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, agricultural economies extremely volatile places in which to live.
  - Incomes fall
  - Prices of important consumption goods rise
  - ⇒ 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: stabilize
  - 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

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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

Figure 1: Annual Rainfall by Indian Province, 1875-1919. This figure plots the average amount of annual rainfall by province, averaging over the British districts within each province. Source: see text.
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: 1900-1909 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 ‘shrank distance’ by a factor of 8 relative to roads.
Railroad Network: 1860
Railroad Network: 1870
Railroad Network: 1880
Railroad Network: 1890
Railroad Network: 1900
Railroad Network: 1910
Railroad Network: 1920
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.” ⇒ 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 ($\geq 2$) regions
  - Many ($\geq 2$) 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: \( q^k_o(j) = L^k_o z^k_o(j) \quad p^k_{oo}(j) = \frac{r^o_o}{z^k_o(j)} \)

\[
z^k_o(j) \sim F^k_o(z) = \exp(-A^k_o z^{-\theta_k})
\]
Model Environment

- **Technology:** \( q_o^k(j) = L_o^k z_o^k(j) \quad p_o^k(j) = \frac{r_o}{z_o^k(j)} \)

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

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

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

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

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

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

\[
\begin{align*}
\frac{d}{dT_{do}^k} \left| \frac{dp_d^k}{dA_d^k} \right| & > 0 \\
\text{less own responsiveness} \\
\frac{d}{dT_{do}^k} \left| \frac{dp_d^k}{dA_o^k} \right| & < 0 \\
\text{more ‘connected’ responsiveness}
\end{align*}
\]
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):

$$\frac{d}{dT_{od}^k} \left| \frac{d}{dA_o} \frac{r_o}{p_o} \right| > 0$$
Outline

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Conclusion
Econometric Specification

• Estimate regressions of following form:

\[ Y_{dt} = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} \]
\[ + \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt} \]

• We think of \( \gamma_3 \) 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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Conclusion
Price Responsiveness

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

\[
\ln p^k_{dt} = \beta^k_d + \beta^k_t + \beta_{dt} \\
+ \chi_1 RAIN^k_{dt} + \chi_2 RAIN^k_{dt} \times RAIL_{dt} + \varepsilon^k_{dt}
\]

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

\[
\ln p^k_{dt} = \beta^k_d + \beta^k_t + \beta_{dt} + \chi_1 RAIN^k_{dt} + \chi_2 RAIN^k_{dt} \times RAIL_{dt} + \varepsilon^k_{dt}
\]

<table>
<thead>
<tr>
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<th>OLS (3)</th>
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<tbody>
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<td>Local rainfall</td>
<td>-0.256</td>
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<td></td>
<td>(0.102)**</td>
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<tr>
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<tr>
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<td>Observations</td>
<td>73,000</td>
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<tr>
<td>R-squared</td>
<td>0.89</td>
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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

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\ln p^k_{dt} = \beta^k_d + \beta^k_t + \beta^k_{dt} + \chi_1 RAIN^k_{dt} + \chi_2 RAIN^k_{dt} \times RAIL_{dt} + \varepsilon^k_{dt}
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## Price Responsiveness Results

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Price Responsiveness Results

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

Conclusion
Nominal Income Responsiveness

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

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

- Data:
  - \( r_{ot}L_o = \sum_k p_{ot}^k q_{ot}^k \) (NB: \( \neq \int p_{ot}(j)q_{ot}(j)dj \)), 17 agricultural crops (ignores: taxes/transfers, intermediate inputs, income from other sectors, income inequality)
  - Annually for 239 districts, 1870-1930.
### Results: Nom. Income Responsiveness

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

<table>
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<tr>
<th>Dependent variable:</th>
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<tr>
<td>log nominal agricultural income</td>
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<tbody>
<tr>
<td>Railroad in district</td>
<td>0.241</td>
<td>(0.114)*</td>
</tr>
<tr>
<td>Rainfall in district</td>
<td>1.410</td>
<td>(0.632)**</td>
</tr>
<tr>
<td>(Railroad in district)*(Rainfall in district)</td>
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</table>

| 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

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

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<tr>
<td></td>
<td>(0.632)**</td>
<td>(0.249)**</td>
</tr>
<tr>
<td>(Railroad in district)*(Rainfall in district)</td>
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<td>0.901</td>
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<tr>
<td></td>
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<td>(0.444)**</td>
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<tr>
<td>Observations</td>
<td>14,340</td>
<td>14,340</td>
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<tr>
<td>R-squared</td>
<td>0.771</td>
<td>0.775</td>
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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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Conclusion
Real Income Responsiveness

- Recall Prediction 3: \[ \frac{d}{d T_{dot}} \left| \frac{d \left( \frac{r_{dt}}{\bar{P}_{dt}} \right)}{d A_{dt}} \right| > 0 \]

- Suggests linear approximation:

