How Does Trade Openness Affect Real Income Volatility?

Evidence from India's Famine Era

Robin Burgess[1] Dave Donaldson[2]

[1]LSE, CEPR and NBER

[2]MIT, CIFAR and NBER

This work was supported by the Economic and Social Research Council [RES-167-25-0214]

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

Outline

Background: Rainfall, Famine and Railroads

Theoretical Framework

Method and Results

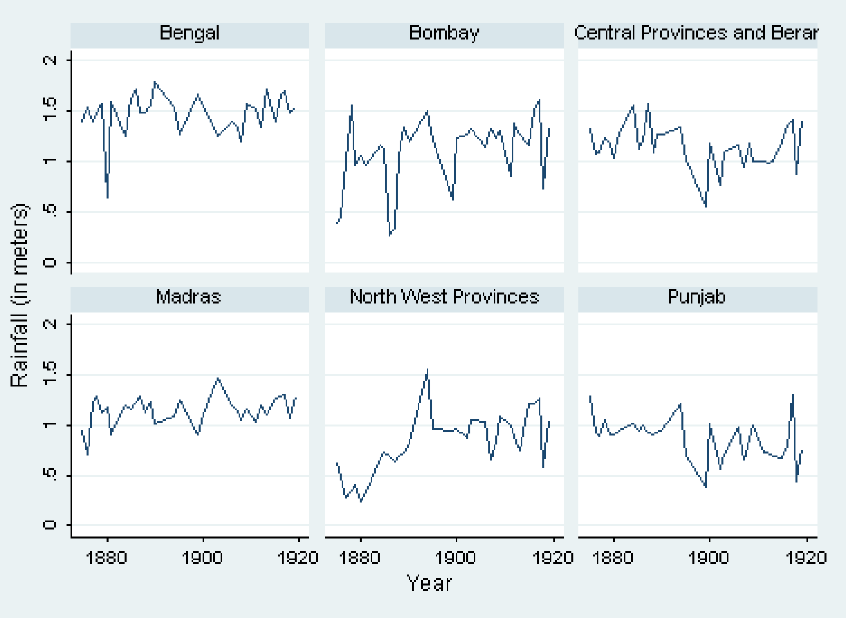
- Price responsiveness
- Nominal income responsiveness
- Real income responsiveness
- Mortality responsiveness
- “Famine” index responsiveness

Conclusion

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



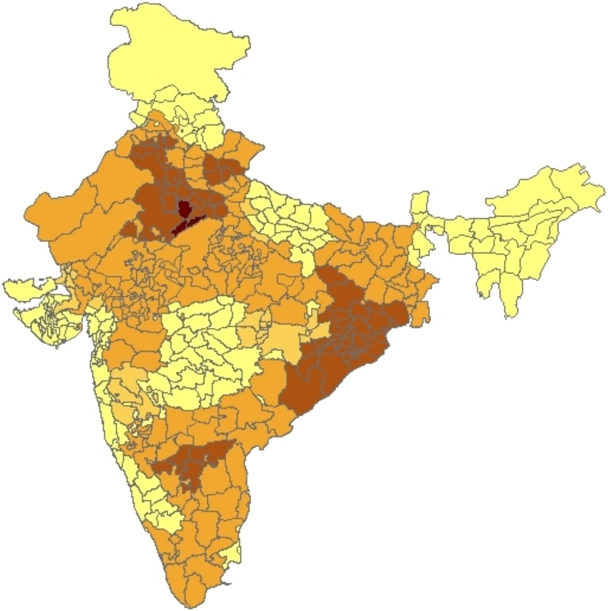
Famines in Colonial India

- 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

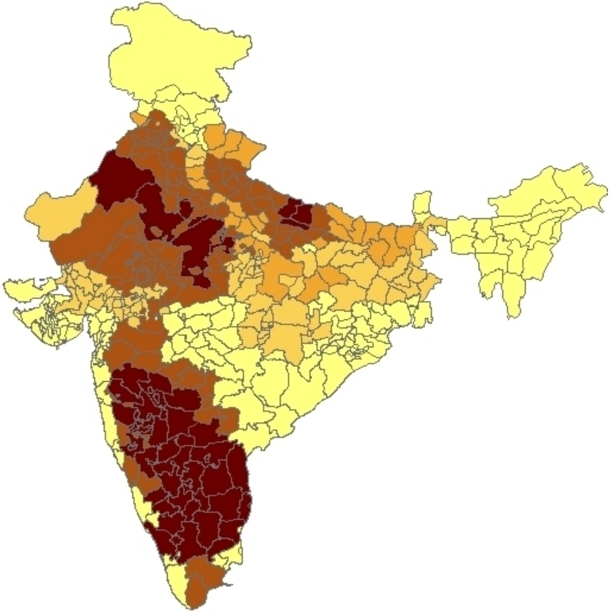
An Index of Famine Severity

- 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”

