The Cyclone's Shadow:
Historical Storm Impacts and Population Displacement in Bangladesh, West Bengal and Odisha

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Abstract

This paper analyzes the effects of historical cyclone impacts on the spatial pattern of population change in Bangladesh, West Bengal and Odisha during the period 2000 - 2015. We develop high-resolution spatial impact measures using historical information about storm tracks, storm radii and wind speeds. For each population point, gridded at 30-arc-second resolution, we compute storm impacts in three periods: 1970-1984, 1985-1999, and 2000-2014. We assess population impacts using a model that embeds household migration decisions in locational comparisons based on current and expected future income streams.

We estimate a reduced form of the model that specifies point-level population change during 2000 - 2015 as an adjustment by households to contemporaneous and past cyclone impacts, as well as locational economic factors and government policies that compensate households for cyclone damage and disadvantages related to location. India maintains extensive compensation programs, while Bangladesh is closer to a laissez-faire regime. We estimate the model using appropriate spatial econometric methods. Our estimates for present and past cyclone impacts are highly significant and consistent with a lagged adjustment process that spans several decades. In Bangladesh, we also find a substantial impact for economic disadvantages due to location. We find smaller cyclone impact parameter values for India and no significance for locational disadvantages, which suggest that the Indian compensation regime has significantly dampened responsiveness to both factors.

We explore the implications of our findings with model-based predictions of point-level population changes with no cyclones since 1970. Comparison of predicted and actual populations in 2015 suggests that affected regions are 8-10% less populous in Bangladesh because of past and expected cyclone impacts and locational disadvantages, but only 2% less populous in India. We combine our econometric results and historical cyclone impact measures to produce a high-resolution map of implied population displacement within 125 km of the coastline in Bangladesh, West Bengal and Odisha. The map provides a clear picture of the cyclone population displacement "shadow", which varies greatly across coastal sub-regions.

We conclude the paper with a discussion of the implications for alternative policy regimes as climate change proceeds, sea-level rise continues, and coastal inundation moves inland. We consider the efficiency and equity implications of damage compensation and laissez-faire regimes, and suggest a third alternative that may promote relatively efficient and equitable adaptation by focusing public resources on compensation for households that choose to relocate as the coastal threat mounts.

1. Introduction

Recurrent cyclonic storms in the Bay of Bengal inflict massive damage on the coastal regions of Bangladesh and India. Extensive research has investigated the incidence, power and impacts of cyclones in Bangladesh (Ali 1999; Dasgupta et al. 2014; Hoque 1992; Khalil 1992; Khalil 1993), India (Mishra 2014; Srivastava et al. 2000) and the Bay of Bengal more generally (Bhaskar Rao 2001; Dash et al. 2004; Mandke and Bhide 2003; Mooley and Mohile 1983; Mooley 1980; Muni Krishna 2009; Rao 2002; Yu and Wang 2009).

Previous studies of coastal community adaptation in the region have focused on responses to specific cyclones or generally-defined coastal hazards (Brouwer et al. 2007; Khalil 1993; Khan et al. 2015; Mallick et al. 2011; Mallick and Vogt 2013; Shameem and Momtaz 2014; Siddiqui et al. 2013; Sultana and Mallick 2015). In this paper, we extend the analysis using a georeferenced panel database of past cyclonic storms (Bandyopadhyay et al. 2018) for Bangladesh, West Bengal and Odisha that includes dates, coastal landfall points, subsequent interior paths, and measures of relative power. We investigate the cyclones' impact on recent population change in the area, using a spatial econometric model based on the economics of migration.

The remainder of the paper is organized as follows. In Section 2, we develop an econometric estimating equation from a model of household location decisions based on comparative present and expected future income streams. Section 3 describes the data used for this exercise, while Section 4 discusses model estimation methods and results. We assess the implications for coastal-region population change in Section 5 and potential policy implications in Section 6. Section 7 summarizes and concludes the paper.

2. Model Specification

A structural model of population change in the coastal regions of Bangladesh, West Bengal and Odisha should incorporate at least three factors: net migration of individuals and households, the resident population of fertile-age females, and the fertility rate. Individuals and households respond to economic incentives when deciding whether to migrate into or out of a locale (Harris and Todaro 1970; Krichel and Levine 1999; Zhao 1999; Quinn 2006) . Origin/destination comparisons consider the present values of expected income streams, which incorporate standard locational economics factors (transport costs to market, local soil productivity, etc.) as well as past asset destruction and expected future damage by cyclonic storms. Expected compensation for cyclone damage and locational disadvantages by governments or aid agencies also enter the migration calculus. Past migration in response to these factors affects both the number of remaining fertile-age females and their educational status.[1] The fertility rate is affected by the latter variable, as well as expected future income (Wheeler 1984; Cochrane 1988; Pritchett 1994; Sanderson 1998; Gatti 1999; Birdsall et al. 2001).

Without compensating intervention by governments or aid agencies, migration should favor locations with economic advantages and more moderate storm damage histories, ceteris paribus. Past migration to such advantaged areas should also have expanded their population of fertile-age females. On the other hand, educational "sorting" in migration and higher expected income may negatively affect fertility rates in advantaged areas. In addition, locational "sorting" by socioeconomic status may occur if poor, uneducated, high-fertility females move away from advantaged areas with higher rents for land and other fixed factors.

[1] Migration will be accompanied by educational "sorting" if urban job markets assign a wage premium to educational status.

