Can Openness Mitigate the Effects of Weather Fluctuations? Evidence from India’s Famine Era

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A weakening dependence on rain-fed agriculture has been a hallmark of the economic transformation of countries throughout history. Rural citizens in developing countries today, however, remain highly exposed to fluctuations in the weather. This exposure affects the incomes these citizens earn and the prices of the foods they eat. Recent work has documented the significant mortality stress that rural households face in times of adverse weather (Robin Burgess, Olivier Deschenes, Dave Donaldson & Michael Greenstone 2009, Masayuki Kudamatsu, Torsten Persson & David Stromberg 2009). Famines—times of acutely low nominal agricultural income and acutely high food prices—are an extreme manifestation of this mapping from weather to death. Lilian. C. A. Knowles (1924) describes these events as “agricultural lockouts” where both food supplies and agricultural employment, on which the bulk of the rural population depends, plummet. The result is catastrophic with widespread hunger and loss of life.

Though now confined to the world’s poorest countries food shortages and famines were features of most pre-industrial societies. Over time there has been intense debate over what role openness to trade in food might play in mitigating or exacerbating the mortality impacts of weather shocks. One group of thinkers dating back to at least Adam Smith (1776) argues that: “...drought [in “rice countries”] is, perhaps, scarce ever so universal as necessarily to occasion a famine, if the government would allow a free trade.” (IV.5.45). This school of thought sees greater openness to trade as a key means of protecting human life by reducing volatility in real incomes. But others have argued along the lines of Mahatma Gandhi (1938),
that greater trade openness may “have...increased the frequency of famines, because, owing to facility of means of [movement], people sell out their grain, and it is sent to the dearest markets.” (p. 36) Indeed many see trade as having played a key role in converting mild food scarcities into full-blown famines.

Results from the theoretical and empirical international trade (eg, David M.G. Newbery & Joseph E. Stiglitz (1981), and Julian di Giovanni & Andrei Levchenko (2009)) and famine literatures (eg, Amartya Sen (1981)) are both ambiguous and inconclusive as regards this issue. The fundamental ambiguity here is that openness makes nominal incomes more responsive to production shocks (due to both increased specialization and dampened offsetting price movements), but consumer prices less volatile, such that the net effect on real incomes is unclear.

The colonial era provides us with an opportunity to delve into this critical issue. Prior to colonization countries were poorly integrated both domestically and internationally. Investments in new infrastructure such as railroads and roads radically changed the situation by slashing transport costs and enabling domestic and international trade. The gradual integration of different parts of a country via connection to these transportation infrastructures thus provides us with a window into how trade changed the weather-death relationship.

In this paper we employ a colonial era Indian district-level database for the period 1875 to 1919 to provide some preliminary insights into how trade changes the weather-to-death relationship. This time period contained one of the worst strings of famines in recorded history, with an estimated death toll of between 15 and 30 million people (Leela Visaria & Pravin Visaria 1983). It also covers the period when the bulk of the railroad network was built in British India. And just as railroads were, by 1919, reaching into every last corner of the country, India saw the end of peacetime famine (many decades before democracy came with independence in 1947).
Our district panel regression results suggest that the arrival of railroads in Indian districts dramatically constrained the ability of rainfall shocks to cause famines in colonial India. On average, before the arrival of railroads, local rainfall shortages led to a significant rise in our index of famine intensity. But after a district gained railroad access the effect of local rainfall shortages on famine intensity was significantly muted.

In what follows we begin in Section 1 by describing the colonial Indian environment between 1875 and 1919, and the data on rainfall, famine intensity and railroad penetration that we have constructed. Section 2 then presents our results on whether the arrival of railroads mitigated or exacerbated the ill effects of rainfall shortages on famine intensity. Finally, Section 3 offers conclusions and directions for future work.

