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ADAPTING TO FLOOD RISK:
EVIDENCE FROM A PANEL OF GLOBAL CITIES

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ABSTRACT

Urban flooding poses danger to people and places. People can adapt to this risk by moving to safer areas or by investing in private self-protection. Places can offset some of the risk through urban planning and infrastructure investment. By constructing a global city data set that covers the years 2012 to 2018, we test several flood risk adaptation hypotheses. Population growth is lower in cities that suffer from more floods. Richer cities suffer fewer deaths from flood events. Over time, the death toll from floods is declining. Cities protected by dams experience faster population growth. Using lights at night to measure short run urban economic dynamics, we document that floods cause less damage to richer cities and cities with protective dams. Cities with more past experience with floods suffer less from flooding.

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1 Introduction

Rising greenhouse gas emissions raise the likelihood of more extreme precipitation events that increase the risk of local flooding (Trenberth, 2005; AghaKouchak *et al.*, 2020). Such floods often kill, displace people, and destroy capital. Areas that experience such disasters suffer from a disruption in economic activity (Hsiang and Jina, 2014; Elliott *et al.*, 2015; Kocornik-Mina *et al.*, 2020). Roughly 2,600 floods took place each year from 2012 to 2018, leading to an estimated 31,000 total deaths and US $240 billion in damages (Guha-Sapir *et al.*, 2016).

Households and firms are not passive victims in the face of such natural disasters. People can adapt through three different strategies. First, they can invest in self-protection by avoiding living in increasingly risky areas and by investing in strategies to reduce their place based risk exposure (see Collado and Wang, 2020; Douglas *et al.*, 2008). Second, government can invest in local public goods to offset risk (Kousky *et al.*, 2006). Third, they can purchase insurance or demand public insurance such that they receive financial transfers if a disaster does take place (Ehrlich and Becker, 1972). Economic theory emphasizes that these strategies can sometimes be regarded as complements, and at other times as substitutes. Publicly provided insurance for flood damage or fire damage can crowd out purchase of private insurance. Similarly, public investment in resilience infrastructure can crowd out private self protection strategies (Kousky *et al.*, 2006). On the other hand, a complementary strategy would involve the government adopting a matching grant formula such that for every private dollar invested in resilience, the government spends a dollar on local public goods. At a given point in time, an urban population's risk exposure and the place's risk exposure depends on the complex interplay of these various factors.

We use both time series and cross-sectional approaches to test several natural disaster adaptation hypotheses. We use a global city data set of 9,468 cities, complemented by data on night lights and disasters from 2012 to 2018, to shed light on the net effects for cities of private self protection efforts and public investment in resilience. We first analyse the population growth rate in flood prone cities to test if people are migrating away from vulnerable areas. Second, we study the death toll from flood events across different cities, and ask if deaths per disaster have been declining over time. Third, we examine the impact of floods on economic activity, as proxied by intensity of night lights[1], and how that differs across developed and developing nations. Additionally, we test whether geographical and topographical characteristics of cities matter in determining the extent of impact. Fourth, we analyse the pattern of recovery in the aftermath of a flood to ascertain how long it takes for cities to come back to their pre-disaster level of night lights. Finally, we test three different flood adaptation hypotheses — whether higher income or productivity helps a city to mitigate the effect of floods; whether repeated exposure to flooding reduces the negative impact of subsequent events (the *novelty factor* as defined by Guiteras *et al.* (2015)); and if flood protection infrastructure does in fact attenuate the effect of floods. Places with a higher likelihood of flooding can invest in costly infrastructure, such as dams, to offset risk. Such public investments may attract more people to move to the city because the area is now perceived to be safer. They may also re-

[1] A growing number of studies use night lights intensity as a proxy for economic activity (Henderson *et al.*, 2011; Donaldson and Storeygard, 2016).

duce the marginal effect on economic activity of a flood in such a city. We quantify these effects using data from four major nations – China, India, Mexico, and the United States.

We report three main findings. First, we document that urban population growth is significantly lower in cities that experienced more severe floods in the recent past (categorised as $Risky$ cities). The results hold when we separately analyse high income and low income countries, but are only significant for the former group. However, the effects are small, with population growth in risky cities lower by 0.4-0.5 percentage points. This provides suggestive evidence that cities with recurrent floods do lose some of their desirability for potential and current residents. Furthermore, deaths from urban floods are lower (1.1 percent) in risky cities, but only for high income countries. For vulnerable cities in low income countries, the death rate is actually 2.7 percent higher.

Second, using monthly night lights data, we show that floods have a significant negative impact on economic activity. The effect is unsurprisingly higher in cities in low income countries, with night lights falling by 8.3 percent, as opposed to 1.4 percent in high income countries. Importantly, we find that high altitude cities suffer more, but only in low income countries. Our findings are robust to using extreme precipitation events as a measure of floods. In addition, the recovery dynamic results indicate that economic activity is restored to pre-disaster levels within one month in cities in high income countries. However, it takes two months for night lights to recover in low income countries, with the effect size still a significantly negative 4.9 percent after the first month.

Third, we find some evidence of adaptation and resilience to climate shocks. Richer cities, as measured by city level GDP per capita, experience a lower fall in night lights during a flood event, controlling for country specific income. Specifically, the effect of floods on low income cities is 9.3 percent, but the same is attenuated by 75-86 percent in the case of medium and high income cities, respectively. Furthermore, high risk cities or cities that experienced recurrent severe floods in the past suffer less from flooding by almost half than cities that don't face recurrent floods. Lastly, cities protected by dams suffer more floods, but the effect of each flood is mitigated by a substantial 40 percent. Thus, flood protection infrastructure does aid in reducing the negative impact on economic activity. In terms of population growth, we find that high risk cities with dams experience a fall in population growth, but low risk cities with dams experience a 9.5 percentage point increase in growth over cities with no dams. Together, our various pieces of empirical work support the adaptation progress.

Our work is most closely related to Kocornik-Mina *et al.* (2020), who study the short-run effects of 53 large flood events around the world. They use flood maps from 2003 to 2008 for 1,868 cities located primarily in developing countries. They find that urban economic activity tends to concentrate in low-lying areas and is vulnerable to flood risks. Using annual lights at night data, they document that large floods lead to a decline in the intensity of night lights by 2 to 8 percent in the year of the flood. However, economic activity recovers to pre-flood levels in the year immediately following the flood event. Finally, they document that economic activity does not relocate to safer areas in the aftermath of floods, with the exception of newly populated parts of cities.

We build on their work by focusing on adaptation, and expanding the scope and extent of the analysis in five different ways. First, our study is based on a large, globally representative sample of 9,468 cities from 175 countries. Second, we focus on a more recent time period from 2012 to 2018, and include the universe of floods (18,420) during this time period in our study. Third, we proxy economic activity using monthly night lights data from Visible and Infrared Imaging Suite (VIIRS) instruments, which have a higher spatial and radiometric resolution than its predecessors.[2] Importantly, the monthly frequency of the night lights data allows us to study short run effects and recovery dynamics, which is not possible with data at an annual frequency. Fourth, we look at the heterogeneous effects of floods based on income classification of countries, which gives us an insight into the differential impact and recovery from disasters based on economic development. Finally, our major focus is adaptation, and we study the role of income, infrastructure and familiarity in mitigating the impact of disasters.

Our paper contributes to three strands of literature. First, we contribute to the literature on adaptation to climate shocks. Desmet and Rossi-Hansberg (2015) have shown using a dynamic spatial model that the consequences of global warming can be mitigated by the ability of agents and goods to move across space. Therefore, migration is an important and effective adaptation method to limit the negative economic impact of climate change, and many studies have extensively documented the same. Boustan *et al.* (2012) use US migration data from 1920's and 1930's to document evidence of private self protection by men who move away from tornado hit areas. Hornbeck (2012) analyzes the aftermath of American Dust Bowl in 1930's, and finds that the main margin of economic adjustment was out-migration from affected areas. Strobl (2011) analyses the economic impact of hurricanes between 1970-2005 in the US, and estimates that a quarter of the economic effect of an average hurricane is due to richer people moving out as a consequence of the hurricane. In contrast, Deryugina (2011) looks at the effects of hurricanes in the 1980's and 1990's in the US, and finds no impact on population. Similarly, Kocornik-Mina *et al.* (2020) find little evidence of adaptation, at least in the sense of a relocation of economic activity away from the most vulnerable locations, except for newly populated parts of cities.

Migration, however, is just one instrument in the adaptation toolbox.[3] Barreca *et al.* (2016) study the effect of high temperatures on mortality in the US, and find that the diffusion of residential air conditioning has helped facilitate a decline in hot day–related fatalities by 75 percent since 1960's. Likewise, Park *et al.* (2020) show that heat inhibits learning and that school air conditioning helps mitigate this effect. Bunten and Kahn (2017) argue in favor of building less durable structures as an adaptation technique to preserve an option value to walk away from areas facing a higher climate risk. Aragón *et al.* (2021) examine the adaptation response of Peruvian farmers to extreme heat. They document that the farmers adapt by increasing the area planted, using more domestic labor on the farm, and changing the crop mix to attenuate the effect of extreme heat on output.

Hsiang and Narita (2012) estimate the extent of adaptation to tropical cyclones using the global cross-section of countries. They find evidence that countries with more intense tropical cyclone climates suffer lower marginal losses from an actual event, indicating adaptation to climatological risk. Burke and Emerick (2016) study adaptation in the context of agriculture in the US, and

[2]See Section 3 for a detailed discussion on night lights.

[3]See Klein *et al.* (2015) for an extensive survey of the key adaptation opportunities available in response to climate change.

find that longer run adaptation only partially mitigate the adverse impacts of heat on agricultural productivity. Our paper extends the scale of the analysis to the entire globe, and indicates that migration is an adaptation tool, but it is more pertinent in high income countries. Additionally, evidence of richer countries adapting can also be seen in the form of lower deaths per flood. Moreover, productive cities are better adept at mitigating the impact of floods. Familiarity with floods also helps as a tool to reduce the impact, and dams are an effective infrastructure to reduce the effect of floods.

Second, we contribute to the nascent literature on *Climate Justice* which predicts that disruptions from extreme weather will disproportionately affect the developing world, particularly the poor and most vulnerable (Mendelsohn *et al.*, 2000; World Bank *et al.*, 2003; Mendelsohn *et al.*, 2006; Stern, 2006; Tol, 2009). Various reports by the Intergovernmental Panel on Climate Change (IPCC) (Portner *et al.*, 2022; Houghton *et al.*, 2001) estimate that poor countries will suffer the bulk of the damages from climate change, with economic damages per capita from climate change for developing countries higher as a fraction of income. This is mainly due to the economic importance of climate-sensitive sectors for these countries. Moreover, the limited capacity to anticipate and respond to climate change can also impact adaptation in poor nations. Our results tend to support this discouraging hypothesis. We don't find any significant movement of people away from vulnerable cities in low income countries, even though the death rate is higher. Also, the economic impact as measured by fall in night lights is 6 times higher (8.3 percent as opposed to 1.4 percent). Furthermore, economic activity in low income nations take longer to return to pre-flood levels post a disaster (two months versus one). Low income nations also tend to be have a large proportion of low productivity cities, and we find that these cities are worse affected during floods. Thus, we do find strong evidence of disproportionate effects of floods on low income countries, and slower adaptation progress.

A key equation in global Integrated Assessment Models is the "climate damage function" (Barrage, 2019; Nordhaus, 2019). This function relates changing climate conditions, often proxied for by using the world's average temperature, to economic outcomes. Most of these parametric models do not incorporate adaptation progress over time as they assume a stationary climate damage function. Our paper's third contribution, by documenting that the flood damage function flattens over time, is to this emerging empirical literature.

Section 2 introduces rising place based natural disaster risk in a spatial equilibrium where individuals and locations can invest in adaptation strategies. Section 3 discusses the data used in this paper. Section 4 reports our population growth regressions and Section 5 looks at the death toll from flood regressions. Section 6 studies night light dynamics. Section 7 reports additional adaptation hypothesis tests based on the night light dynamics. Section 8 concludes.

2 Adaptation to Place Based Shocks

Cities differ with respect to their local amenities and physical features. In the hedonic spatial equilibrium, more people will live in a city and its real estate rent will be higher if the area is more productive and features better amenities (Henderson, 1974; Roback, 1982). If an area's quality of life declines because of extreme weather, the afflicted area will suffer population loss and home prices will decline (Glaeser and Gyourko, 2005).