When all relevant variables are taken into account, the overall impact of locational economics factors and cyclonic storms on population change cannot be determined unambiguously. Compensation payments by governments or aid agencies may neutralize economic and climatic advantages, and the joint effects of educational and socioeconomic sorting could neutralize the effects of economic factors and cyclonic storm strikes.

In this paper, we test for overall effects using a reduced-form model that relates population change in a locale to its cyclone history, locational economics factors and government compensation policies. We focus on national differences in the latter variable, since Bangladesh has little compensation activity while national and regional governments in India offer several major programs that compensate localities for locational disadvantages or damage by cyclones (Guha, 2017). Indian national programs include Antyadaya Anna Yojana, which provides highly-subsidized food to the rural poor, and the Mid Day Meal program for school children. State-sponsored efforts include the following programs in West Bengal: Khadya Sathi, which provides subsidized rice and wheat to residents of cyclone-vulnerable areas; Geetanjali and Amar Thikana, which provide free basic residential structures to the rural poor; Nirmal Bangla, which subsidizes basic public health measures; Kanyashree Prakalpa, which provides cash transfers to poor rural families that keep girls in school; and Swasthya Sathi, a comprehensive health insurance program.

By the logic of our model, we would expect compensation payments in Indian localities to weaken the migration response to cyclonic storm impacts and locational economic disadvantages, ceteris paribus. We test this proposition by fitting the India and Bangladesh models separately and comparing the estimated response parameters. We also introduce dummy variable controls to allow for interregional differences within the two countries that are due to

unobservable sources of locational attraction. We formally specify the population change model for each country as follows. We use logarithms of population to allow for interpretation of results in terms of change rates.[2]

$$(1)\ log\, p_{it} = \beta_0 + \beta_1\, log\, p_{i,t-k} + \beta_2 \log a_i + \sum_{n=1}^{N} \delta_n S_n + \sum_{m=1}^{M} \gamma_m C_{i,[(t-mk),(t-(m-1)k)]} + \varepsilon_i$$

where

p_{it}	=	Population in locale i, period t
$p_{i,t-k}$	=	Population in locale i, period (t-k)
a_i	=	Economic isolation (transit time to urban market) of locale i
S_n	=	Dummy variable for administrative division n
$C_{i,[(t-mk),(t-(m-1)k)]}$	=	Mean cyclone intensity during period [(t-mk),(t-(m-1)k]
ε_i	=	Regression error term, which may have spatial autocorrelation

Prior expectations: $\beta_1 = 1$; $\beta_2 < 0$; $\gamma_m < 0$; $|\gamma_m| > |\gamma_{m+1}|$

The past population parameter (β_1) will be effectively one if there are no autonomous sources of population change for all locales that are not accounted for by the model. We expect the economic isolation parameter (β_1) to be negative, reflecting migrants' smaller expected income streams in locales with higher transport costs to market. We expect the parameters for past cyclones (γ) to be negative, reflecting their impact on current and expected income. Expectations formation should also weight recent events more heavily, so the absolute value of γ should diminish with distance from the present.

3. Data

3.1 Population

We estimate the model for population change in Bangladesh, West Bengal and Odisha during the period 2000-2015. Our exercise requires high spatial resolution to gauge the local impacts of

[2] We retain the log of past population ($p_{i,t-k}$) on the right-hand side of the model because the value of β_1 may well differ significantly from 1 (implying "autonomous" change due to common unobserved factors).

past cyclones whose track coordinates are identified. For comparability between India and Bangladesh, we also require compatible population data. Accordingly, we employ population estimates for 2000 ($p_{i,t-k}$ in our model) and 2015 (p_{it}) from the CIESIN[3] Gridded Population of the World, Version 4 (GPWv4). These data have 30 arc-second resolution (approximately 1 kilometer at the equator).

3.2 Market Isolation

We proxy market isolation (a_i in our model) using Nelson-Uchida measures. These are high-resolution estimates of travel time along the existing road network to the nearest urban area with 50,000+ population (Nelson and Uchida 2008, 2009).[4]

3.3 Cyclonic Storm Intensity

We compute cyclonic storm intensities for each CIESIN population point in a multi-stage exercise. First, we assemble complete georeferenced records for cyclonic storms in the region. For the period since 1960, we use georeferenced track information on major cyclones striking Bangladesh from the Bangladesh Meteorological Department (BMD). Equivalent information for the Indian coastal region comes from the India Meteorological Department (IMD). For cyclones prior to 1960, we add information from the IBTrACS database maintained by the Global Data Center for Meteorology, operated by the US National Oceanic and Atmospheric Administration. The IBTrACS data for the Indian Ocean have been provided by meteorological institutions in the region. We also use them for a few post-1960 cyclones that are not included in the data available to us from BMD and IMD.

[3] CIESIN is the Center for International Earth Science Information Network, Columbia University.

[4] The assumption that the Nelson-Uchida (NU) Index is exogenous seems warranted in this context. Our regression model relates the change rate of population in 2000-2015 to market access along the road network that existed at the beginning of that period. At worst, the NU Index would have lagged endogeneity from past adjustments of the road network to population change. In this case, however, analysis of the CIESIN data reveals essentially no correlation between the population change rate in 2000-2015 and the rate in the previous 20-year period. The correlation coefficients for Bangladesh and India are 0.09 and 0.06, respectively.