1. Rain, Railroads and Famine

Throughout the period that we consider (1875-1919), India’s economy was overwhelmingly agricultural – even by 1921 almost two-thirds of the employed worked in the agricultural sector (Census Commissioner of India 1922). Very little of this agriculture was irrigated, so agricultural production was heavily dependent on rainfall. And the annual amount of rainfall with which farmers and farm workers had to make do was extremely volatile leading agriculture in this period to be described as ‘a gamble in monsoons’ (see Figure 1).[1]

Insert Figure 1 here.

This rainfall volatility took place against the backdrop of extremely low – essentially subsistence – average rural income levels (Alan Heston 1983) and rudimentary health infrastructure. Subsistence living in average years meant a public health crisis in years of scanty rainfall and correspondingly meager agricultural incomes.[2] Years where widespread death resulted from acute rainfall shortages were referred to, officially and unofficially, as ‘famines’.

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[1] See Dave Donaldson (2008) for sources of rainfall and railroad data used in this paper.
[2] The rainfall-to-death relationship, working through food production, was at the core of public health concerns in this period. The Sanitary Reports, the annual reports of British India’s public health administration, collected and published just three forms of data: death rates, rainfall amounts, and prices of staple foods.
However, as there was no consistent official system for declaring famine across our period we code the food scarcities and famines described in Hari S. Srivastava (1968) to construct a measure of famine intensity at the district level annually from 1875-1919: 0 if the district was ‘normal’ (no mention of scarcity or famine), 1 if it was affected by food scarcity (but not famine), 2 if it experienced a mild famine, or 3 if it experienced a severe famine, in each year.

Figure 2 illustrates our cumulative famine index for each district for each of the three fifteen-year periods between 1875 and 1919. What is apparent from this figure is that food scarcities and famines tended to be local events affecting individual districts or groups of districts with the spatial pattern changing over time. At no point of time was the whole of British India affected by famine.

Despite the enormous human tragedy posed by famine, the British colonial government was reluctant to intervene. They instead believed that allowing free inter-regional trade would prevent famine and that it was the responsibility of the state only to enable these trades to occur (Eric Stokes 1959). It was obvious to many observers that India’s new and expanding railroad network—also illustrated in Figure 2—held significant promise in this endeavor (J. Johnson 1963). The fact that India’s famines were regional calamities, rather than national ones, reinforced this belief that lower trade costs brought about by rail transport could allow surplus regions to sell food to deficit regions and thereby limit the effect of local rainfall variation on local famine intensity. Our empirical results below explore this possibility.

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3Based on extensive analysis of reports from British colonial administrators, Srivastava (1968) catalogs twenty-five food shortages and famines during our sample period, in each case documenting both the geographical area affected and the relative severity of the shortage across this area.

4These figures include all regions of modern-day India—areas that were both ‘British districts’ under direct British rule and ‘Native States’ that were under indirect British rule. Our analysis focuses entirely on the British districts (referred to throughout as simply districts) because rainfall records (from meteorological stations) are unavailable for the Native States.

5Naturally, this spatial concentration of famine becomes even more apparent in annual plots rather than plots that average over fifteen year periods.
To look at whether growing openness to trade, brought about by railroad expansion, mitigated or exacerbated the ability of local rainfall shortages to cause local famines we model famine intensity, $F_{dt}^*$, in district $d$ and year $t$ as:

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

Here, $\alpha_d$ is a district fixed-effect, $\beta_t$ is a year fixed-effect, $RAIN_{dt}$ is the amount of local rainfall enjoyed by district $d$ in year $t$ and $RAIL_{dt}$ is a dummy variable indicating whether district $d$ has a railroad line in the district in year $t$ or not. We do not observe $F_{dt}^*$, but instead an ordered, qualitative index based on the true famine intensity which can take one of four values, as described in Section 2 above. For this reason we estimate equation (1) using a fixed-effects ordered logit model.\(^6\)

One would expect to see $\gamma_1 < 0$ if rainfall shortages do contribute to famine. This is likely, as Donaldson (2008) found that rainfall shortages significantly damaged agricultural productivity in this time period in India. The coefficient on railroad access, $\gamma_2$, captures the extent to which the expansion of railroads was associated with declining famine intensity. And finally the coefficient on the rainfall-railroad interaction term, $\gamma_3$, attempts to answer the key question we have posed in this paper—did railroads mitigate ($\gamma_3 > 0$) or exacerbate ($\gamma_3 < 0$) the ill-effects of a given rainfall shortage on famine intensity?