Revealed preference logic teaches us that if people choose to locate in "harm's way", there must be offsetting factors that attracted them to the location. Such individuals can protect themselves either by avoiding risky areas or by making private and local public investments to offset the risks. Whether private self protection and defensive public goods investments are complements or substitutes plays a key role in determining how natural risks actually impact people and the local economy (Kousky *et al.*, 2006). Some cross-country studies find that richer countries are at some advantage in terms of coping with natural disasters (Kahn, 2005; Kellenberg and Mobarak, 2008). Kocornik-Mina *et al.* (2020) document surprisingly little adaptation (defined as movement within cities from riskier to safer areas) in the aftermath of floods. Mård *et al.* (2018) find that high protection levels (in the form of dams and levees) in flood-prone urban areas in rich countries are effective in mitigating the damage in the aftermath of floods. On the other hand, a study by Ferdous *et al.* (2020) finds that flood fatalities are higher in areas in the floodplains where flood protection measures like building levees were undertaken.

We do not observe the individual level, city level, and national expenditures on disaster risk offsetting. Such cost data is both difficult to collect and will depend on many location specific and microeconomic factors. Given this data challenge, we proceed with a reduced form approach that captures the net effects of a variety of choices that people, firms and governments have made that together determines an urban population's disaster exposure risk and ex-post damage realizations.

We test several place based adaptation hypotheses as we study the circumstances such that flooding and extreme rainfall causes less economic damage. Our unit of analysis is either the city/year or the city/year/month. The benefit of our aggregate approach is that we can track how different places cope with shocks. Some places will be better able to cope because they are richer. Other places may be better able to cope due to their geography and the investments in the place's infrastructure. Other places may have central governments who can act faster both ex-ante and ex-post after a disaster hits to invest in resilience strategies. We assume that the quality of government is directly related to the nation's degree of economic development.

3 Data

In this section, we first explain what is our unit of analysis and how we measure economic activity. Next, we discuss how we measure flood events and the data sources used to measure public investment in flood protection infrastructure

A Cities

To conduct our longitudinal analysis, we must define the boundary of each city around the world. The Global Human Settlement Urban Center Database (GHS-UCDB), created in 2015, applies one such definition to identify urban centers and their boundaries. This definition uses "*contiguous grid cells with a density of at least 1,500 inhabitants per km2 of permanent land or with a built-up surface share on permanent land greater than 0.5, and has at least 50,000 inhabitants in the cluster with smoothed boundaries*." (Florczyk *et al.*, 2019, p.3). The urban extent of cities so identified include the city centres and suburbs. Figure A.1 shows the urban extents using this method for the cities of Mumbai and Los Angeles. The GHS-UCDB database covers 13,135 cities having 50,000 people or more in 2015 and provides data on population for the years 1975, 1990, 2000, and 2015. Further, we only include cities that had at least 10,000 people in 1990 and 2000. This gives us a sample of 9,468 cities from 175 countries belonging to high-, middle-, and low-income groups.[4]

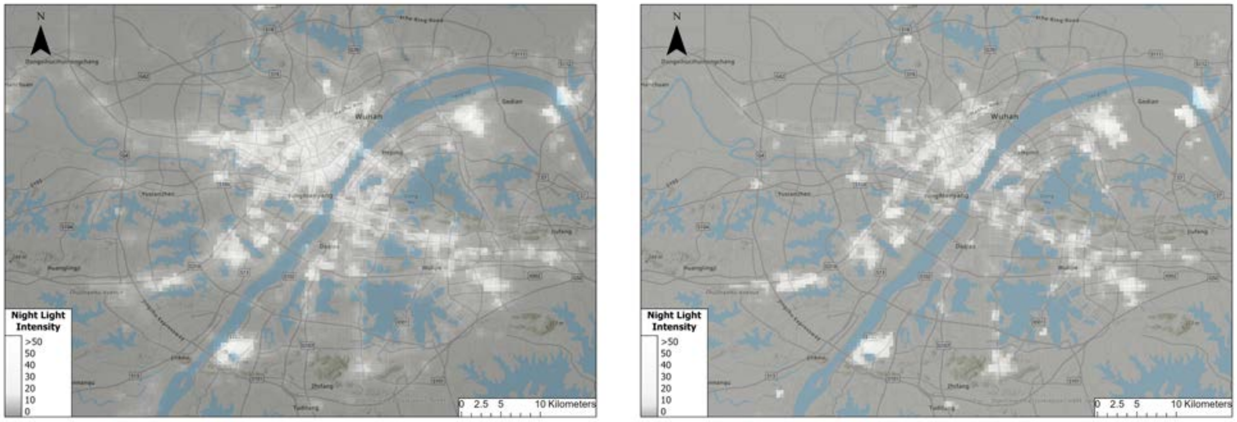
The GHS-UCDB database uses underlying data on built-up areas and population from the Global Human Settlement Layer (GHSL) database. The GHSL primarily uses satellite remote sensing to identify built-up area grids and thus delineate the physical extent of settlements(Florczyk *et al.*, 2019). The GHSL combines the built-up area of settlements with countries' official census data to produce absolute population at a grid of 1 km resolution. This is done for four points in time: 1975, 1990, 2000, and 2015. Summing up the population over all grids within the urban extent boundaries gives the total population of cities for each of four periods. The city GDP in the GHS-UCDB database is calculated by summing up the total GDP value (in PPP values expressed in US dollars in 2007) for each grid cell provided in Kummu *et al.* (2018) over all the grids within the urban extent.

B Night Lights

Our key outcome variable for measuring economic dynamics is night lights (NTL). Night light data are collected by satellites at a uniform and disaggregated spatial scale for the whole world. This allows for a comparison of economic activity across time and place at a finer spatial scale and circumvents the issue of poorly measured or missing estimates of GDP at a local level. For these reasons, a number of studies use night lights as a proxy for economic activity (Henderson *et al.*, 2011; Donaldson and Storeygard, 2016; Henderson *et al.*, 2018). Research studies make use of two major sources of night lights data: Defence Meteorological Satellite Program (DMSP) and Visible Infrared Imaging Radiometer Suite (VIIRS) Day-Night Band on the Suomi satellite. The DMSP night light data has been shown to have some flaws. The values are top coded, leading to saturation in core cities (Hsu *et al.*, 2015), and the data do not correlate well with output in less dense areas (Chen and Nordhaus, 2011). While some of the issues were rectified in an updated Radiance Calibrated Nighttime Light data set, the data are only available annually and only for seven years up until 2010. We use VIIRS night lights data[5], which have been calibrated and do not feature top coding (Elvidge *et al.*, 2017). The data have been shown to be accurate and reliable (Gibson *et al.*, 2021). It has a spatial resolution of 465m X 465m (grids) and provides monthly frequency since April 2012. This measure is a proxy for urban economic activity, population/ density, and built-up

[4]Throughout this study, we use the country income groups and regional classifications as defined by the World Bank.
[5]The data are provided by the Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines

Figure 1: Night Lights Before and After Floods in Wuhan: 2016



(a) April 2016 **(b) May 2016**

Notes: Average monthly night light intensity in Wuhan of Hubei province, China. Wuhan suffered from major floods between May-July 2016, causing economic losses estimated to be greater than $350m. Figure 1a and 1b show the light intensity in April and May of 2016, respectively.

area.[6]

Figure 1 shows VIIRS night light for Wuhan before and during the months the city faced floods in 2016. The light is dimmer for the month of May when it was hit with floods (see Figure 1b).

In the aftermath of a flood, lights at night can dim for several reasons that include temporary power failures, disruption of essential services, damage to property, temporary closure of offices and factories. If a specific geographic neighborhood is evacuated in the aftermath of a flood, this displacement effect may increase economic activity in another part of the city where the people move to. Our city level aggregate measures will capture this if the people remain within the geographic boundary as we have defined them.[7]

C *Flood Events*

Our flood data are from The Geocoded Disasters (GDIS) dataset, which is an open-source database that provides GIS locations and polygons for disaster-affected areas in the Emergency Events Database (EM DAT). It includes the dominant geophysical, meteorological, hydrological, and climatological disaster types: floods, storms, earthquakes, volcanic activity, extreme temperatures, landslides, droughts, and (dry) mass movements. This dataset includes all disasters between 1960 and 2018. Our main focus is on storms and floods, which are the majority of total disasters during the time period of the study for our sample cities. EM DAT classifies storms as meteorological disasters "*caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from min-*

[6] There are two caveats to note. First, low lit areas could have negative pixel values if the areas are darker than the background light that is subtracted from them (Beyer *et al.*, 2022). Second, monthly data are missing for high-latitude countries during summer months because the data are contaminated by solar illumination. Data could also be affected due to heavy cloud coverage (Beyer *et al.*, 2022).

[7] Economic activity can be displaced by a shock to areas outside the city's boundaries. In this case, people adapt to the shock but the place's lights at night metric shrinks and will not recover if this economic activity is permanently displaced.

utes to days" and floods as hydrological disasters "*caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater*".[8] Previous studies have used EM-DAT data at the nation level to explore various issues related to the impact of natural disasters (see for example Cavallo *et al.*, 2013; Kahn, 2005).

The GDIS provides geolocation information at various levels of administrative divisions – city level, province or state level, and country level. However, as our analysis is at the city level, using administrative divisions that are larger than the city poses a risk of misclassifying a flood as having taken place in a city where it did not take place. To address this issue, we conducted an extensive Google search for newspaper articles, government reports, maps by aid agencies, etc. to find the cities affected by the disaster amongst all urban areas in the larger administrative division. However, when no clear information was available from the search, we classified all cities in our database that fell within the affected administrative division as being hit by the disaster.

D Precipitation

Precipitation intensity data allow us to create a metric of the severity of a natural disaster based on a consistent criteria. To measure rainfall intensity, we use data from TerraClimate, which provides monthly climate and climatic water balance for global terrestrial surfaces from 1958-2019. All data have a monthly temporal resolution and a c.4-km (1/24th degree) spatial resolution.

We use the TerraClimate data to create a distribution of precipitation for each city. We classify months that witnessed a precipitation greater that 95th or 90th percentile of the city specific distribution as an extreme precipitation event. In the results we report below, we document the positive correlation between flood events and extreme rainfall and we report results where our measure of a disaster is an extreme rainfall event. This shock's intensity is city specific as we measure an outlier event based on the city's past empirical distribution of rainfall.[9]

E Elevation

We calculate the mean elevation for each city by averaging the elevation (in meters) for all 30 arc second grids (which is approximately one kilometre) in a city. The data are available in the GTOPO30 dataset.[10]

F Dams

We identify cities that were protected by dams in four major countries; China, India, Mexico and the United States. Due to the time costs of accurately identifying cities protected by dams and

[8] https://www.emdat.be/classificationHydrologicals

[9] Due to the topography and hydrology of cities and due to their investments in dam flood protection, there may not be a one to one mapping of extreme local rainfall events with local flooding. The water may accumulate in nearby geographic areas (see Guiteras *et al.* (2015))

[10] https://developers.google.com/earth-engine/datasets/catalog/USGS$_{G}TOPO30$ This data has been compiled with the help of a number of organizations. The team was led by U.S. Geological Survey's Center for Earth Resources Observation and Science (EROS).

the requirement of having comprehensive country maps of rivers, we focus on these four major nations. For the location of dams, we rely on a comprehensive geocoded global database of 7,320 large dams.[11]

Identifying cities in our sample that are downstream from a dam involved first identifying the rivers on which the dams were built and then identifying whether a city was near a river. We used four different sources for geocoded maps of rivers for each of the four countries.[12] We assume that the dam was built before 2013.

We define a dam as protecting a city if the following two conditions are satisfied; first, the dam is located upstream of ”the nearby rivers” of this city. If the distance from any point of a river to the geometric center of a city is greater than 15km, we consider this river is not near the city; otherwise, this river is near the city. Second, the distance between the upstream dam and the geometric center of the city is less than or equal to 100km. If a city has one or more dam that has protection power, it is a city ”protected by dams”; otherwise, this city is ”not protected by dams.”