We ensure cross-source compatibility by using WMO standards for the two commonly-available measures of cyclonic storm strength: maximum wind speed (measured in knots (kt)) and radial distance from a storm's center to its zone of maximum wind speed. We exclude all storms rated as tropical depressions because their maximum wind speeds are below 34 kt.

For each storm, we compute the primary impact zone along its track as the area within the radius from centroid to zone of maximum wind speed.[5] Using a methodology of the US National Hurricane Center (USNHC 2018), we compute wind speed at each point after landfall as a function of wind speed at landfall and elapsed time after landfall.[6] We compute wind damage potential using a standard exponential formulation (NOAAHRC 2018).[7] We intersect the complete set of CIESIN population points with the complete set of historical cyclone impact zones, generating an historical series of estimated storm damage potentials for each CIESIN point. We divide the historical storm data into 15-year periods, with the latest period from 2000 to 2014, and compute the mean estimated storm damage potential in each period for the locale at each CIESIN point. These provide our proxies for the cyclonic storm intensities experienced by inhabitants of that locale in each period ($C_{i,[(t-mk),(t-(m-1)k)]}$) in our regression model).

Figure 1 maps estimated storm intensities for three periods: 1970-1984, 1985-1999 and 2000-2014. Each point is color-coded by relative intensity, from blue or green (no or very weak cyclone intensity, respectively) to red and purple (high and extremely high intensity, respectively). In each 15-year period, intensity is high in some areas and zero in others. Bangladesh and West Bengal have the most high-intensity areas in 1970-1984; Bangladesh has

[5] For a complete discussion of database construction and impact area computation, see Bandyopadhyay et al. (2018).
[6] In the USNHC model, the ratio [wind speed/wind speed at landfall] decays exponentially with time after landfall. The absolute value of the exponential parameter is a positive function of wind speed at landfall (i.e., the rate of decay is greater for storms with higher initial wind speeds).
[7] In our computation, wind damage potential is proportional to the square of wind speed.

the most in 1985-1999, although West Bengal and Odisha also have high-intensity areas; overall cyclone intensity is lower in 2000-2014, although Bangladesh and Odisha both have areas of high intensity.

3.4 Geographic Controls

We include controls for first-level administrative divisions (states in India, divisions in Bangladesh) and second-level administrative divisions (districts in India, upazilas in Bangladesh) that overlap with the three major urban centers in each country that serve as poles of attraction for coastal out-migrants (Kolkata, Cuttack and Bhubaneswar in India; Dhaka, Chittagong and Khulna in Bangladesh).

4. Model Estimation and Results

Our estimation database contains records for 428,006 points (162,660 in Bangladesh, 97,318 in West Bengal, 168,028 in Odisha). The close spacing of these points (30 arc-seconds, approximately 1 kilometer) entails a high likelihood that the error term in our estimation model has significant spatial autocorrelation. Accordingly, we restrict our estimation exercise to sparse random samples of 1,000 observations whose point spacing makes spatial autocorrelation less likely. We estimate a standard spatial autoregressive model developed by Pisati (2001)[8] and test for the significance of spatial autocorrelation.

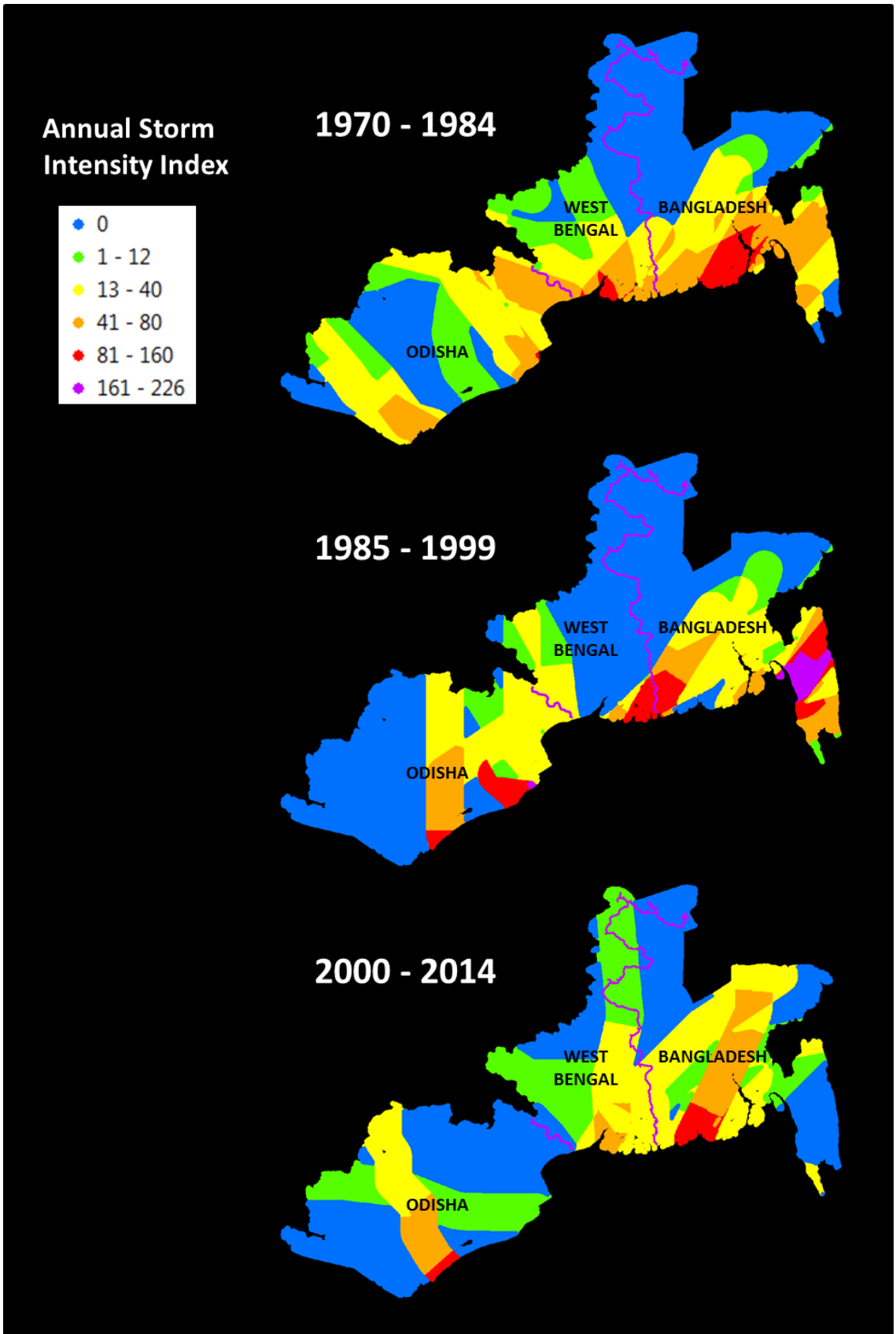
Tables 1 and 2 report estimation results from 10 random samples for Bangladesh and the Indian states, respectively.[9] A priori, we had the following expectations for parameter estimates: log population 2000: effectively 1.0 for both countries; cyclone intensity: negative, with