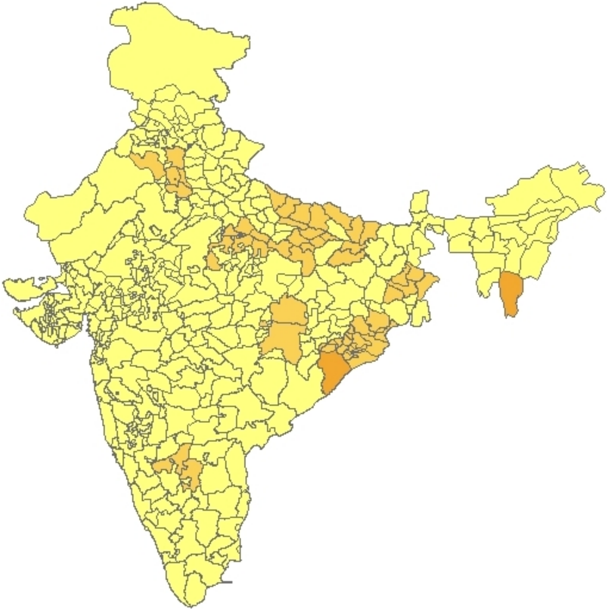
Famine Intensity: 1860-1869 Average



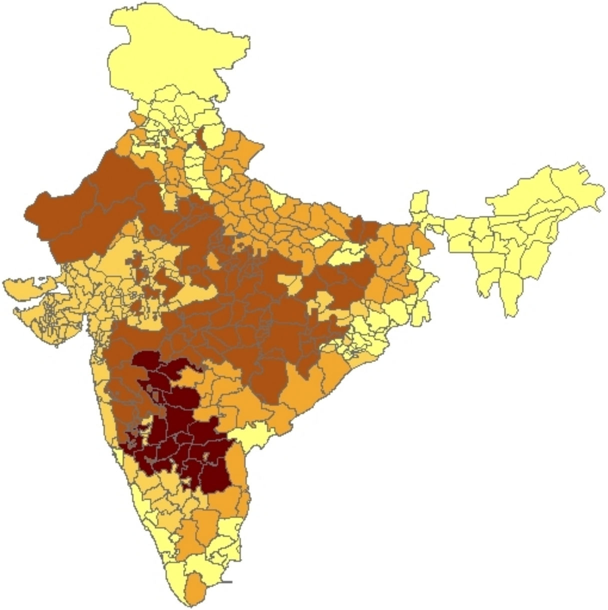
Famine Intensity: 1870-1879 Average



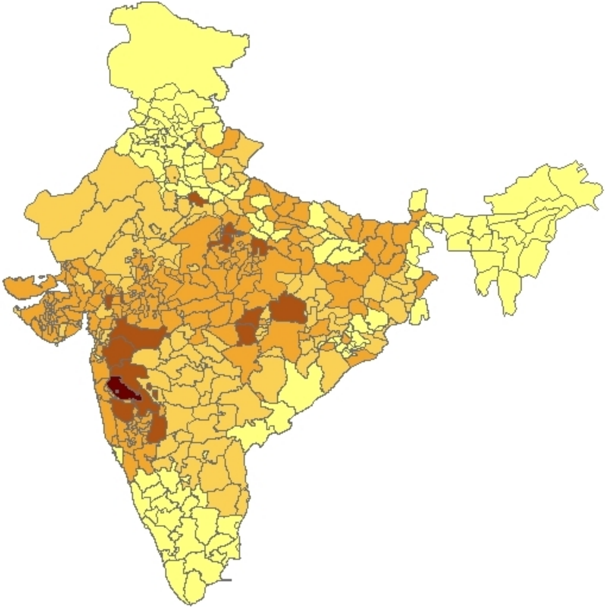
Famine Intensity: 1880-1889 Average



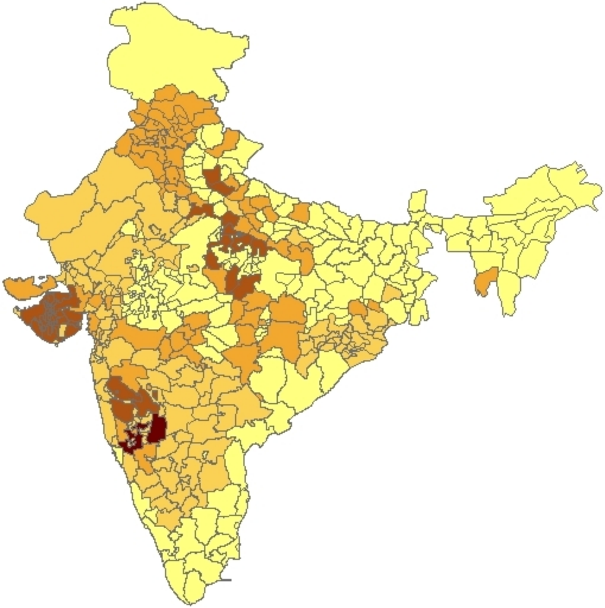
Famine Intensity: 1890-1899 Average



Famine Intensity: 1900-1909 Average



Famine Intensity: 1910-1919 Average