[11] The dams database is compiled by the Global Water System Project as part of the Global Reservoir and Dam Database (GRanD) which is available at: https://hub.arcgis.com/datasets/panda::global-dams-and-reservoirs/about?layer=2.

[12] Mexico from ArcGIS hub(https://hub.arcgis.com/), the US from Esri ArcGIS online (https://www.esri.com/en-us/arcgis/products/arcgis-online/overview), India from Stanford Lib Earthworks and China from 1998 China River Location Map(downloaded in a Chinese website)

Table 1: Summary Statistics

Variable	All Cities	High Income Cities					Low Income Cities				
		Coastal	Inland	Low Elevation	High Elevation	All High Income Cities	Coastal	Inland	Low Elevation	High Elevation	All Low Income Cities
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A											
Number of Cities	9,468	777	4,325	2,859	2,243	5,102	437	3,929	1,947	2,419	4,366
(% of Total)		(8.21)	(45.68)	(30.19)	(23.69)	(53.89)	(4.62)	(41.49)	(20.56)	(25.55)	(46.11)
Mean Elevation (m)	370.53	38.59	426.96	55.15	766.35	385.54	35.28	388.84	54.39	594.17	354.49
	[514.41]	[45.00]	[564.29]	[44.30]	[610.78]	[557.99]	[47.25]	[470.89]	[46.68]	[499.20]	[462.75]
Night Lights (nW/cm2/sr)	14.23	27.43	20.21	20.69	22.08	21.31	8.84	5.63	6.49	5.52	5.95
	[16.12]	[22.30]	[16.83]	[18.24]	[17.56]	[17.96]	[12.71]	[6.89]	[8.24]	[7.27]	[7.73]
GDP per capita (US$)	8,237.39	17,966.07	11,470.26	13,791.01	10,761.95	12,459.52	4,305.93	3,192.04	3,919.16	2,808.02	3,303.53
	[9,156.55]	[14,380.46]	[9,249.45]	[11,200.41]	[9,163.29]	[10,460.82]	[4,311.26]	[2,750.52]	[3,326.65]	[2,527.03]	[2,962.48]
Population Growth (%)	20.51	19.71	12.86	13.15	14.86	13.90	35.26	27.46	23.76	31.84	28.24
	[38.01]	[34.50]	[27.52]	[27.38]	[30.49]	[28.793]	[78.53]	[39.89]	[49.63]	[41.18]	[45.32]
Built-up Area (%)	34.68	45.99	44.41	46.52	42.28	44.65	25.20	22.78	22.52	23.43	23.03
	[18.15]	[14.04]	[16.02]	[15.16]	[16.15]	[15.75]	[13.61]	[13.06]	[12.91]	[13.30]	[13.13]
Panel B											
Number of Floods	18,420	958	10,726	6,183	5,501	11,684	585	6,151	3,033	3,703	6,736
(% of Total)		(5.20)	(58.23)	(33.57)	(29.86)	(63.43)	(3.18)	(33.39)	(16.46)	(20.10)	(36.57)
Avg. Floods	1.95	1.23	2.48	2.16	2.45	2.29	1.34	1.57	1.56	1.53	1.54
	[3.08]	[1.85]	[3.85]	[3.24]	[4.09]	[3.64]	[1.72]	[2.24]	[2.01]	[2.33]	[2.19]
Extreme Precip. Events	32,946	3,177	13,450	9,617	7,007	16,627	1,874	14,445	7,050	9,269	16,319
(% of Total)		(9.64)	(40.82)	(29.19)	(21.27)	(50.47)	(5.69)	(43.84)	(21.40)	(28.13)	(49.53)
Avg. Extreme Precip. Events	3.48	4.09	3.11	3.36	3.12	3.26	4.29	3.68	3.62	3.83	3.74
	[2.31]	[2.08]	[2.19]	[2.21]	[2.21]	[2.21]	[3.01]	[2.31]	[2.62]	[2.20]	[2.40]

Notes: Column 1 provides the summary statistics for all 9,468 cities, while columns (2)-(6) and (7)-(11) provide summary statistics for *High Income* and *Low Income* cities, respectively. *High Income* and *Low Income* cities have been further classified into coastal or inland cities (columns (2)-(3) and (7)-(8)), and low elevation and high elevation cities (columns (4)-(5) and (9)-(10)). Columns (6) and (11) provide summary statistics for the universe of *High Income* and *Low Income* cities, respectively. The sum of coastal and inland cities equals the total number of cities in the respective income group, as do the sum of low and high elevation cities. Panel A provides information on geographical and economic characteristics, while Panel B focuses on floods and extreme precipitation events. *GDP per capita* is measured in PPP 2015 US$. *Population Growth* is computed as the change in the population of a city between years 2015 and 2000. *Built-up Area* is defined as the percentage of the total area of the city (km^2) that contains built-up structures. *Polity* is a continuous variable computed by subtracting the *Autocracy* score from the *Democracy* score. The resulting unified polity scale ranges from +10 (strongly democratic) to -10 (strongly autocratic).Both the *Autocracy* and the *Democracy* scores are an additive eleven-point scale (0-10). The operational indicators of *Autocracy* and *Democracy* are derived from codings of the competitiveness of political participation, the openness and competitiveness of executive recruitment, and constraints on the chief executive. Since Polity scores are only available at a country level, we cannot calculate them separately based on the geography of the city. Extreme Precipitation Events are a a dummy indicating whether the precipitation in the month m and year y in city c in country j (between the years 2012-2018) was greater than the 95th percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. The *Average Floods* and *Average Extreme Precipitation Events* refer to the average number of such events during the years 2012-2018. Standard deviation for all variables are reported in brackets.

Table 1 reports the summary statistics. The upper panel reports the count of cities in our data set overall and divided into high income and low income nations. We also report the count of cities in different geographic categories including coastal cities and inland cities and cities at high elevation. The bottom panel of Table 1 reports the flood disaster conditional means. In our sample of cities, over 18,000 flood events took place and roughly 63 percent took place in richer nations. The average city experienced two floods during our sample period. Below we will discuss how this fact affects our econometric estimation strategy.

4 Adaptation by Migrating Away from Flood Prone Cities

We test whether cities that have experienced more floods in recent years experience lower population growth.

We report population growth regressions using data from 2000-2015. Our regression specification takes the following form:

$$\Delta\ Population_{cj} = \alpha + \beta_1\ Risky_{cj} + \beta_2\ ln(GDP/capita)_{cj} + \beta_3\ ln(Builtup\ Area)_{cj} + \beta_4\ ln(Population)_{cj} + \delta_c + \xi_{cj} \quad (1)$$

where, the dependent variable $\Delta\ Population_{cj}$ is the population growth (in percent) between years 2000 and 2015 in city c in country j. The variable of interest is $Risky_{cj}$, which is a proxy for the vulnerability of the city. It is a continuous variable that measures the number of extreme precipitation events between 2000-15, where we define an extreme event based on two different cutoffs. For each city, we construct a distribution of monthly rainfall between 1958-2015, and then sum the total number of 90th (or 95th) percentile events that struck the city between 2000-15. Thus, a city that was frequently hit with extreme events, relative to its own distribution, over the course of the first 15 years of the new millennium will have a higher value for the $Risky_{cj}$ variable. We control for baseline economic opportunity measured by the the natural log of the year 2000 values of GDP per capita, built-up area (per square km.), and population of the city, and also include country fixed effects (δ_c) to account for time-invariant country characteristics. Table 2 presents the results, first at the aggregate level, and then divided by income groups.

We find that cities that experienced higher frequency of extreme events between 2000-15 saw lesser growth in population in the same period (columns 1-2 in Table 2). This is only significant for cities in high-income countries (column 4) and not for cities in low-income countries (columns 5-6). The effect is quantitatively small as the percentage change in population in high flood risk cities is .5 percent lower than cities facing less flood risk.

Recent empirical research studying localized shocks such as bombings generally does not find strong evidence of population decline in shocked areas. Studies set in Japan and Vietnam have documented that cities bombed during war time have proved to be resilient in the face of extreme shocks in the long run (Davis and Weinstein, 2002; Miguel and Roland, 2011).

Table 2: Effect of Extreme Events on Population Growth

	Dependent Variable: Δ Population$_{cj}$					
	All		High Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)
Risky (90th Perc)$_{cj}$	-0.004^{*}		-0.003		-0.005	
	(0.002)		(0.002)		(0.004)	
Risky (95th Perc)$_{cj}$		-0.005^{*}		-0.004^{*}		-0.006
		(0.003)		(0.002)		(0.005)
GDP/capita (2000)$_{cj}$	0.033^{**}	0.033^{**}	0.061^{***}	0.061^{***}	0.015	0.016
	(0.014)	(0.014)	(0.013)	(0.013)	(0.016)	(0.016)
Builtup Area (2000)$_{cj}$	-0.038^{*}	-0.039^{**}	-0.018	-0.020	-0.050^{**}	-0.049^{**}
	(0.020)	(0.019)	(0.023)	(0.022)	(0.024)	(0.023)
Population (2000)$_{cj}$	-0.020^{**}	-0.020^{**}	-0.024^{***}	-0.024^{***}	-0.018	-0.017
	(0.009)	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)
Fixed Effects						
Country	✓	✓	✓	✓	✓	✓
Num. obs.	9,468	9,468	5,102	5,102	4,366	4,366
Adj. R^2	0.261	0.261	0.328	0.329	0.193	0.193

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, Δ *Population*$_{cj}$, refers to the population growth between years 2000 and 2015 in city c in country j. *Risky*$_{cj}$ is a continuous variable that measures the number of extreme precipitation events in city c in country j between years 2000 and 2015, where extreme precipitation is a dummy indicating whether the precipitation in the month m and year y in city c in country j fell in the 90th (or 95th) percentile of the distribution of rainfall in the said city. The distribution was created using precipitation data from 1958-2015. Log values of *GDP per capita*, *Builtup Area* (*per sq. km*), and *Population* pertain to the year 2000. Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. All standard errors are clustered by country.

Unlike bombed areas, natural disasters prone areas are likely to be repeatedly shocked. Such a time series persistence should act as a tax on investing in capital in the affected area because investors expect that the area will be struck again. Given this logic it is surprising that recent empirical work on disasters has found that incumbents tend to remain in the shocked area unless their housing is destroyed (Boustan *et al.*, 2012; Kocornik-Mina *et al.*, 2020). This could be explained by positive migration costs and built up local social capital. Existing residents, especially the poor, may find it difficult to finance the migration costs to move to a safer city. Shocks can trigger huge federal transfer payments in richer nations. The expectation of such ex-post relief can create a moral hazard effect that acts to anchor people to risky places.

Recent empirical studies (Deryugina *et al.*, 2018; Nakamura *et al.*, 2016) have documented a "silver lining" such that people displaced from their origin due to a natural disaster actually enjoy an improvement in their material standard of living in subsequent years. Access to family and social capital may anchor people to risky places (Glaeser *et al.*, 2002). If the poor are less likely to "vote with their feet" to move to higher ground, then environmental justice issues are exacerbated as climate change will cause the poor to be exposed to greater risks but their rents for living in such places will be lower.

5 The Death Toll from Floods

One important natural disaster adaptation metric is the death count. During our sample period, this is a highly skewed variable with many zero counts and some truly deadly disasters.

To test whether floods cause less deaths in richer cities, or in cities with more past experience with flood events, we run the following regression:

$$ln(Deaths\ per\ disaster_{cjr}) = \alpha + \beta_1\ Risky_{cjr} + \beta_2\ ln(GDP/capita)_{cjr} + \beta_3\ ln(Population)_{cjr} + \mathbf{X}_{cjr} + \delta_r + \xi_{cjr} \quad (2)$$

Here, the dependent variable is the natural log of the ratio of total deaths caused by floods and the total number of floods between the years 2010 and 2018, for each city c in country j and region r. Cities that suffered no disasters between 2010-18 were dropped from the analysis[13]. The independent variable $Risky_{cjr}$ reflects vulnerability, but we slightly change its definition as compared to Equation (1). Firstly, the distribution of monthly rainfall is constructed using data between 1958-2018, and secondly, we sum the number of extreme precipitation events between 1970-2010. Thus, cities that have been most affected by natural disasters over the course of the 40 years between 1970-2010 will have a higher value for $Risky_{cjr}$. We control for city characteristics as measured by the natural log of the year 2015 values of GDP per capita and population.