[8] We use Posati's spatreg in Stata.

[9] We have also experimented with sparse-sample estimation of a non-linear model that allows for variation in responsiveness to storm intensity with distance from the coastline. In all cases, we find no significant effect for distance from the coastline. Results are available from the authors on request.

declining weights for past periods and lower absolute values for India (reflecting compensation payment policies); market isolation index: negative, with a lower absolute value

Figure 1: Cyclonic storm intensities in Bangladesh, West Bengal and Odisha, 1970 - 2014



for India (reflecting locational compensation policy); ρ (autocorrelation parameter): insignificant for random samples of 1,000 widely-scattered points).

The results in Tables 1 and 2 are highly robust across 10 random samples of 1,000 observations[10] and confirm our prior expectations, with one exception (for market isolation in India). All estimates for log population 2000 are effectively 1.0 (no autonomous common trend). All estimates for contemporaneous and one-period-lagged cyclone intensity have the expected negative sign and are highly significant, with lower weights for lagged cyclone intensity and much lower weights overall for India, as expected. For both countries, the parameters for two-period lagged cyclone intensity all have the expected negative sign but only attain classical significance in 1 of 10 cases. We obtain the expected results for market isolation for Bangladesh, with negative signs in all 10 cases and classical significance in 8 of 10 cases. The Indian market isolation results are much weaker, as expected, with classical significance in only 3 of 10 cases. However, the sign is also positive in 9 of 10 cases, which suggests that Indian locational policy may have slightly over-compensated for locational disadvantages, if anything.

Our results for the geographic controls are generally significant, and their varying signs suggest substantial variation in unobserved regional characteristics that affect population change. We have excluded Dhaka from the Bangladesh district set (one dummy has to be excluded to avoid total collinearity), so the results should be interpreted as population growth rate differences from Dhaka district, after other model variables are taken into account. Our results indicate that Chittagong and Sylhet districts had significantly faster population growth than Dhaka district, ceteris paribus, while Barisal, Khulna and Rajshahi had significantly slower population growth. Among major urban centers, population growth was significantly higher than otherwise predicted

[10] These are 0.61% and 0.38% samples for Bangladesh and India, respectively.

by the model in Dhaka, lower in Khulna, and as predicted (no significant deviation) in Chittagong.

For the Indian states we have excluded the dummy variable for Odisha (again, to avoid total collinearity), so the result for West Bengal should be interpreted as the difference from population growth in Odisha. The result for West Bengal attains classical significance in 8 of 10 cases and is positively-signed for all, suggesting faster population growth there (ceteris paribus). Our results for major urban centers are mixed. The estimates for Kolkata are significant in only 2 of 10 cases, both positive (suggesting faster growth than expected, ceteris paribus), but sign variations and the general weakness of the results suggest little actual difference from expectation once other model variables are accounted for. The results for Cuttack have consistently-negative signs and classical significance in 7 of 10 cases, suggesting slower-than-expected population growth (ceteris paribus). The converse is true for Bhubaneswar, which has consistently-positive signs and classical significance in all 10 cases.

The results for the spatial autocorrelation parameter ρ strongly suggest that our use of sparse random samples has neutralized the problem. For Bangladesh, the ρ estimates are all very small, attain classical significance in only 3 of 10 cases, exhibit alternating signs within that subset of 3, and also across the 7 of 10 that are insignificant. For India, the ρ estimates are all extremely small, attain significance in only 2 of 10 cases, and have a sign variation in the other cases.