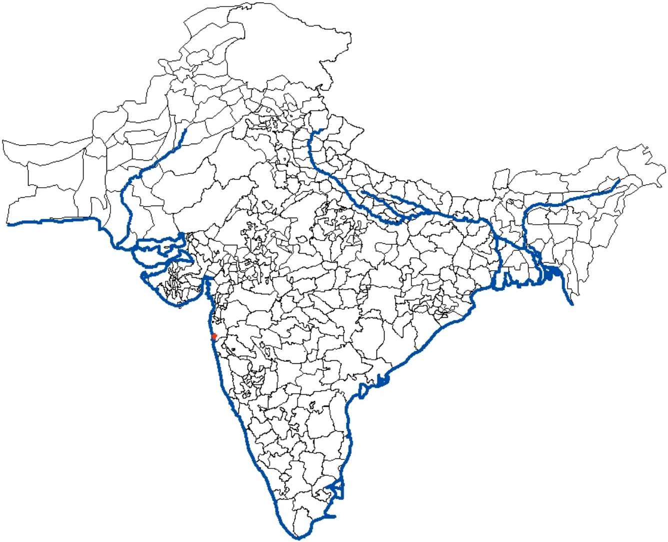


Transportation in Colonial India

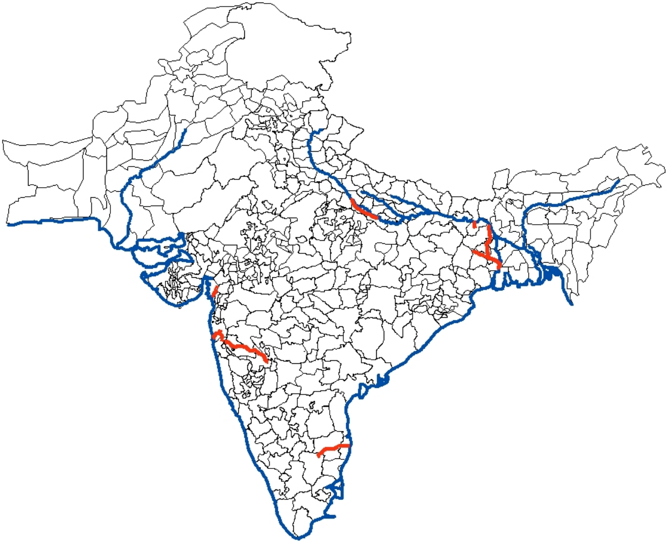
- Pre-rail transportation (Deloche 1994, 1995):
  - Roads: bullocks, 10-30 km per day (ie 2-3 months to port)
  - Rivers: seasonal, slow
  - Coasts: limited port access for steamships

- 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.