We add in a vector of city-specific time-invariant dummies ($\mathbf{X}_{cjr}$) for geography and topography. The first, $High\ Elevation_{cjr}$, indicates whether city c in country j has an elevation[14] that falls in the top 50th percentile of the distribution of elevations across all the 9,468 cities. The second, $Coastal_{cj}$, signifies whether the city has a coast line. We also control for $Capital_{cj}$, which is a dummy that indicates whether city c is the capital of country j. Finally, we add in *World Bank* region[15] fixed effects (δ_r) to control for any time invariant heterogeneity between cities in different regions. Standard errors are clustered at the *World Bank* region level. Results are presented in Table 3.[16]

We find that cities in high-income countries having higher frequency of extreme events between 1970-2010 saw fewer deaths per disaster between 2010-2018 (columns 3-4 in Table 3). Conversely, cities in low-income countries that had a higher number of extreme events in the past saw higher deaths per disaster (columns 5-6). Cities in high-income countries have been able adapt to recur-

[13]For cities with disasters but no deaths, the dependent variable is $log\left(\frac{1+deaths}{total\ disasters}\right)$.

[14]Calculated as median elevation across all 30 arc second grids in a city.

[15]There are 7 *World Bank* regions, namely East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia, and Sub-Saharan Africa.

[16]One caveat related to the death toll results is the measurement error in the dependent variable. EM DAT provides deaths and injuries for each disaster, and not the affected cities therein. This is not a concern if the administrative unit affected by the disaster comprises a single city. However, when the death toll is provided for an administrative unit larger than the city, we have made the assumption that total deaths were divided equally between all the cities in our sample that are located within the disaster zone. This implies a certain degree of measurement error in the regressand, as there is bound to be variation in deaths between cities in the same region. However, it is important to note that this only makes the estimates less precise, but the coefficients would still remain unbiased.

Table 3: The Death Toll from Floods

	Dependent Variable: $\ln(\text{Deaths per disaster}_{cjr})$					
	All		**High Income**		**Low Income**	
	(1)	(2)	(3)	(4)	(5)	(6)
Risky (90th Perc)$_{\text{cjr}}$	0.008		-0.008^{**}		0.017^{**}	
	(0.006)		(0.003)		(0.005)	
Risky (95th Perc)$_{\text{cjr}}$		0.011		-0.011^{**}		0.027^{**}
		(0.009)		(0.003)		(0.008)
GDP/capita (2015)$_{\text{cjr}}$	-0.097^{***}	-0.095^{***}	-0.042^{*}	-0.043^{*}	-0.036^{**}	-0.035^{*}
	(0.014)	(0.015)	(0.018)	(0.019)	(0.014)	(0.014)
Population (2015)$_{\text{cjr}}$	0.074^{***}	0.074^{***}	0.055^{***}	0.055^{***}	0.094^{***}	0.093^{***}
	(0.014)	(0.013)	(0.015)	(0.015)	(0.006)	(0.007)
High Elev$_{\text{cjr}}$	-0.075	-0.073	0.050	0.052	-0.215^{*}	-0.212
	(0.102)	(0.102)	(0.038)	(0.036)	(0.101)	(0.105)
Capital$_{\text{cjr}}$	0.424	0.415	0.171	0.188	0.703^{*}	0.719^{*}
	(0.279)	(0.281)	(0.166)	(0.158)	(0.303)	(0.288)
Coastal$_{\text{cjr}}$	0.209^{**}	0.210^{**}	0.024	0.026	0.418^{*}	0.425^{*}
	(0.061)	(0.063)	(0.045)	(0.044)	(0.171)	(0.175)
Fixed Effects						
WB Region	✓	✓	✓	✓	✓	✓
Num. obs.	7,032	7,032	3,874	3,874	3,158	3,158
Adj. R^2	0.131	0.131	0.137	0.137	0.113	0.114

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, *ln(deaths per disaster)*$_{cjr}$, refers to the natural log of deaths per disaster for each city c in country j and region r between the years 2010 and 2018. *Risky*$_{cj}$ is a continuous variable that measures the number of extreme precipitation events in city c in country j between years 1970 and 2015, where extreme precipitation is a dummy indicating whether the precipitation in the month m and year y in city c in country j fell in the 90$^{\text{th}}$ (or 95$^{\text{th}}$) percentile of the distribution of rainfall in the said city. The distribution was created using precipitation data from 1958-2018. Log values of *GDP/capita* and *Population* pertain to the year 2015. *High Elev*$_{cj}$ is a dummy indicating whether city c in country j has a median elevation that ranks in the top 50$^{\text{th}}$ percentile of the distribution of the median elevation across all cities. *Coastal*$_{cj}$ and *Capital*$_{cj}$ are dummies that indicate whether city c in country j is a coastal or capital city, respectively. Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. All standard errors are clustered by World Bank Region.

ring shocks of extreme flooding in the past. This could be due to people moving to safer areas in high-income countries as seen in Table 2. India, which is classified as a lower middle-income country, has far fewer large cities than what the Zipf's law would suggest (Chauvin *et al.*, 2017).

We find that GDP/capita$_{\text{cjr}}$ has a negative relationship to deaths per disaster in both high- and low-income countries. Comparing the coefficient values in columns (3) and (6), we find that the negative impact of GDP/capita$_{\text{cjr}}$ on deaths per disaster is marginally greater in high-income countries than in low-income countries. This result supports the hypothesis that the relationship between income and damage caused by flooding is non-linear and depends on the stage of development (see Kellenberg and Mobarak, 2008).

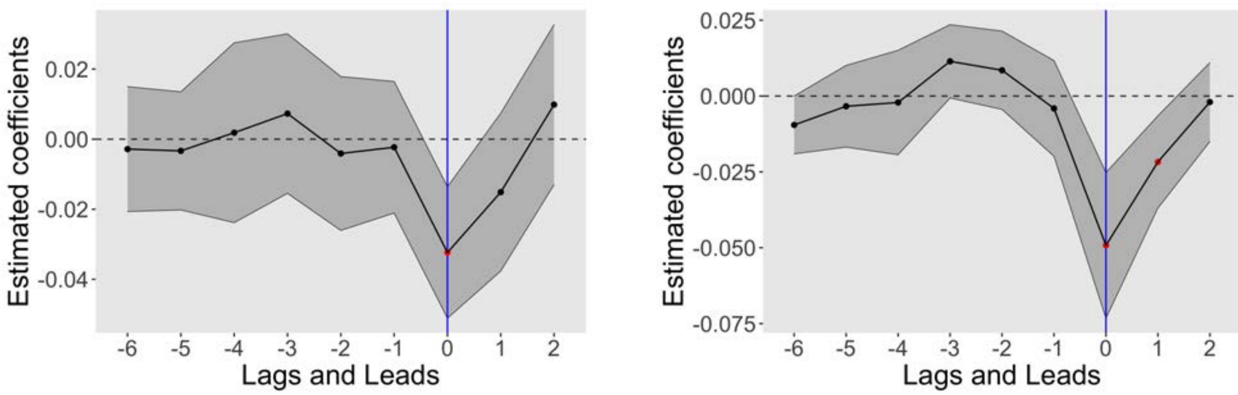
We include a time trend to capture overall trends in adaptation (see Table B.1). Many Integrated Assessment Models (IAM) assume that the climate damage function is stationary over time (Pindyck, 2013). We reject this pessimistic hypothesis as we find that richer cities suffer less death and the death gradient with respect to flood events flattens over time.[17]

[17] We also test if deaths from disasters are declining over time. We run a regression of the log of deaths per disaster on a linear and quadratic function of time, with city and country-month fixed effects. The sample only includes city-

6 Urban Resilience and Flood Shocks

We now turn to presenting our findings on how flood shocks affect economic activity as based on lights at night dynamics. Floods could lead to temporary power failures, disruption of essential services, damage to property, temporary closure of offices and factories, and in all cases will affect the normal functioning of economic life for sometime. The flood's impact on economic activity depends on the resilience of the city's core infrastructure. Richer cities should have more resilient infrastructure. We now test whether cities in high income countries suffer less from floods than cities in low income countries and we test for whether cities in low income countries take longer to bounce back after flood events.

Figure 2: Pre-Trend Analysis of Night Lights Intensity for All Cities



(a) Floods **(b) Extreme Precipitation**

Notes: Figure 2a show the 6 month lag and 2 month lead around a flood event. The coefficients in the plot is estimated by running a regression of $ln(\textit{Night Lights})_{cjmy}$, which is the natural log of mean light intensity in city c in country j in month m of year y, on the contemporaneous and 8 month leads and lags of the flood dummy, where $Flood_{cjmy}$ is a dummy indicating whether city c in country j was hit by a flood in month m of year y. The model includes the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. 8 month leads and lags for these two disaster types have also been included as controls. Figure 2b show the 6 month lag and 2 month lead around an extreme precipitation event, which is a dummy indicating whether the precipitation in the month m and year y in city c in country j was greater than the 95$^{\text{th}}$ percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. The shaded ribbons in each plot represent the 95$^{\text{th}}$ confidence interval band. In all regressions, observations include city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

A The Effect of Floods on Economic Activity

We examine the impact of floods on economic outcomes by running the following regression:

$$ln(\textit{Night Lights}_{cjmy}) = \alpha + \sum_{i=-2}^{2} \left(\beta_i \, Flood_{cj\{m+i\}y}\right) + \gamma_1 \, Flood_{cjmy} \times \textit{High Elev}_{cj} +$$
$$\gamma_2 \, Flood_{cjmy} \times Coastal_{cj} + \gamma_3 \, Flood_{cjmy} \times Capital_{cj} + \mathbf{X}_{cjmy} + \delta_c + \Gamma_{jmy} + \epsilon_{cjmy} \quad (3)$$

month combinations in which there was a flood. Clustering the standard errors at the city level, we find a negative and significant coefficient on the time trend. Running the same regression separately for cities in high income and low income countries yields a negative and significant coefficient for the former, but a positive and insignificant coefficient for the latter.

where $ln(Night\ Lights)_{cjmy}$ refers to the natural log of the average value of night lights in city c in country j in month m and year y. This is calculated as the mean of the radiance values of all grids within the city in a given month and year. $Flood_{cjmy}$ is a dummy variable that equals 1 if city c in country j was hit by a flood in month m of year y. We include two month lags and leads of the flood dummy to account for (i) early flood warning or heavy rainfall prior to floods affecting economic outcomes, and (ii) recovery dynamics post floods. Similar to the death toll regressions, we add in a dummy for capital cities, and use $High\ Elev_{cj}$ and $Coastal_{cj}$ as controls for city-specific time-invariant dummies for geography and topography. $\mathbf{X}_{cjmy}$ represents a vector of city-specific controls, specifically whether the city was affected by storms or landslides in month m of year y, and the corresponding two month lags and leads. δ_c and Γ_{jmy} represent city, and country-month-year fixed effects, respectively. Finally, to account for possible noise in the measurement of night lights intensity in the city due to cloud cover, we weight each observation by the proportion of cloud free cover images used to create a monthly composite for the city. To account for spatial and temporal correlation, we cluster the standard errors at the city and month-year level. The results are presented in columns (1) and (2) of Table 4.

We find that on average cities that suffer from floods see a decline in mean night lights by around 3%. This decline is associated with disruptions to economic activity caused due to floods. Counter-intuitively, the effect is attenuated for cities located on coasts compared to cities located away from the coast. Similarly, cities in low elevation areas on average see a smaller decline in mean night lights.