Table 1: Bangladesh: spatial estimates

Dependent variable: log Population 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Pop. 2000	0.997	0.988	0.998	0.995	1.003	1.003	0.999	0.982	0.995	0.996
	(174.07)**	(181.92)**	(154.75)**	(150.85)**	(166.94)**	(163.89)**	(179.83)**	(172.99)**	(157.38)**	(178.09)**
Cyclone Intensity, 2000-2014	-1.162	-1.470	-1.486	-1.426	-1.733	-1.497	-1.499	-1.393	-1.507	-1.530
	(7.15)**	(9.29)**	(8.49)**	(7.79)**	(11.31)**	(9.61)**	(8.15)**	(8.35)**	(7.97)**	(9.36)**
Cyclone Intensity, 1985-1999	-0.573	-0.511	-0.590	-0.632	-0.645	-0.844	-0.678	-0.584	-0.655	-0.702
	(5.84)**	(5.04)**	(5.51)**	(5.85)**	(6.90)**	(8.63)**	(7.30)**	(5.50)**	(5.54)**	(7.01)**
Cyclone Intensity, 1970-1984	-0.440	-0.129	-0.306	-0.056	-0.202	-0.007	-0.063	-0.152	-0.271	-0.309
	(2.64)**	(0.82)	(1.75)	(0.32)	(1.24)	(0.04)	(0.36)	(0.88)	(1.36)	(1.84)
log Market Isolation Index	-0.011	-0.011	-0.009	-0.006	-0.007	-0.010	-0.004	-0.008	-0.008	-0.010
	(3.39)**	(3.36)**	(2.41)*	(1.73)	(1.99)*	(3.02)**	(1.35)	(2.50)*	(2.01)*	(2.83)**
<u>Districts</u>										
Barisal	-0.070	-0.079	-0.098	-0.104	-0.098	-0.106	-0.091	-0.067	-0.087	-0.067
	(3.85)**	(4.60)**	(5.01)**	(5.40)**	(5.93)**	(5.88)**	(4.87)**	(3.69)**	(4.11)**	(3.49)**
Chittagong	0.092	0.099	0.072	0.075	0.065	0.075	0.085	0.100	0.070	0.077
	(8.03)**	(8.72)**	(5.42)**	(5.91)**	(5.23)**	(6.31)**	(6.36)**	(8.46)**	(5.07)**	(6.21)**
Khulna	-0.087	-0.092	-0.138	-0.124	-0.125	-0.126	-0.113	-0.097	-0.139	-0.111
	(8.65)**	(8.73)**	(12.12)**	(11.68)**	(11.56)**	(11.80)**	(10.96)**	(9.27)**	(10.98)**	(10.65)**
Rajshahi	-0.035	-0.048	-0.081	-0.062	-0.075	-0.058	-0.058	-0.042	-0.076	-0.063
	(3.71)**	(4.94)**	(7.49)**	(6.17)**	(7.45)**	(6.06)**	(5.92)**	(4.51)**	(6.63)**	(6.44)**
Sylhet	0.107	0.108	0.070	0.082	0.081	0.098	0.100	0.100	0.093	0.095
	(9.14)**	(9.41)**	(5.15)**	(6.47)**	(6.72)**	(8.64)**	(8.67)**	(8.50)**	(6.94)**	(8.26)**
<u>Urban Centers</u>										
Dhaka	0.238	0.262	0.263	0.240	0.287	0.263	0.276	0.346	0.226	0.242
	(8.76)**	(8.71)**	(8.50)**	(7.71)**	(12.20)**	(9.39)**	(8.74)**	(14.27)**	(6.82)**	(8.32)**
Chittagong	0.011	0.002	-0.013	0.009	-0.012	0.019	0.006	0.021	0.011	0.028
	(0.32)	(0.06)	(0.29)	(0.21)	(0.30)	(0.65)	(0.16)	(0.70)	(0.32)	(0.71)
Khulna	-0.146	-0.132	-0.134	-0.129	-0.145	-0.130	-0.135	-0.119	-0.123	-0.145
	(4.32)**	(3.93)**	(2.37)*	(2.81)**	(3.27)**	(3.88)**	(4.06)**	(2.77)**	(3.96)**	(3.24)**
Constant	0.559	-0.036	0.465	0.399	0.663	0.950	0.413	0.082	0.492	0.595
	(3.37)**	(0.21)	(3.00)**	(2.25)*	(4.47)**	(5.59)**	(2.92)**	(0.43)	(2.76)**	(3.69)**
ρ (spatial autocorrelation)	-.039	.060*	-.021	-.013	-.059*	-.103*	-.021	.046	-.024	-.042
	(1.36)	(2.06)	(0.77)	(0.42)	(2.22)	(3.44)	(0.82)	(1.44)	(0.79)	(1.51)
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Absolute value of z statistics in parentheses
*** significant at 5%; ** significant at 1%**