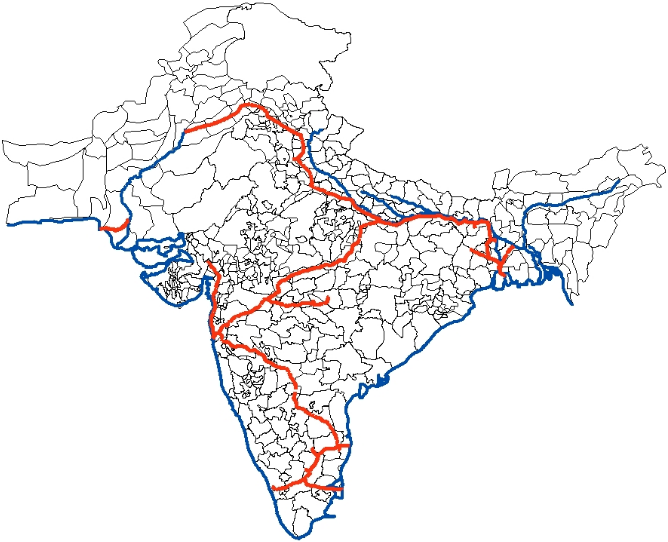
Railroad Network: 1853



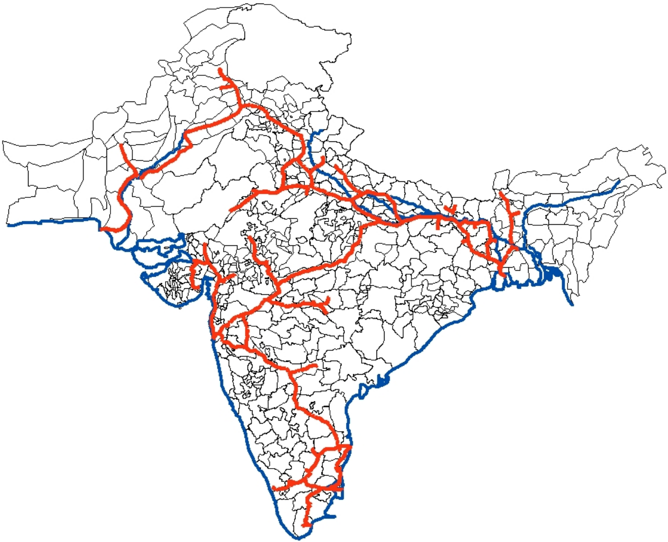
Railroad Network: 1860



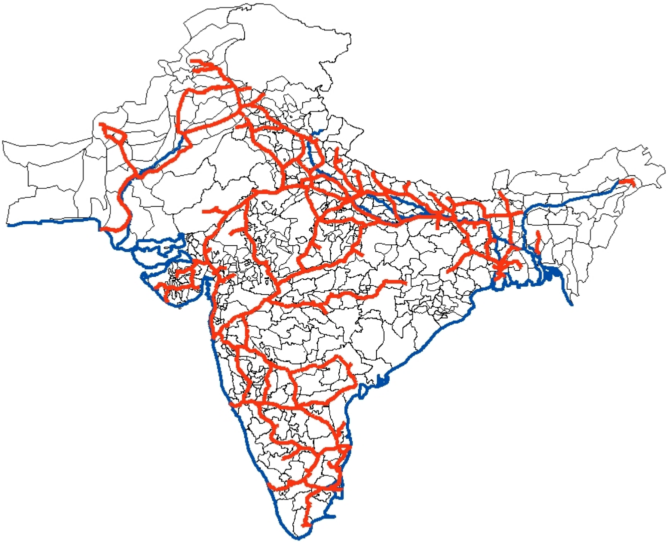
Railroad Network: 1870



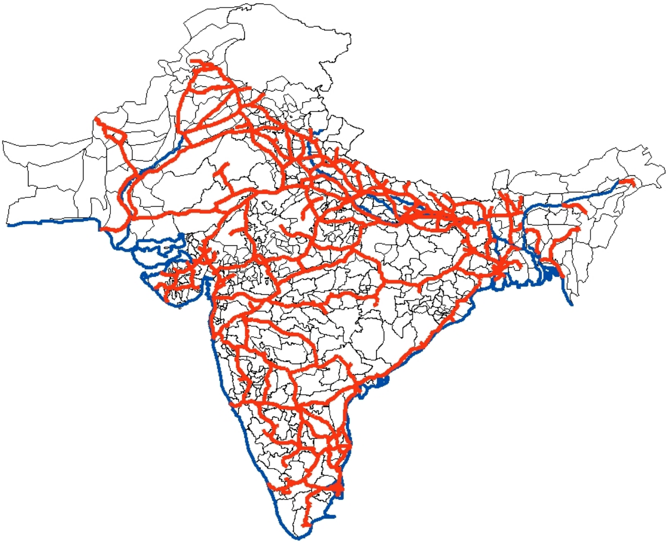
Railroad Network: 1880



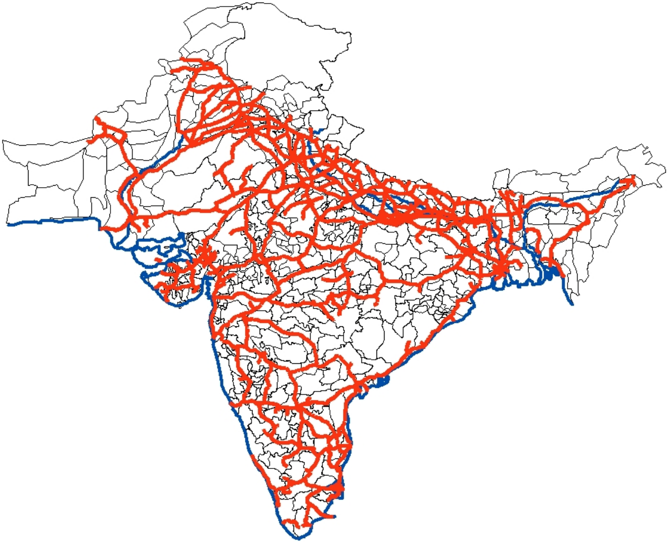
Railroad Network: 1890



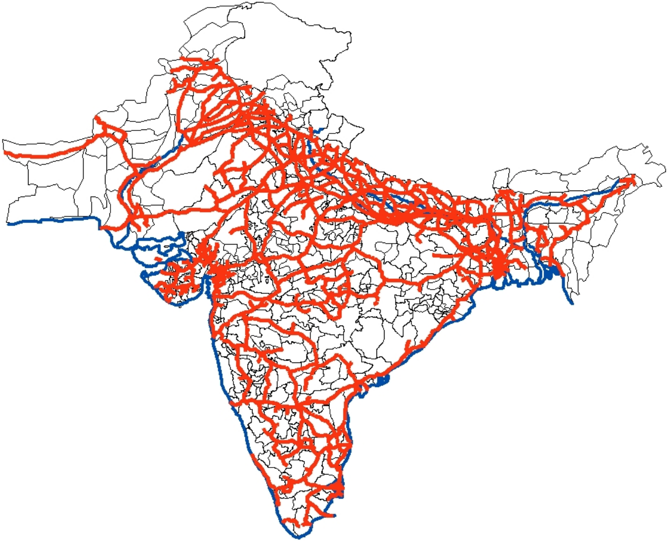
Railroad Network: 1900



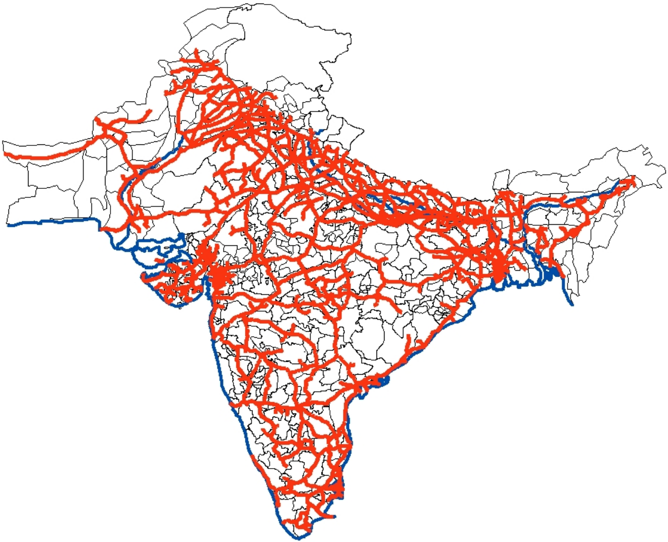
Railroad Network: 1910



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."

Outline

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

Background: Rainfall, Famine and Railroads

Theoretical Framework

Method and Results
- Price responsiveness
- Nominal income responsiveness
- Real income responsiveness
- Mortality responsiveness
- "Famine" index responsiveness

Conclusion