Table 4: Effect of Floods on Economic Activity

	Dependent Variable: $ln(Night\ Lights_{cjmy})$					
	All		High Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)
$Flood_{cjmy}$	-0.034^{***}	-0.070^{***}	-0.014^{**}	-0.020	-0.083^{***}	-0.162^{***}
	(0.009)	(0.017)	(0.007)	(0.027)	(0.021)	(0.041)
$Flood_{cjmy} \times High\ Elev_{cj}$		-0.019^{***}		-0.002		-0.049^{***}
		(0.007)		(0.011)		(0.014)
$Flood_{cjmy} \times Coastal_{cj}$		0.029^{***}		0.027^{**}		0.032
		(0.009)		(0.011)		(0.023)
$Flood_{cjmy} \times Capital_{cj}$		0.005		-0.006		0.049
		(0.028)		(0.017)		(0.076)
$Flood_{cjmy} \times Time\ Trend_{my}$		0.002^{*}		0.000		0.003^{*}
		(0.001)		(0.001)		(0.002)
Fixed Effects						
City	✓	✓	✓	✓	✓	✓
Country × Month × Year	✓	✓	✓	✓	✓	✓
Num. obs.	663,161	663,084	341,899	341,822	321,262	321,262
Adj. R^2	0.952	0.952	0.935	0.935	0.930	0.930

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(NightLights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Flood_{cjmy}$ is a dummy indicating whether city c in country j was hit by a flood in month m of year y. $High\ Elev_{cj}$ is a dummy indicating whether city c in country j has a median elevation that ranks in the top 50th percentile of the distribution of the median elevation across all cities. $Coastal_{cj}$ and $Capital_{cj}$ are dummies that indicate whether city c in country j is a coastal or capital city, respectively. $Time\ Trend_{my}$ is a continuous variable that takes the value from 1 to 81, with 1 representing the first month of the sample (April 2012), and 81 representing the last month (September 2018. Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. All regressions include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. One month lead and two month lags for all three disaster types have also been included in controls. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

We posit that richer cities suffer less from floods than poorer cities. To test this, we ran Equation (3) separately for high income and low income countries. The results are presented in columns (3)-(6). We find cities in both high and low income countries see, on average, a decline in night lights after being hit by a flood. Further, the coefficients for cities in high income countries are much lower compared to the coefficients for cities in low income countries, which are around 0.05-0.08 (columns 5-6 in Table 4).

We plot the estimated coefficients of the effect of floods on night lights for all cities six months prior and two months after a flood event in Figure 2a. We observe no pre-existing trend prior to the flood event and a negative effect in the month of the flood followed by an upward trend in the months after the flood event. Figures for high income and low income countries are available in appendix A.2a and A.2c respectively.

B *The Effect of Extreme Rain on Economic Activity*

In this section, we change the specification and now examine the impact of extreme rainfall events on lights at night dynamics. To construct the variable, we first calculate the city specific distribution of rainfall for each of the 9,468 cities in our sample, using monthly precipitation data from TerraClimate for the time period 1958-2018. Next, for each city, we classify all months with precipitation greater than the 95$^{\text{th}}$ percentile of the city specific distribution as having experienced an extreme event. This gives us a list of months for each city when it experienced precipitation that was extreme relative to its recent 60 year history.

The regression specification is the same as in Equation (3), except that the regressor is $\textit{Extreme Rain}_{cjmy}$, and we don't include the vector of controls, $\mathbf{X}_{cjmy}$. Results from this specification are presented in Table 5, with the estimates broken down by high income countries (columns 3 and 4) and low income countries (columns 5 and 6).

The coefficient for all cities are negative and significant and, at 4%. Extreme rain affect cities in both rich and poor nations. For cities in high income countries, extreme rain is associated with a 5% decline on mean night lights — higher than the average impact of flood events. Given that our variable for precipitation measures extreme events, the results show that high income countries are also vulnerable to such disasters.

We plot the coefficient estimates of the effect of extreme rain on night lights for all cities six months prior and two months after a flood event in Figure 2b. We observe no pre-existing trend prior to the flood event and a negative coefficient in the month of the extreme precipitation event followed by an upward trend in the months after the flood event. Pre-trends figures for high income and low income countries are available in appendix A.2b and A.2d respectively.

C *Recovery Dynamics From Floods*

In the aftermath of a flood, how many months does it take for the city to recover? In Figure 3a, we report one case study. Chennai, a major city in India, suffered from major floods between November-December 2015. Figure 3a shows the light intensity in October before the flood events.

Table 5: Effect of Extreme Rain on Economic Activity

	Dependent Variable: $ln(Night\ Lights_{cjmy})$					
	All		High Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)
$Extreme\ Rain_{cjmy}$	-0.051^{***}	-0.081^{***}	-0.046^{***}	-0.037^{***}	-0.059^{***}	-0.144^{***}
	(0.010)	(0.008)	(0.009)	(0.009)	(0.018)	(0.016)
$Extreme\ Rain_{cjmy} \times High\ Elev_{cj}$		-0.022^{***}		-0.012^{**}		-0.033^{***}
		(0.005)		(0.005)		(0.009)
$Extreme\ Rain_{cjmy} \times Coastal_{cj}$		0.013^{**}		0.022^{***}		-0.016
		(0.006)		(0.006)		(0.014)
$Extreme\ Rain_{cjmy} \times Capital_{cj}$		-0.039		-0.019		-0.096
		(0.026)		(0.020)		(0.075)
$Extreme\ Rain_{cjmy} \times Time\ Trend_{my}$		0.003^{***}		0.001		0.005^{***}
		(0.000)		(0.000)		(0.001)
Fixed Effects						
City	✓	✓	✓	✓	✓	✓
Country × Month × Year	✓	✓	✓	✓	✓	✓
Num. obs.	663,161	663,084	341,899	341,822	321,262	321,262
Adj. R^2	0.952	0.952	0.935	0.935	0.930	0.930

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(Night\ Lights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Extreme\ Rain_{cjmy}$ is a dummy indicating whether the precipitation in the month m and year y in city c in country j was greater than the 95th percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. $High\ Elev_{cj}$ is a dummy indicating whether city c in country j has a median elevation that ranks in the top 50th percentile of the distribution of the median elevation across all cities. $Coastal_{cj}$ and $Capital_{cj}$ are dummies that indicate whether city c in country j is a coastal or capital city, respectively. $Time\ Trend_{my}$ is a continuous variable that takes the value from 1 to 81, with 1 representing the first month of the sample (April 2012), and 81 representing the last month (September 2018) Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. One month lead and two month lags for the *Extreme Rain* dummy have been included as controls. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

This intensity reduced during the the months of flooding (Figure 3b & Figure 3c). By January 2016, the intensity of lights in Chennai started recovering to pre-flood levels (see 3d).

In this section, we analyse the pattern of recovery following a flood event, i.e. the length of time it takes cities to recover from floods on average. To test for this, we estimate the following regression:

$$ln(Night\ Lights_{cjmy}) = \alpha + \sum_{i=-6}^{3} \left(\beta_i\ Flood_{cj\{m+i\}y}\right) + \mathbf{X}_{cjmy} + \delta_c + \Gamma_{jmy} + \epsilon_{cjmy} \qquad (4)$$

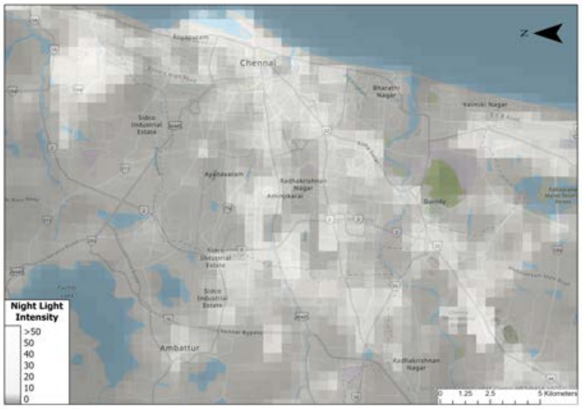
where $Flood_{cj\{m+i\}y}$ is a dummy that equals 1 if there was a flood in month $\{m+i\}$.

The coefficient on this variable can, thus, be interpreted as the effect of a flood in month $\{m+i\}$ on night lights in month m. We include lags for six months, allowing us to trace the economic recovery immediately after the flood event. $\mathbf{X}_{cjmy}$ represents a vector of city-specific controls, specifically whether the city was affected by storms or landslides in month m of year y, and the corresponding lags and leads.

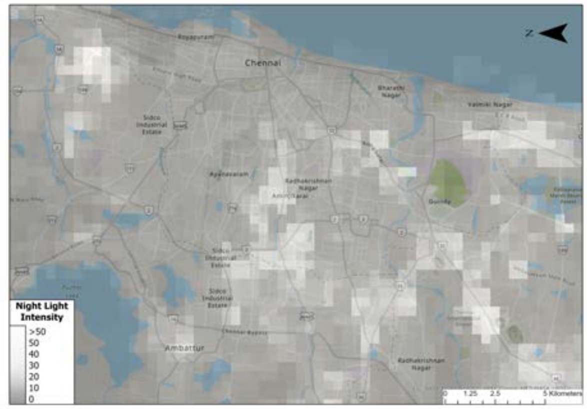
The results are presented in Panel A of Table 6. As a robustness check, we also test for recovery dynamics after extreme rain events, with results presented in Panel B. In the interest of brevity, we have only presented the estimates on lags of floods and extreme rain for three months. However, the coefficients on leads and the remaining lags for all the specifications are insignificant.

We see that negative impact of floods persist for at least one month after the disaster and is more severe for low-income countries relative to high-income countries.

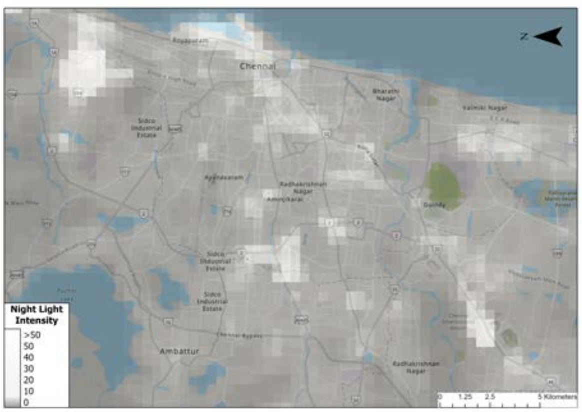
Figure 3: Night Lights Before and After Floods in Chennai: 2015-16



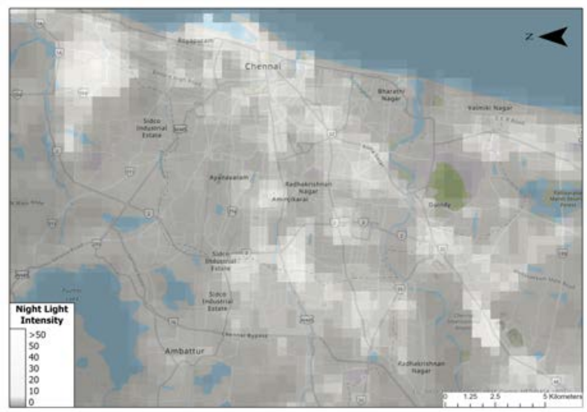
(a) October 2015



(b) November 2015



(c) December 2015



(d) January 2016

Notes: Average monthly night light intensity in Chennai, capital of Tamil Nadu state, India. Chennai suffered from major floods between November-December 2015, with economic losses estimated to be US$1bn. Figure 3a and 3b show the light intensity in October and November of 2015, respectively, whereas Figure 3c and 3d show the light intensity in December 2015 and January 2016, respectively.

7 Testing Flood Adaptation Hypotheses

We have found that economic activity in cities declines in the immediate aftermath of floods and extreme rain and that poorer nations suffer more. In this section, we test several resilience hypotheses. We ask: Are richer cities with productive capital resilient to shocks? Does past experience with extreme events result in better preparedness for future disasters? Do investments in protective infrastructure such as flood control dams reduce the effect of floods?

A Do Richer Cities Suffer Less?