Table 2: India spatial estimates

Dependent variable: log Population 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log Pop. 2000	1.000	1.001	0.998	1.000	0.994	1.003	0.995	0.998	1.000	1.001
	(425.41)**	(360.54)**	(380.30)**	(382.32)**	(343.98)**	(377.19)**	(366.00)**	(364.99)**	(374.66)**	(351.63)**
Cyclone Intensity, 2000-2014	-0.548	-0.446	-0.447	-0.319	-0.439	-0.546	-0.370	-0.397	-0.475	-0.499
	(6.01)**	(4.86)**	(5.49)**	(3.53)**	(4.67)**	(6.34)**	(4.80)**	(4.44)**	(5.53)**	(5.49)**
Cyclone Intensity, 1985-1999	-0.185	-0.263	-0.184	-0.226	-0.239	-0.368	-0.323	-0.302	-0.170	-0.261
	(2.99)**	(4.58)**	(3.33)**	(3.87)**	(4.17)**	(6.04)**	(5.86)**	(5.09)**	(3.04)**	(4.27)**
Cyclone Intensity, 1970-1984	-0.118	-0.103	-0.006	-0.210	-0.004	-0.091	-0.114	-0.003	-0.004	-0.124
	(1.65)	(1.27)	(0.08)	(2.89)**	(0.05)	(1.23)	(1.57)	(0.04)	(0.06)	(1.67)
log Market Isolation Index	0.004	0.004	0.003	0.002	0.001	0.004	0.003	0.001	-0.001	0.000
	(2.67)**	(2.35)*	(1.86)	(1.10)	(0.51)	(2.36)*	(1.93)	(0.67)	(0.55)	(0.20)
States										
West_Bengal	0.020	0.018	0.030	0.010	0.028	0.017	0.008	0.021	0.038	0.027
	(3.00)**	(2.35)*	(4.34)**	(1.39)	(3.96)**	(2.33)*	(1.02)	(3.00)**	(5.32)**	(3.45)**
Urban Centers										
Kolkata	-0.001	0.008	0.014	-0.010	-0.005	0.044	0.003	0.022	-0.003	0.014
	(0.06)	(0.82)	(1.57)	(0.97)	(0.54)	(4.53)**	(0.38)	(2.03)*	(0.30)	(1.57)
Cuttack	-0.026	-0.040	-0.035	-0.039	-0.018	-0.026	-0.029	-0.020	-0.037	-0.045
	(1.64)	(3.31)**	(2.87)**	(2.77)**	(1.43)	(2.00)*	(2.34)*	(1.47)	(3.02)**	(3.51)**
Bhubaneswar	0.037	0.071	0.073	0.049	0.025	0.036	0.047	0.059	0.049	0.065
	(2.10)*	(5.58)**	(4.90)**	(3.60)**	(1.56)	(2.11)*	(3.20)**	(3.48)**	(3.40)**	(4.75)**
Constant	0.245	0.255	0.289	0.201	0.278	0.278	0.155	0.273	0.408	0.361
	(4.94)**	(4.73)**	(5.78)**	(3.99)**	(5.28)**	(5.35)**	(3.04)**	(5.29)**	(8.67)**	(6.86)**
ρ (spatial autocorrelation)	-.010	-.012	-.016	-.0002	-.009	-.019	.012	-.011	-.037*	-.030*
	(1.03)	(1.10)	(1.60)	(0.02)	(0.80)	(1.76)	(1.11)	(1.04)	(3.70)	(2.71)
Observations	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

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We conclude that spatial autocorrelation is not a significant problem for our sparse random sampling approach, so significance tests for non-spatial estimators will not be affected by this problem. Accordingly, we obtain summary results for each country via OLS bootstrap estimation with 100 random samples of 1000 observations. Table 3 displays the results, which are all consistent with the results we report for Tables 1 and 2.

5. Implications of the Results for Population Displacement

Our econometric results provide strong evidence that cyclonic storms have significantly affected the spatial distribution of population in Bangladesh, West Bengal and Odisha. However, they do not provide a sense of the orders of magnitude involved. To explore this issue, we use the estimation results in Table 3 to extrapolate the experience of coastal areas that were completely or largely cyclone-free during the past several decades. We predict population changes by locale in 2000-2015 under cyclone-free conditions, compute predicted 2015 populations using 2000 populations, and compare the results with actual populations in 2015.

Table 3: Bootstrap estimation results

Dependent variable: log Population 2015

	Bangladesh	India
log Population 2000	0.989 (265.04)**	0.998 (518.02)**
Cyclone Intensity, 2000-2014	-1.459 (7.71)**	-0.408 (6.02)**
Cyclone Intensity, 1985-1999	-0.639 (8.49)**	-0.292 (5.30)**
Cyclone Intensity, 1970-1984	-0.101 (0.76)	-0.089 (1.42)
log Market Isolation Index	-0.010 (2.76)**	0.003 (1.55)
Bangladesh Districts		
Barisal	-0.101 (5.54)**	
Chittagong	0.070 (4.26)**	
Khulna	-0.125 (8.57)**	
Rajshahi	-0.069 (4.76)**	
Sylhet	0.081 (5.40)**	
Bangladesh Urban Centers		
Dhaka	0.277 (7.29)**	
Chittagong	0.014 (1.01)	
Khulna	-0.134 (13.07)**	
India States		
West_Bengal		0.012 (3.05)**
India Urban Centers		
Kolkata		0.011 (0.77)
Cuttack		-0.035 (2.97)**
Bhubaneswar		0.055 (3.75)**
Constant	0.374 (9.93)**	0.208 (15.32)**
Observations	162,657	265,343
Samples	100	100
Sample Size	1000	1000

t statistics in parentheses
* significant at 5%; ** significant at 1%

5.1 Overall Impact Magnitudes

Table 4 displays comparative results for actual and predicted populations in 2015, at varying distances from the coastline. The results highlight both the overall magnitude of cyclone impacts and the strongly-neutralizing effect of compensation policies in the Indian states. In Bangladesh, the results suggest that cyclone impacts are accountable for population reductions of 7.7% - 9.7% in zones at varying distances from the coastline: 450,000 fewer people within 10 km, 750,000 (20 km), 1.4 million (50 km) and 3.1 million (100 km). Significantly-lower responsiveness on the Indian side translates to percent reductions of 1.9 - 2.6 % (75,000 fewer people, 161,000, 368,000 and 1.2 million at 10, 20, 50 and 100 km, respectively).