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	OLS	OLS	OLS
	(1)	(2)	(3)	(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 (1)	OLS (2)	OLS (3)	OLS (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 (Connected to neighbor by rail)			-0.082	Salt
			(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.

Outline

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:
  - $r_{ot} L_o = \sum_k p_{ot}^k q_{ot}^k$ (NB: $\neq \int p_{ot}^k(j) q_{ot}^k(j) dj$), 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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- Price responsiveness
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Conclusion

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.

Outline

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

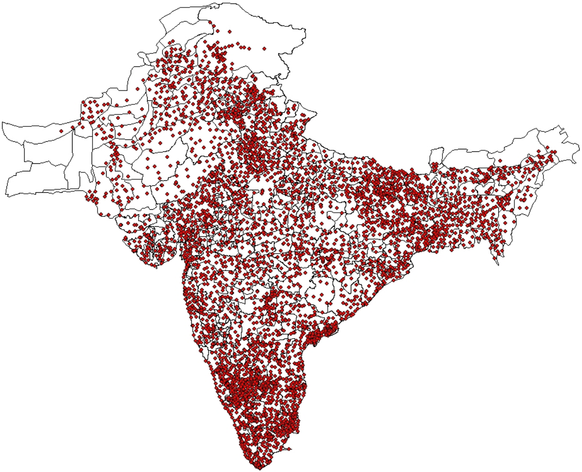
Conclusion

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