Cities that are economically productive have better infrastructure and resources to cope with extreme events. We hypothesize that richer cities, as measured by their per capita GDP, will be less affected by disasters. We test this using the following regression equation:

Table 6: Recovery Dynamics for Floods and Extreme Rain

	Dependent Variable: $ln(Night\ Lights_{cjmy})$		
	All	**High Income**	**Low Income**
Panel A			
$Flood_{cj\{m\}y}$	-0.033^{***}	-0.016^{**}	-0.079^{***}
	(0.009)	(0.007)	(0.021)
$Flood_{cj\{m-1\}y}$	-0.017	-0.002	-0.049^{*}
	(0.011)	(0.009)	(0.025)
$Flood_{cj\{m-2\}y}$	0.010	0.007	0.016
	(0.011)	(0.009)	(0.028)
$Flood_{cj\{m-3\}y}$	0.020	0.013^{*}	0.029
	(0.013)	(0.008)	(0.030)
Panel B			
$Extreme\ Rain_{cjmy}$	-0.049^{***}	-0.047^{***}	-0.052^{***}
	(0.011)	(0.009)	(0.018)
$Extreme\ Rain_{cj\{m-1\}y}$	-0.022^{***}	-0.014^{**}	-0.034^{**}
	(0.007)	(0.006)	(0.014)
$Extreme\ Rain_{cj\{m-2\}y}$	0.003	0.001	0.005
	(0.008)	(0.007)	(0.015)
$Extreme\ Rain_{cj\{m-3\}y}$	0.011	0.015^{**}	0.007
	(0.009)	(0.006)	(0.017)
Fixed Effects			
City	✓	✓	✓
Country × Month × Year	✓	✓	✓
Num. obs.	606,353	311,287	295,066
Adj. R^2	0.953	0.938	0.932

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(Night\ Lights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Flood_{cj\{m-t\}y}$ ($Extreme\ Rain_{cj\{m-t\}y}$) indicates whether city c in country j was hit by a flood (extreme precipitation) event t months prior. $Extreme\ Rain_{cjmy}$ is a dummy indicating whether the precipitation in the month m and year y in city c in country j was greater than the 95$^{\text{th}}$ percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. Observations include all city-country-month-year observations which had a non-zero value of nightlights. *Panel A* presents the recovery dynamics for floods, and *Panel B* focuses on extreme precipitation. All regressions in *Panel A* include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. The controls in *Panel B* include 7 lags and 3 leads for each of the three disaster types. Controls in Panel B include 7 lags and 3 leads for extreme precipitation events. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

$$ln(Night\ Lights_{cjmy}) = \alpha + \sum_{i=-2}^{2} \beta_i\ Flood_{cj\{m+i\}y} + \sum_{k\in\{mid,high\}} \gamma_k\ Flood_{cjmy} \times GDP/capita_{kcj} + \mathbf{X}_{cjmy} + \delta_c + \Gamma_{jmy} + \epsilon_{cjmy} \quad (5)$$

We divide the log of per capita GDP into three quantiles, namely *Low* (omitted category), *Medium* and *High*. Thus, $GDP/capita_{kcj}$ is a factor variable that represents whether the log of per capita GDP of city c in country j in 2015 fell into the k^{th} quantile. The coefficient of interest in Equation (5) is γ_k, which represents the mitigating effect of being in the k^{th} income group on the impact of floods. The result is presented in column (1) of Table 7. Cities in middle income and high income categories see a much lower effect of floods on night light intensity compared to cities that have low incomes.

Table 7: Heterogeneous Effect of Floods based on Wealth and Risk

	Dependent Variable: $\boldsymbol{ln(Night\ Lights_{cjmy})}$	
	All	
	(1)	**(2)**
$Flood_{cjmy}$	-0.093^{***}	-0.042^{***}
	(0.017)	(0.010)
$Flood_{cjmy} \times Medium\ GDP/capita_{cj}$	0.070^{***}	
	(0.015)	
$Flood_{cjmy} \times High\ GDP/capita_{cj}$	0.080^{***}	
	(0.020)	
$Flood_{cjmy} \times High\ Risk_{cj}$		0.020^{*}
		(0.010)
Fixed Effects		
City	✓	✓
Country × Month × Year	✓	✓
Num. obs.	663,161	663,161
Adj. R^2	0.952	0.952

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(Night\ Lights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Flood_{cjmy}$ is a dummy indicating whether city c in country j was hit by a flood in month m of year y. $ln(GDP/capita)_{cj}$, measured in PPP US$ (2007), pertains to the year 2015. To create factor variables, $ln(GDP/capita)_{cj}$ was divided into three quantiles of equal size, with the omitted category in regressions being quantile 1, i.e. $Low\ GDP/capita_{cj}$. $High\ Risk_{cj}$ is a dummy variable that equals 1 if the number of extreme precipitation events in city c in country j, between years 1970 and 2011, were greater than the median number of extreme events across all 9,468 cities. Extreme precipitation is a dummy indicating whether the precipitation in the month m and year y in city c in country j fell in the 90th percentile of the distribution of rainfall in the said city. The distribution was created using precipitation data from 1958-2018. All regressions include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. Two month leads and lags for all three disaster types have also been included as controls. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at city and month-year level.

B Does Repeated Experience with Flooding Reduce the Marginal Effect of the Next Flood?

In the previous sections, we focus on the occurrence of a flood event without considering whether the city had previous experience of such flood events. The impact of a disaster could also depend on whether it was an unexpected event or something that people were used to dealing with in the past (Guiteras *et al.*, 2015).

Cities that are faced with recurring weather shocks may be better able to cope with future shocks. Public authorities and citizens with past experience with extreme weather events know what to expect and can plan better for future events. An alternative hypothesis is that places that face repeat flooding experience disinvestment as the repeat events act as a tax on capital investment.

To test whether cities facing recurring extreme disasters in the past have become resilient, we estimate the following regression equation:

$$ln(Night\ Lights_{cjmy}) = \alpha + \sum_{i=-2}^{2} \beta_i\ Flood_{cj\{m+i\}y} + \beta_2\ Flood_{cjmy} \times High\ Risk_{cj} + \mathbf{X}_{cjmy} + \delta_c + \Gamma_{jmy} + \epsilon_{cjmy} \quad (6)$$

where $High\ Risk_{cj}$ is a dummy variable that equals 1 if the number of extreme precipitation events in city c in country j between 1970 to 2012 were above the median number of extreme precipitation events across all cities in the sample. To determine the number of extreme precipitation events that struck a city, we construct a distribution of monthly rainfall between 1958-2015 for each city, and then sum the total number of 90$^{\text{th}}$ percentile events between 1970-2012. The assumption here is that the extreme precipitation events led to flooding, and therefore, a higher number of events between 1970-2012 would indicate recurrent shocks which we hypothesize should enable a city to adapt.

The result is presented in column (2) in Table 7. Cities that had flood events in the past see a lower impact of floods relative to cities that had no such prior experience.

C *Does Flood Protection Infrastructure Protect Cities?*

Using data on dams for four countries – China, India, Mexico, and the United States – we examine whether cities protected by dams are more likely to experience flood events, higher population growth, and importantly, if dams help to mitigate the impact of a flood shock. The four countries include 3,820 cities out of our total sample of 9,468 cities.

First, we analyse the heterogeneity in the number of dams between different countries. China and US, which fall in the *high income* category, have 71 percent and 67 percent of their river cities protected by a dam.[18] Surprisingly, India, which is classified as a *low income* country, has the exact same percentage of cities with dams as the US. Only for Mexico does this number drop slightly to 58 percent. In terms of new dams that were built during the time period of our analysis, *i.e.* post 2012, the numbers are negligible with 10 new dams in China, 3 in India, 2 in Mexico, and none in the US. Thus, most of the cities in these countries already had an established flood protection infrastructure before the time period of our analysis.

There are some interesting differences within countries between cities with and without a protective dam. We provide summary statistics in Table A.2 on country specific geographical, economic, and disaster related characteristics, classified based on the presence or absence of a protective dam. Cities with protective dams in high income countries have experienced a lower population growth as compared to cities without dams in these countries. However, for India and Mexico, the difference in population growth in cities with and without dams is minimal. Indian cities without dams are considerably richer than cities with dams, with GDP per capita 25 percent

[18] We define a city as protected by a dam if the river flowing though the city has a dam upstream of the city and the geodesic distance between the city, and the dam is less than or equal to 100 kilometers

Table 8: Dams and Adaptation

	$Flood_{cjmy}$	Δ $Population_{cj}$		$ln(Night\ Lights_{cjmy})$	
	(1)	(2)	(3)	(4)	(5)
$Dams_{cj}$	0.003**	−0.015**	0.095**		
	(0.001)	(0.007)	(0.037)		
$Risky_{cj}$			−0.002		
			(0.002)		
$Risky_{cj} \times Dams_{cj}$			−0.006***		
			(0.002)		
$Flood_{cjmy}$				−0.042***	
				(0.006)	
$Extreme\ Rain_{cjmy}$					−0.071***
					(0.005)
$Flood_{cjmy} \times Dams_{cj}$				0.017**	
				(0.008)	
$Extreme\ Rain_{cjmy} \times Dams_{cj}$					−0.008
					(0.006)
Fixed Effects					
City				✓	✓
Country	✓	✓	✓		
Month × Year	✓				
Country × Month × Year				✓	✓
Num. obs.	292,459	3,820	3,820	277,179	277,179
Adj. R^2	0.107	0.123	0.132	0.919	0.919

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in column (1) is $Flood_{cjmy}$, a dummy indicating whether city c in country j was hit by a flood in month m of year y. The regression includes log values of *GDP per capita*, *Builtup Area* (*per sq. km*), and *Population* pertaining to the year 2015 as controls. The dependent variable in columns (2) and (3), Δ *Population*$_{cj}$, refers to the population growth between years 2000 and 2015 in city c in country j. *Risky*$_{cj}$ is a continuous variable that measures the number of extreme precipitation events in city c in country j between years 2000 and 2015, where extreme precipitation is a dummy indicating whether the precipitation in the month m and year y in city c in country j fell in the 90$^{\text{th}}$ percentile of the distribution of rainfall in the said city. The distribution was created using precipitation data from 1958-2015. Both regressions include log values of *GDP per capita*, *Builtup Area* (*per sq. km*), and *Population* pertain to the year 2015 as controls. The dependent variable in columns (5) and (6), $ln(NightLights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. Both regressions include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. Two month lead and lags for all three disaster types have also been included as controls. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation in the two regressions was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city level.

higher in the former. Another sharp distinction between high and low income nations exists in terms of number of flood events. While cities protected by dams in *high income* countries faced twice as many floods as cities without dams, in *low income* countries, the ratio was close to 1.

To analyse these differences more formally, we run the following regression:

$$Flood_{cjmy} = \alpha + \beta_1\ Dams_{cj} + \beta_2\ ln(GDP/capita)_{cj} + \beta_3\ ln(Builtup\ Area)_{cj} + \beta_4\ ln(Population)_{cj} + \delta_j + \Gamma_{my} + \epsilon_{cjmy} \quad (7)$$

where $Dams_{cj}$ is a dummy that equals 1 if the river flowing through city c in country j has a dam upstream within a 100km radius. We control for GDP per capita, built-up area and population, and also include country and month-year fixed effects. The coefficient of interest is β_1 which signifies the likelihood of floods in cities with dams. Results are presented in Table 8.

Column (1) presents the correlation between cities with dams and flood events. As expected based on the summary statistics (see Table A.2), cities with dams face a higher number of floods, and this result is primarily driven by the *high income* countries. This is not surprising given that dams are more likely to be placed in areas at greater risk. Columns (2) and (3) report population growth regressions and use a similar cross-section specification to the one in Equation (1) except that we add the covariate $Dams_{cj}$, and interact it with the proxy for vulnerability of the city ($Risky_{cj}$). The coefficient on $Dams_{cj}$ in column (2) informs us about the population growth in cities with dams, while the coefficient on the interaction term ($Risky_{cj} \times Dams_{cj}$) in column (3) indicates whether vulnerable cities with dams have a differential population growth rate as compared to low risk cities with dams. On average, cities protected by dams have a significant 1.5 percentage point lower population growth rate (column 2). The summary statistics indicate that this result too is being driven mostly by cities in high income countries. However, as column (3) shows, this masks considerable heterogeneity between high risk and low risk cities. Low risk cities with dams actually experience a higher population growth rate, and it is the risky cities with dams which experience a lower population growth.

The final two columns focus on adaptation, as we explore the extent to which dams mitigate the impact of floods and extreme rain. To estimate this, in column (4) we run a regression similar to Equation (3) without the geography and capital dummies, and add $Dams_{cj}$ and its interaction with the contemporaneous flood dummy as regressors of interest. The coefficient on the interaction term signifies the magnitude by which the effect of the floods on economy activity is mitigated by the presence of a dam within a 100km radius. Finally, we replace $Flood_{cjmy}$ with *Extreme Rain*$_{cjmy}$ in column (5). Our results suggest that cities protected by dams experience a lesser decline in night lights during floods. As column 4 shows, the effect of floods is negative and significant, with night lights falling by a 4.2 percent in the case of a flood. However, the effect is attenuated by 1.7 percentage points in cities with dams. Surprisingly, we do not observe any mitigating effect of dams during extreme precipitation events. We hypothesize that dams are beneficial in mitigating the effects of riverine flooding which may be caused by factors upstream. This is not the case with extreme precipitation, which falls directly on the city, and may cause waterlogging in low-lying areas. This last result, therefore, represents a puzzle that merits future research.