Table 4: Population displacement predictions

Country	Distance from Coastline (km)	\Population, 2015	Population With No Cyclones, 1970-2014	Population Difference	% Reduction from Cyclone Impacts
Bangladesh	**10**	**5,432,276**	**5,882,710**	**450,434**	**7.66**
India	**10**	**3,389,520**	**3,464,402**	**74,882**	**2.16**
Bangladesh	**20**	**8,885,658**	**9,615,253**	**729,595**	**7.59**
India	**20**	**7,113,229**	**7,273,730**	**160,501**	**2.21**
Bangladesh	**50**	**15,482,855**	**16,835,231**	**1,352,376**	**8.03**
India	**50**	**19,017,167**	**19,385,000**	**367,833**	**1.90**
Bangladesh	**100**	**28,997,224**	**32,123,010**	**3,125,786**	**9.73**
India	**100**	**45,354,009**	**46,539,978**	**1,185,969**	**2.55**

5.2 The Cyclone's Shadow

As Figure 1 shows, cyclonic storm intensities have differed greatly over space and time since 1970. Our econometric results indicate that local populations have responded significantly, with progressively-lower weights on impacts in past periods. In addition, the results suggest that Indian compensation policies have lowered responsiveness in West Bengal and Odisha. Figure 2

combines the point-scale cyclone intensity information displayed in Figure 1 with the population responsiveness results in Table 3. It displays the "cyclone's shadow" -- the relative population displacement attributable to cyclonic storm activity since 1970.

Figure 2: The cyclone's shadow: relative population displacement impacts since 1970

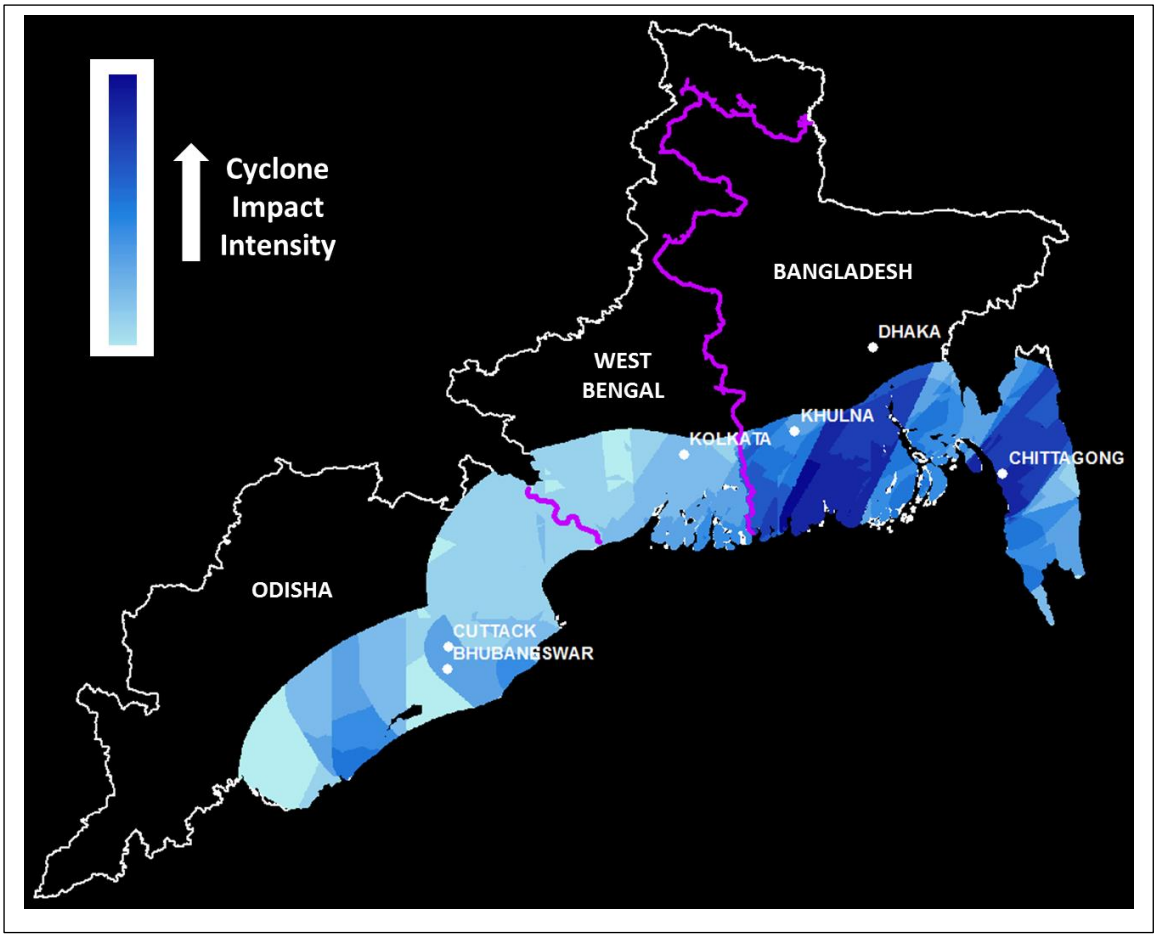

Figure 2 clearly shows the overall differences between Bangladesh and India that are summarized in Table 4. However, differences within areas are also pronounced. In Bangladesh, two broad bands of heavy displacement impact are surrounded by lighter bands in the west, center and south. Odisha also exhibits pronounced differences, with relatively heavy displacement impacts in southern and central coastal areas. West Bengal displays a rough geographic impact progression from west to east.