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

- Data:
  - \(\bar{P}_{ot}\) = (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}}{P_{dt}} \right) = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}
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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}}{P_{dt}} \right) = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} + \gamma_3 RAIN_{dt} \times RAIL_{dt} + \varepsilon_{dt}
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<tr>
<td>log real agricultural income</td>
<td>(1)</td>
<td>(2)</td>
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<tr>
<td>Railroad in district</td>
<td>0.186 (0.085)**</td>
<td>0.252 (0.132)*</td>
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<tr>
<td>Rainfall in district</td>
<td>1.248 (0.430)***</td>
<td>2.434 (0.741)***</td>
</tr>
<tr>
<td>(Railroad in district)*(Rainfall in district)</td>
<td>-1.184 (0.482)**</td>
<td></td>
</tr>
</tbody>
</table>

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

Background: Rainfall, Famine and Railroads

Theoretical Framework

Method and Results

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

Conclusion
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

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

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>OLS</th>
</tr>
</thead>
<tbody>
<tr>
<td>log mortality rate</td>
<td>(1)</td>
</tr>
</tbody>
</table>

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Railroad in district</td>
<td>-0.080</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
</tr>
</tbody>
</table>

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall in district</td>
<td>-0.064</td>
</tr>
<tr>
<td></td>
<td>(0.032)**</td>
</tr>
</tbody>
</table>

(Railroad in district) \*(Rainfall in district)

<table>
<thead>
<tr>
<th>Observations</th>
<th>13,512</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.642</td>
</tr>
</tbody>
</table>

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

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

<table>
<thead>
<tr>
<th>Dependent variable: log mortality rate</th>
<th>OLS (1)</th>
<th>OLS (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Railroad in district</td>
<td>-0.080</td>
<td>-0.143</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.078)*</td>
</tr>
<tr>
<td>Rainfall in district</td>
<td>-0.064</td>
<td>-0.145</td>
</tr>
<tr>
<td></td>
<td>(0.032)**</td>
<td>(0.062)***</td>
</tr>
<tr>
<td>(Railroad in district)*(Rainfall in district)</td>
<td>0.123</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.059)**</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>13,512</td>
<td>13,512</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.642</td>
<td>0.647</td>
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</tbody>
</table>

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

\[ F_{dt}^* = \alpha_d + \beta_t + \gamma_1 RAIL_{dt} + \gamma_2 RAIN_{dt} \]
\[ + \gamma_3 RAIL_{dt} \times RAIN_{dt} + \varepsilon_{dt} \]

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. var.: Famine intensity index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Railroad in district</td>
<td>0.194</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rainfall in district [year t]</td>
<td>-0.855***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.
## Results: “Famine” Index

<table>
<thead>
<tr>
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<th>(1)</th>
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<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Railroad in district</td>
<td>0.194</td>
<td>-1.625***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td>(0.572)</td>
<td></td>
</tr>
<tr>
<td>Rainfall in district [year t]</td>
<td>-0.855***</td>
<td>-2.218***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.532)</td>
<td></td>
</tr>
<tr>
<td>(Railroad in district) x (Rainfall in district, year t)</td>
<td></td>
<td></td>
<td>1.858***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.541)</td>
</tr>
</tbody>
</table>

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.
## Results: “Famine” Index

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<tr>
<td>Railroad in district</td>
<td>0.194</td>
<td>-1.625***</td>
<td>0.309</td>
</tr>
<tr>
<td></td>
<td>(0.374)</td>
<td>(0.572)</td>
<td>(0.390)</td>
</tr>
<tr>
<td>Rainfall in district [year t]</td>
<td>-0.855***</td>
<td>-2.218***</td>
<td>-0.860***</td>
</tr>
<tr>
<td></td>
<td>(0.208)</td>
<td>(0.532)</td>
<td>(0.204)</td>
</tr>
<tr>
<td>(Railroad in district) x (Rainfall in district, year t)</td>
<td></td>
<td>1.858***</td>
<td>(0.541)</td>
</tr>
<tr>
<td>Rainfall in district [year t-1]</td>
<td></td>
<td></td>
<td>-0.699***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.215)</td>
</tr>
</tbody>
</table>

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.
### Results: “Famine” Index

<table>
<thead>
<tr>
<th>Dep. var.: Famine intensity index</th>
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<th>(5)</th>
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</thead>
<tbody>
<tr>
<td>Railroad in district</td>
<td>-2.178***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.690)</td>
<td></td>
</tr>
<tr>
<td>Rainfall in district [year t]</td>
<td>-2.316***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.518)</td>
<td></td>
</tr>
<tr>
<td>(Railroad in district)</td>
<td>1.848***</td>
<td></td>
</tr>
<tr>
<td>(Rainfall in district, year t)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.521)</td>
<td></td>
</tr>
<tr>
<td>Rainfall in district [year t-1]</td>
<td>-1.171***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.395)</td>
<td></td>
</tr>
<tr>
<td>(Railroad in district)</td>
<td>0.692*</td>
<td></td>
</tr>
<tr>
<td>(Rainfall in district, year t - 1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.404)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Ordered logit regressions that include district fixed effects and year fixed effects. Standard errors clustered by district.
## Results: “Famine” Index

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

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

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- “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