, and in mitigating the weather-to-death mapping
- Cluster of results consistent with railroads enabling freer movement of food goods (and goods sold to pay for food)
- But other plausible interpretations for reduced-form mortality results:
    - Freer movement of people
    - Freer movement of capital
    - Freer movement of official famine relief (but there wasn't much of this)
    - Railroads made people richer (Donaldson, 2008)

Outline

Background: Rainfall, Famine and Railroads

Theoretical Framework

Method and Results

- Price responsiveness
- Nominal income responsiveness
- Real income responsiveness
- Mortality responsiveness
- “Famine” index responsiveness

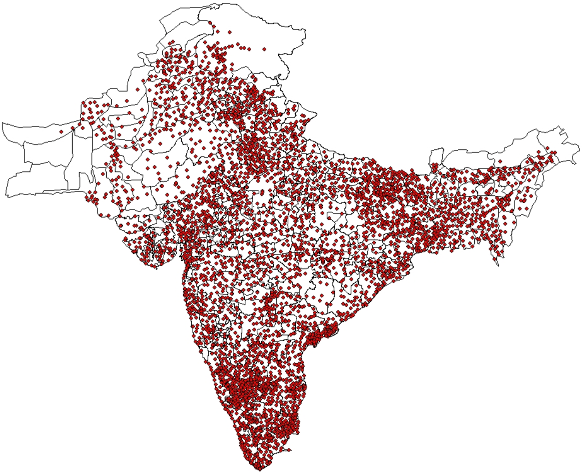
Conclusion

Conclusion

- Climate-induced volatility matters a great deal in some settings—eg Famines.
- Can trade openness mitigate the riskiness of economic life in developing countries?
- Dramatic change brought about by Indian railroads suggests that 'openness' can make a big difference:
  - Railroads virtually eliminated the effects of rainfall on famine/death in India.
  - Auxiliary results consistent with this phenomenon working through dampening real income volatility.

Daily Rainfall Data

3614 meteorological stations with rain gauges



◂ Return Trade ◂ Return Prices