6. Policy Implications

We draw three major conclusions from our results. First, largely-uncompensated cyclone impacts and locational economic disadvantages in Bangladesh have yielded 8-10% population displacements from affected areas since 2000, via net effects on migration, fertile-age female residence and the fertility rate. The magnitudes are large, involving millions of people. Second, displacements from affected areas in India during the same period have been much smaller in both absolute and percentage terms, because Indian compensation policies have significantly reduced responsiveness to cyclonic storm threats and locational economic disadvantages. Third, cyclone intensities exhibit great geographic variation, and this is reflected in spatially-varied population displacement in both countries. Where local cyclone history is relatively benign, people have tended to stay put.

We consider the potential implications of these findings in light of our previous paper (Bandyopadhyay et al. 2018) on cyclonic storms in the region since 1877. Three patterns are most evident. First, the median locus of cyclone strikes during the past century has shifted progressively eastward, from north-central Odisha to western Bangladesh. Second, the locational variance of strikes has increased, so that all sections of the coast remain threatened despite the eastward trend. Third, cyclonic wind speeds have increased by about 36% since 1960 It is probably not accidental that these changes have occurred during the period of pronounced global warming since 1960 (NASA/Goddard 2018).

In light of our results and a large body of scientific evidence, the following predictions seem warranted: Global warming will continue for decades, and sea level rise may well accelerate. Although timing remains uncertain, mainstream projections of sea-level rise now include an increase of one meter or more by 2100 (NOAA 2017). An increase of this magnitude

would submerge large coastal areas by the end of the century (Dasgupta et al. 2009, 2010). And the previously-cited association between global warming and the intensity of cyclonic storms in the Indian Ocean region since 1960 suggests that cyclone impacts and potentially-catastrophic storm surges will not diminish and may well increase.

In consequence, millions of coastal inhabitants may well retreat inland, either by choice or by force majeure. The forced outcome would be tragic, and our empirical results for Bangladesh and India suggest that the pace and welfare implications of voluntary migration depend on government policies. In a laissez-faire regime, population relocation will occur as households respond to perceived threats, bearing the displacement cost themselves. Laissez-faire will ensure relocation by default as coastal conditions worsen, but at the cost of potentially-severe inequity among households differentiated only by location. In a compensation regime motivated by equity concerns, households will tend to stay put until force majeure intervenes via ocean encroachment and potentially-deadly storm surges. Maintaining equity in the compensation regime will entail escalating expenditures as the ocean moves inland and cyclone impacts intensify. Ultimately, the budgetary strain may prove intractable, leaving millions to fend for themselves.

In light of equity and budgetary concerns, neither laissez-faire nor automatic on-site compensation seems desirable, given the inexorable advance of the sea level and deadly cyclone threats. Rather, policy makers concerned with both efficiency and equity may want to consider a third approach: successive designation of threat zones as encroachment continues, with compensation from available funds focused on households that choose to relocate. While administration of this approach would have its own problems, it might well yield superior outcomes. And it would have the additional virtue of signaling the inevitability and severity of

the encroachment problem, while promoting dialog on efficiency/equity trade-offs, appropriate budgetary allocations, and the time-phasing of threat-zone delineation.

7. Summary and Conclusions

This paper has analyzed the effects of historical cyclone impacts on the spatial pattern of population change in Bangladesh, West Bengal and Odisha during the period 2000 - 2015. We develop high-resolution spatial impact measures using historical information about storm tracks, storm radii and wind speeds. For each population point, gridded at 30-arc-second resolution, we compute storm impacts in three periods: 1970-1984, 1985-1999, and 2000-2014. We assess population impacts using a model that embeds household migration decisions in locational comparisons based on current and expected future income streams.

We estimate a reduced form of the model that specifies point-level population change during 2000 - 2015 as an adjustment by households to contemporaneous and past cyclone impacts, as well as locational economic factors and government policies that compensate households for cyclone damage and disadvantages related to location. India maintains extensive compensation programs, while Bangladesh is closer to a laissez-faire regime. We estimate the model using appropriate spatial econometric methods. Our estimates for present and past cyclone impacts are highly significant and consistent with a lagged adjustment process that spans several decades. In Bangladesh, we also find a substantial impact for economic disadvantages due to location. We find smaller cyclone impact parameter values for India and no significance for locational disadvantages, which suggest that the Indian compensation regime has significantly dampened responsiveness to both factors.

We explore the implications of our findings with model-based predictions of point-level population changes with no cyclones since 1970. Comparison of predicted and actual

populations in 2015 suggests that affected regions are 8-10% less populous in Bangladesh because of past and expected cyclone impacts and locational disadvantages, but only 2% less populous in India. We combine our econometric results and historical cyclone impact measures to produce a high-resolution map of implied population displacement within 125 km of the coastline in Bangladesh, West Bengal and Odisha. The map provides a clear picture of the cyclone population displacement "shadow", which varies greatly across coastal sub-regions.

We conclude the paper with a discussion of the implications for alternative policy regimes as climate change proceeds, sea-level rise continues, and coastal inundation moves inland. We consider the efficiency and equity implications of damage compensation and laissez-faire regimes, and suggest a third alternative that may promote relatively efficient and equitable adaptation by focusing public resources on compensation for households that choose to relocate as the coastal threat mounts.

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