**Insert Table 1 here.**

The results from our estimation of equation (1), via ordered logit with district and year fixed effects, are contained in Table 1. Column (1) begins by establishing that, on average over our sample period, a local rainfall shortage in a district would increase the probability of observing a severe famine in that district. However, as demonstrated in column (2), this mapping from rainfall shortages to famine was not an immutable fact of life throughout

the entire sample period. In particular, prior to obtaining railroad access, rainfall shortages had a large (i.e., statistically and economically significant) effect on famine intensity. But after a district obtained railroad access, famine intensity fell significantly (i.e., $\gamma_2 < 0$) and the responsiveness of famine intensity to rainfall fell significantly (i.e., $\gamma_3 > 0$). For a given reduction in rainfall, if a district were connected to the railroad network it faced a significantly lower probability that a food scarcity or famine would occur in that district. This is the key result of the paper. Indeed the ability of rainfall shocks to cause famines almost disappears after a district has been penetrated by the railroad.

In column (3) we ask whether rainfall shocks have effects on famine intensity even in the year after their arrival. On average throughout the period, the estimates in column (3) find support for both contemporaneous and lagged effects of rainfall shortages on famine intensity. These contemporaneous and lagged effects of rainfall are, however, significantly weaker in each district’s post-rail era when compared to its pre-rail era (see column (4)). The entry of railroads thus appears to be offering some protection against both contemporaneous and historical rainfall shocks.

A natural concern with the specification in column (4) is that the $RAIL_{dt}$ component of the $RAIN_{dt} \times RAIL_{dt}$ interaction term in equation (1) may be correlated with unobserved aspects of India’s economy or health infrastructure that, like railroad access, were steadily improving over time. To control for this possibility we include in column (5) an interaction between both contemporaneous and lagged $RAIN_{dt}$ and a trend term. The coefficient estimate of $\gamma_3$ and its lagged rainfall equivalent are not dramatically different from their equivalents in column (4), and they continue to be estimated precisely. This adds to the confidence with which we can assert that railroads—rather than some background trend that is correlated

\[ \hat{\gamma}_2 + \hat{\gamma}_3 = -0.36 \] with a $p$-value of 0.076.

This is plausible, as the vulnerable rural population consisted of both agricultural laborers (whose wages fell immediately as a result of rainfall shortage due to the lack of labor demand during the agricultural season) and small-scale, subsistence farmers (for whom the relevant issue was whether a given year’s harvest would be plentiful enough to provide consumption until the harvest in the following year).
with the unfolding of India’s railroad network—were responsible for reducing the effect of rainfall shocks on famine in India.

Taken as a whole these results paint a coherent picture. Productivity shocks, in the form of rainfall shortages, led to famine in colonial India; but this rainfall-famine relationship was considerably attenuated after the arrival of railroads in a district.

3. Conclusion

In this paper we have conducted a preliminary analysis of the role played by openness to trade, brought about by railroads, in mitigating the effects of agricultural productivity shocks on famine in colonial-era India. The results of our analysis suggest that rainfall shortages had large effects on famine intensity in an average district before it was penetrated by India’s expanding railroad network. But the ability of rainfall shortages to cause famine disappeared almost completely after the arrival of railroads. This lines up with findings in Donaldson (2008), where railroads were seen to significantly reduce the exposure of agricultural prices and real incomes to rainfall shocks.