8 Conclusion

Climate change raises the risk of extreme weather events such as floods. The damage caused by these events can be partially offset through adaptation investments at the individual and government level. We have studied the correlates of flood adaptation progress by estimating how thousands of flood events that have occurred around the world from 2012 to 2018 have affected urban population growth rates, the death count from such shocks, and lights at night dynamics. We find that floods cause a decline in short term economic activity, with a larger negative effect in poorer nations. Though these floods also lead to a higher death rate in vulnerable cities in low income countries, we do not find evidence of significant out-migration from such cities. Cities in poorer nations take a longer time to recover from these disasters, relative to disasters in high income countries. However, the damage caused by flooding in poor nations is declining over time.

Using a global panel of cities, this paper provides evidence of flood adaptation taking place. Cities are becoming more resilient with time. Repeated experience with floods does tend to reduce the marginal economic impact of subsequent floods, while flood protection infrastructure, specifically dams, also helps mitigate a significant portion of the negative impact. The reasons for the differential impact of disasters across cities in low income and high income countries merits further research. Shi *et al.* (2015) point out that strong political leadership, high municipal expenditures, and awareness about climate change are associated with adaptation planning among environmentally progressive cities.

Poorer nations also suffer from poor urban planning and lack of investment in infrastructure. A large proportion of the urban population in poorer nations lives in slum settlements. These countries are also seeing more growth in settlements in flood-risk areas (Rentschler *et al.*, 2022). Much of the urban population growth in developing countries over the last two decades has been in slums (Marx *et al.*, 2013). Slums feature more low quality buildings and are located in areas most vulnerable to climate risk and hence suffer more due to flooding. All these factors could potentially contribute to the large income based heterogeneity of the impact of floods that we document. Detailed flood maps coupled with knowledge of high and low income areas within each city could help to shed light on the mechanisms behind the differences.

A fruitful area of further research involves analysing the interplay between how private and public decisions jointly determines disaster resilience. In this regard, the Ehrlich and Becker (1972) framework offers a model for improving our understanding of producing resilience. In cases where governments anticipate that resilience infrastructure investments could actually encourage greater risk taking by the public, the crowding out effect induced by ”climate proofing” an area, the government must consider introducing complementary policies to limit this substitution effect.

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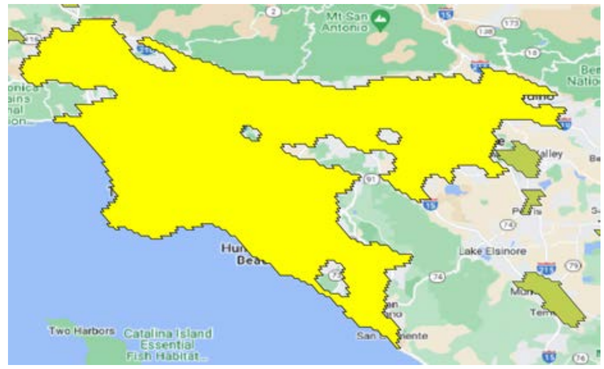
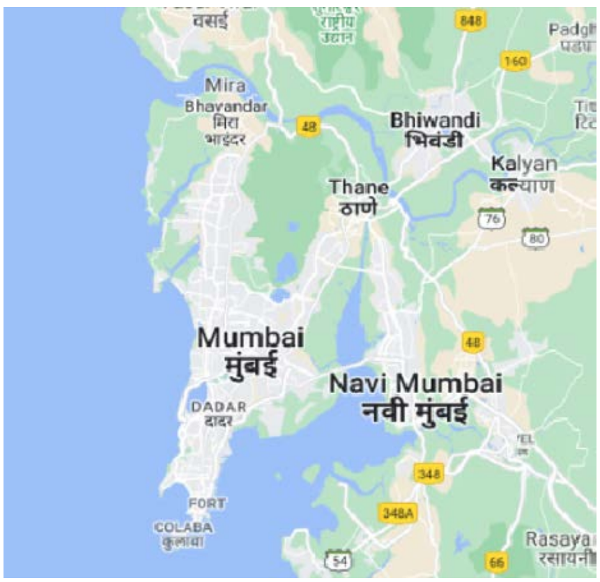
A Appendices

Figure A.1: Urban Extent

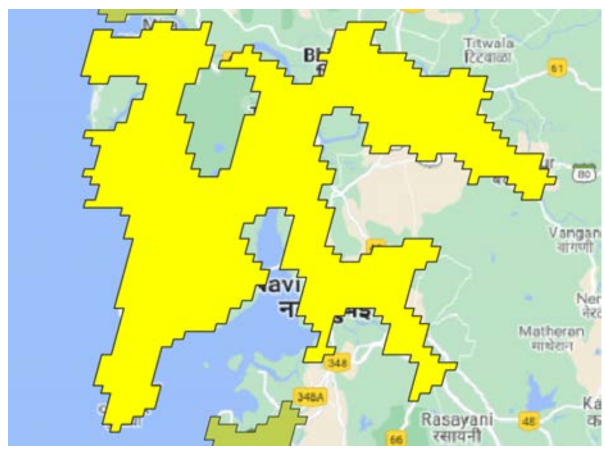
(a) **Los Angeles map**



(b) **Los Angeles GHS-UCDB extent**



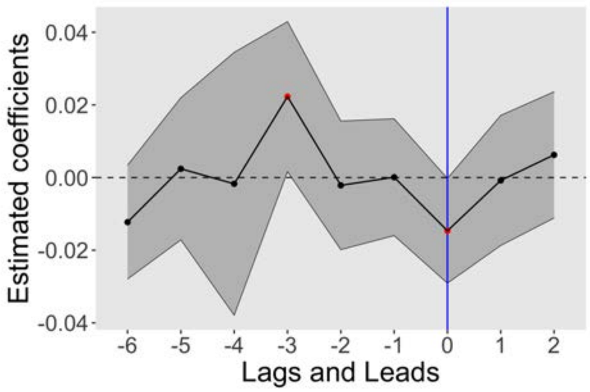
(c) **Mumbai map**



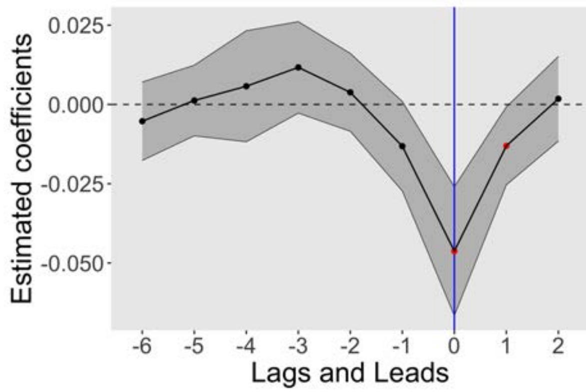
(d) **Mumbai GHS-UCDB extent**

Notes: Figure A.1a and Figure A.1c show the extent of Los Angeles region and Mumbai Metropolitan region. The shaded region in Figure A.1b and Figure A.1d shows the polygons used to define the urban boundaries of these cities in our analysis. Hence, our geographic coverage includes the core city and also covers a large part of the suburban areas.

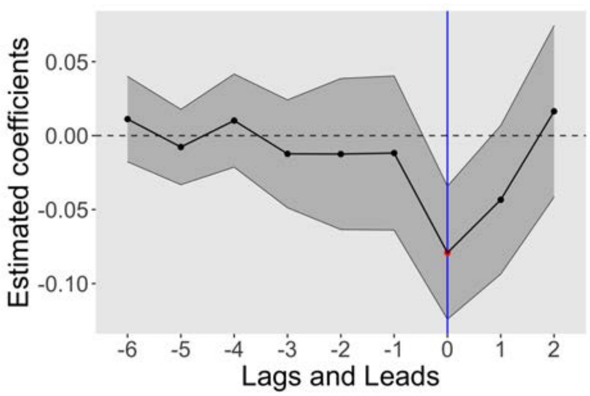
Figure A.2: Pre-Trend Analysis of Night Lights Intensity for high- & low-income countries



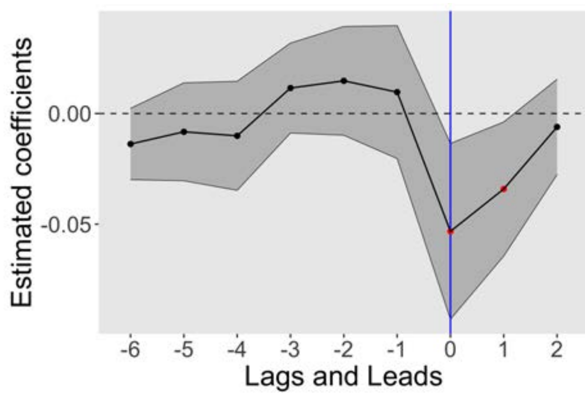
(a) High Income Cities: Floods



(b) High Income Cities: Extreme Precip.



(c) Low Income Cities: Floods



(d) Low Income Cities: Extreme Precip.

Notes: Figure A.2a and A.2c show the 6 month lag and 2 month lead around a flood event for cities in high- and low-income countries. The coefficients in the two plots are estimated by running a regression of $ln(\textit{Night Lights})_{cjmy}$, which is the natural log of mean light intensity in city c in country j in month m of year y, on the contemporaneous and 8 month leads and lags of the flood dummy, where $Flood_{cjmy}$ is a dummy indicating whether city c in country j was hit by a flood in month m of year y. All three models include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. 8 month leads and lags for these two disaster types have also been included as controls. Figure A.2b and A.2d show the 6 month lag and 2 month lead around an extreme precipitation event for cities in high- and low-income countries, which is a dummy indicating whether the precipitation in the month m and year y in city c in country j was greater than the 95$^{\text{th}}$ percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. The shaded ribbons in each plot represent the 95$^{\text{th}}$ confidence interval band. In all regressions, observations include city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

Table A.1: List of countries and share of cities

Country name	# of cities	%
Afghanistan	25	0.26
Albania	6	0.06
Algeria	92	0.97
Angola	42	0.44
Argentina	70	0.74
Armenia	3	0.03
Australia	27	0.29
Austria	6	0.06
Azerbaijan	15	0.16
Bahamas	1	0.01
Bahrain	1	0.01
Bangladesh	80	0.84
Barbados	1	0.01
Belarus	14	0.15
Belgium	12	0.13
Belize	1	0.01
Benin	20	0.21
Bolivia	12	0.13
Bosnia & Herzegovina	5	0.05
Botswana	7	0.07
Brazil	347	3.66
Brunei Darussalam	1	0.01
Bulgaria	7	0.07
Burkina Faso	27	0.29
Burundi	10	0.11
Cabo Verde	1	0.01
Cambodia	8	0.08
Cameroon	45	0.48
Canada	48	0.51
Central African Republic	6	0.06
Chad	23	0.24
Chile	33	0.35
China	1776	18.76
Colombia	87	0.92
Comoros	2	0.02
Congo	114	1.20
Congo	4	0.04
Costa Rica	3	0.03
Côte d'Ivoire	35	0.37
Croatia	6	0.06
Cuba	19	0.20
Curaçao	1	0.01
Cyprus	3	0.03
Czechia	12	0.13
Denmark	4	0.04
Djibouti	1	0.01
Dominican Republic	16	0.17
Ecuador	30	0.32
Egypt	182	1.92
El Salvador	9	0.10
Equatorial Guinea	2	0.02
Eritrea	2	0.02
Estonia	2	0.02
Eswatini	2	0.02
Ethiopia	86	0.91
Fiji	1	0.01
Finland	6	0.06
France	76	0.80
Gabon	3	0.03
Gambia	4	0.04
Georgia	5	0.05
Germany	87	0.92
Ghana	48	0.51
Greece	10	0.11
Guatemala	39	0.41
Guinea	17	0.18
Guinea-Bissau	3	0.03
Guyana	2	0.02
Haiti	21	0.22
Honduras	13	0.14
Hungary	11	0.12
Iceland	1	0.01
India	1563	16.51
Indonesia	311	3.28
Iran	172	1.82
Iraq	69	0.73
Ireland	5	0.05
Israel	9	0.1
Italy	91	0.96
Jamaica	4	0.04
Japan	109	1.15
Jordan	9	0.10
Kazakhstan	27	0.29
Kenya	38	0.40
Korea DPR	76	0.80
Korea Republic of	39	0.41
Kosovo	7	0.07
Kuwait	4	0.04
Kyrgyzstan	9	0.10
Lao	4	0.04
Latvia	3	0.03
Lebanon	7	0.07
Lesotho	1	0.01
Liberia	5	0.05
Libya	15	0.16
Lithuania	6	0.06
Luxembourg	1	0.01
Madagascar	6	0.06
Malawi	8	0.08
Malaysia	36	0.38
Mali	16	0.17
Malta	1	0.01
Mauritania	4	0.04
Mauritius	1	0.01
Mexico	157	1.66
Moldova	5	0.05
Mongolia	1	0.01
Montenegro	1	0.01
Morocco	59	0.62
Mozambique	38	0.40
Myanmar	86	0.91
Namibia	2	0.02
Nepal	9	0.10
Netherlands	37	0.39
New Zealand	8	0.08
Nicaragua	14	0.15
Niger	23	0.24
Nigeria	376	3.97
North Macedonia	7	0.07
Norway	4	0.04
Oman	11	0.12
Pakistan	168	1.77
Palestine, State of	7	0.07
Panama	6	0.06
Papua New Guinea	8	0.08
Paraguay	8	0.08
Peru	41	0.43
Philippines	90	0.95
Poland	46	0.49
Portugal	9	0.10
Puerto Rico	3	0.03
Qatar	3	0.03
Romania	27	0.29
Russian Federation	204	2.15
Rwanda	7	0.07
Saudi Arabia	43	0.45
Senegal	29	0.31
Serbia	13	0.14
Sierra Leone	9	0.10
Singapore	1	0.01
Slovakia	6	0.06
Slovenia	2	0.02
Solomon Islands	1	0.01
Somalia	18	0.19
South Africa	77	0.81
South Sudan	13	0.14
Spain	72	0.76
Sri Lanka	20	0.21
Sudan	52	0.55
Suriname	1	0.01
Sweden	12	0.13
Switzerland	16	0.17
Syrian Arab Republic	24	0.25
Taiwan	21	0.22
Tajikistan	14	0.15
Tanzania	38	0.40
Thailand	41	0.43
Timor-Leste	1	0.01
Togo	13	0.14
Trinidad and Tobago	4	0.04
Tunisia	26	0.27
Turkey	129	1.36
Turkmenistan	10	0.11
Uganda	23	0.24
Ukraine	78	0.82
United Arab Emirates	5	0.05
United Kingdom	138	1.46
Uruguay	6	0.06
USA	324	3.42
Uzbekistan	56	0.59
Venezuela	73	0.77
Viet Nam	128	1.35
Yemen	15	0.16
Zambia	35	0.37
Zimbabwe	19	0.20
Total	**9468**	**100**

Table A.2: Summary Statistics: Dams

Variable	Countries							
	China		India		Mexico		United States	
	Dams (1)	No Dams (2)	Dams (3)	No Dams (4)	Dams (5)	No Dams (6)	Dams (7)	No Dams (8)
Panel A								
Number of Cities	1,043	733	967	596	61	96	216	108
(% of Total)	(58.72)	(41.28)	(61.87)	(38.13)	(38.85)	(61.15)	(66.67)	(33.33)
Mean Elevation (m)	279.36	390.49	312.77	196.26	1187.82	1022.15	287.05	208.35
	[421.26]	[569.15]	[268.43]	[227.60]	[940.51]	[863.07]	[395.34]	[294.17]
Night Lights (nW/cm2/sr)	8.97	10.05	6.37	6.03	26.56	23.72	29.14	29.74
	[5.67]	[7.17]	[4.21]	[4.80]	[12.03]	[15.98]	[8.89]	[12.21]
GDP per capita (US$)	8,275.40	8,755.00	3,521.91	4,399.99	10,075.30	10,298.21	32,977.64	31,979.21
	[3,393.87]	[5,333.17]	[2,042.96]	[3,583.61]	[4,307.90]	[11,502.46]	[4,610.90]	[4,839.27]
Population Growth (%)	3.27	5.70	14.50	14.43	31.44	33.76	18.21	23.67
	[17.09]	[19.37]	[17.02]	[25.63]	[25.64]	[31.35]	[22.02]	[29.12]
Built-up Area (%)	38.60	39.99	19.13	19.73	52.57	49.29	66.24	62.99
	[13.37]	[14.27]	[8.98]	[10.67]	[14.03]	[11.66]	[6.82]	[8.97]
Panel B								
Number of Floods	5,978	2,985	1,228	1,192	20	18	152	77
(% of Total)	(66.70)	(33.30)	(50.74)	(49.26)	(52.63)	(47.37)	(66.38)	(33.62)
Average Floods	5.73	4.07	1.27	2.00	0.33	0.19	0.70	0.71
	[4.92]	[4.27]	[1.41]	[2.13]	[0.79]	[0.47]	[1.09]	[1.15]
Extreme Precip. Events	4,147	2,420	3,346	2,057	302	461	626	390
(% of Total)	(63.15)	(36.85)	(61.93)	(38.07)	(39.58)	(60.42)	(61.61)	(38.39)
Avg. Extreme Precip. Events	3.98	3.30	3.46	3.45	4.95	4.80	2.90	3.61
	[2.14]	[2.27]	[1.63]	[1.66]	[1.63]	[1.62]	[1.86]	[2.31]

Notes: This table provides summary statistics for cities with and without dams for four countries - China, India, Mexico, and the US. We classify the cities in each country based on whether they are protected by a dam. A city is defined as protected by a dam if the river flowing though the city has a dam upstream of the city and the geodesic distance between the city, and the dam is less than or equal to 100 kilometers. Panel A provides information on geographical and economic characteristics, while Panel B focuses on floods and extreme precipitation events. *GDP per capita* is measured in PPP 2015 US$. *Population Growth* is computed as the change in the population of a city between years 2015 and 2000. *Built-up Area* is defined as the percentage of the total area of the city (km^2) that contains built-up structures. Extreme Precipitation Events is a a dummy indicating whether the precipitation in the month m and year y in city c in country j (between the years 2012-2018) was greater than the 95^{th} percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. The *Average Floods* and *Average Extreme Precipitation Events* refer to the average number of such events during the years 2012-2018. Standard deviation for all variables are reported in brackets.

B Additional Results

Table B.1: Effect of Floods on Economic Activity over Time

	Dependent Variable: $ln(Night\ Lights_{cjmy})$					
	All		High Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)
$Flood_{cjmy}$	-0.079^{***}		-0.018		-0.200^{***}	
	(0.017)		(0.026)		(0.040)	
$Flood_{cjmy} \times Time\ Trend_{my}$	0.002^{**}		0.000		0.004^{**}	
	(0.001)		(0.001)		(0.002)	
$Extreme\ Rain_{cjmy}$		-0.062^{***}		-0.021^{***}		-0.136^{***}
		(0.006)		(0.007)		(0.013)
$Extreme\ Rain_{cjmy} \times Time\ Trend_{my}$		0.001^{***}		-0.001		0.004^{***}
		(0.000)		(0.000)		(0.001)
Fixed Effects						
City	✓	✓	✓	✓	✓	✓
Country × Month × Year	✓	✓	✓	✓	✓	✓
Num. obs.	663,161	663,161	341,899	341,899	321,262	321,262
Adj. R^2	0.952	0.952	0.935	0.935	0.930	0.930

Notes: clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(Night\ Lights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Extreme\ Rain_{cjmy}$ is a dummy indicating whether the precipitation in the month m and year y in city c in country j was greater than the 90 extsuperscriptth percentile of the city-specific distribution of precipitation, which was created using data from 1958-2018. $Time\ Trend_{my}$ is a continuous variable that takes the value from 1 to 81, with 1 representing the first month of the sample (April 2012), and 81 representing the last month (September 2018). Models (1), (3) and (5) include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. Two month leads and lags for all three disaster types have also been included as controls in the three models. Models (2), (4) and (6) include the two month lags and leads for *Extreme Rain*. The contemporaneous disaster dummy has been interacted with the linear and quadratic time trend in all models. Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city level.

Table B.2: Effect of Floods based on Productivity

	Dependent Variable: $ln(Night\ Lights_{cjmy})$					
	All		High Income		Low Income	
	(1)	(2)	(3)	(4)	(5)	(6)
$Flood_{cjmy}$	-0.089^{***}	-0.078^{**}	-0.043	-0.018	-0.161^{***}	-0.118^{***}
	(0.031)	(0.036)	(0.033)	(0.056)	(0.057)	(0.043)
$Flood_{cjmy} \times Productivity_{cj}$	0.012^{**}		0.004		0.029^{*}	
	(0.006)		(0.006)		(0.017)	
$Flood_{cjmy} \times Medium\ Productivity_{cj}$		0.029		-0.016		0.036
		(0.037)		(0.056)		(0.052)
$Flood_{cjmy} \times High\ Productivity_{cj}$		0.055		-0.005		0.112^{*}
		(0.037)		(0.058)		(0.060)
Fixed Effects						
City	✓	✓	✓	✓	✓	✓
Country × Month × Year	✓	✓	✓	✓	✓	✓
Num. obs.	61,636	61,636	32,967	32,967	28,669	28,669
Adj. R^2	0.953	0.953	0.926	0.926	0.936	0.936

Notes: two-way clustered robust standard errors in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.
The dependent variable in all regressions, $ln(Night\ Lights)_{cjmy}$, is the natural log of mean light intensity in city c in country j in month m of year y. $Flood_{cjmy}$ is a dummy indicating whether city c in country j was hit by a flood in month m of year y. $Productivity_{cj}$ refers to the average height of the city's buildings within 2 kms of the highest point in the said city. To create factor variables, $Productivity_{cj}$ was divided into three quartiles of equal size, with the omitted category in regressions being quartile 1, i.e. $LowProductivity_{cj}$. All regressions include the controls $Storm_{cjmy}$ and $Landslide_{cjmy}$, dummies indicating whether city c in country j was hit by a storm or landslide, respectively, in month m of year y. Two month leads and lags for all three disaster types have also been included as controls. Models (3) and (4) only include observations from *High Income* and *Upper Middle Income* countries, whereas models (5) and (6) only include observations from *Low Income* and *Lower Middle Income* countries. Observations include all city-country-month-year observations which had a non-zero value of nightlights. Each observation was weighted by the mean of the cloud free coverage for the city-country-month-year observation. Standard errors are clustered at the city and month-year level.

C Robustness Checks based on the New Difference-in-Difference Literature

Our empirical methodology involves using two-way fixed effects (TWFE) regression specification to estimate the effect of floods on economic activity. If we assume that the treatment effects are heterogeneous across time or units, the coefficients from a standard TWFE model may not be robust due to a negative weighting problem (see Roth *et al.*, 2022, for a review of this literature). This is a valid concern for our setting as we have 9,468 groups (each group is a city) and 81 periods (each month, from April 2012 to December 2018, is a period). As long as the effect of a flood varies across cities and/or changes over time, the standard common trends assumption may be violated, which makes it plausible that $\hat{\beta}_{fe}$ may not be robust to heterogeneous effects.

To address this, we first report the number of negative weights attached to the two-way fixed effects regressions for each specification using the *TwoWayFEWeights* package in R. Second, we report the degree of heterogeneity in treatment effects that would be necessary for the estimated treatment effect to have the wrong sign. Specifically, as shown by De Chaisemartin and d'Haultfoeuille (2020), the ratio of the absolute value of the expectation of $\hat{\beta}_{fe}$ and the standard deviation of the weights corresponds to the minimal value of the standard deviation of the treatment effect across the treated groups and time periods under which beta and the average treatment effect on the treated (ATT) could be of opposite signs. A large number signifies that the beta and the ATT can only be of opposite signs if there is substantial treatment effect heterogeneity across groups and time periods. A low number, on the other hand, implies that beta and the ATT can be of opposite signs even if there is not a lot of treatment effect heterogeneity. In that case, treatment effect heterogeneity would be a serious concern for the validity of that coefficient.