Our findings have resonance for those regions in the world’s poorest countries where lack of integration into domestic and international markets may be a source of recurrent food scarcities and famines. Thinking through how to better integrate remote, rural regions of countries where citizens are continuously buffeted by the volatility of their environments represents a key challenge for development practitioners to take up. Our analysis of colonial-era India suggests that investments in transportation infrastructure like railroads that enable trade can play an important part in breaking the link between weather shocks and excess
mortality. Put more simply, a failure in the rains in one part of a country does not have to impose a death sentence on some fraction of the citizens inhabiting the affected region.

**References**

**Burgess, Robin, Olivier Deschenes, Dave Donaldson, and Michael Greenstone.** 2009. “Weather and Death in India.” mimeo MIT.

**Census Commissioner of India.** 1922. *Census of India, 1921.* Calcutta: Government of India.


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9While these preliminary findings are consistent with railroad expansion mitigating famine intensity by facilitating trade in food the same infrastructure investments may also have intervened in the weather-to-death relationship by facilitating movements of people, capital and famine relief. In future work we aim to gain a fuller understanding of how trade openness can mitigate or exacerbate the impact of weather shocks by building up a complete series of mortality statistics for the period and by analyzing data on passenger flows, trade flows, trade imbalances, output, prices and famine relief.


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 and over meteorological stations within each district. Source: Donaldson (2008).

Figure 2: Famines and Railroads in India, 1875-1919. The upper panel illustrates our index, based on Srivastava (1968), of famine intensity. The average famine intensity over each 15-year period is plotted for each British district and native state. Famine intensity was coded as 0 (no mention of famine/scarcity), 1 (food scarcity), 2 (mild famine) or 3 (severe famine). Darker colors reflect higher values of this 0-3 index. The lower panel illustrates the extent of India’s railroad network in each of the three years indicated. Sources: Donaldson (2008) and Srivastava (1968).
### Table 1: Famines, Rainfall and Railroads

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<td>Railroad in district</td>
<td>0.194</td>
<td>-1.625***</td>
<td>0.309</td>
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<td>(0.374)</td>
<td>(0.572)</td>
<td>(0.390)</td>
<td>(0.690)</td>
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<td>Rainfall in district, year t</td>
<td>-0.855***</td>
<td>-2.218***</td>
<td>-0.860***</td>
<td>-2.316***</td>
<td>-17.35</td>
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<td>(0.208)</td>
<td>(0.532)</td>
<td>(0.204)</td>
<td>(0.518)</td>
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<td>(Railroad in district) x (Rainfall in district, year t)</td>
<td>1.858***</td>
<td>1.848***</td>
<td>1.729***</td>
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<td>(0.541)</td>
<td>(0.521)</td>
<td>(0.565)</td>
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<td>Rainfall in district, year t-1</td>
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<td>-1.171***</td>
<td>9.316</td>
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<td></td>
<td>(0.215)</td>
<td>(0.395)</td>
<td>(21.51)</td>
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<td>(Railroad in district) x (Rainfall in district, year t-1)</td>
<td>0.692*</td>
<td>0.758*</td>
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<td></td>
<td>(0.404)</td>
<td>(0.458)</td>
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<tr>
<td>(Rainfall in district) x (trend) interactions</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
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<td>YES</td>
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<td>3809</td>
<td>3809</td>
<td>3551</td>
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<td>Pseudo R-squared</td>
<td>0.248</td>
<td>0.260</td>
<td>0.255</td>
<td>0.271</td>
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**Notes:** Ordered logit regression estimates of equation (1) using our index of famine intensity constructed on the basis of descriptions in Srivastava (1968). All regressions include district and year fixed effects, with 125 British districts in modern-day India and years between 1875 and 1919. 'Railroad in district' is a dummy variable whose value is one if any part of the district in question is penetrated by a railroad line. 'Rainfall in district' is the amount of rainfall that fell in the district and year in question (measured in meters and averaged over available observations from meteorological stations in each district and year). Column (5) controls for terms that interact both 'rainfall in district, year t' and 'rainfall in district, year t-1' with a time trend. Standard errors corrected for clustering at the district level are reported in parentheses. *** indicates statistically significantly different from zero at the 1%, ** at the 5%, and * at the 10% levels, respectively.