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Flooded Cities

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Abstract
Does economic activity relocate away from areas that are at high risk of recurring shocks? We examine this question in the context of floods, which are among the costliest and most common natural disasters. Over the past thirty years, floods worldwide killed more than 500,000 people and displaced over 650,000,000 people. This paper analyzes the effect of large scale floods, which displaced at least 100,000 people each, in over 1,800 cities in 40 countries, from 2003-2008. We conduct our analysis using spatially detailed inundation maps and night lights data spanning the globe's urban areas. We find that low elevation areas are about 3-4 times more likely to be hit by large floods than other areas, and yet they concentrate more economic activity per square kilometre. When cities are hit by large floods, the low elevation areas also sustain more damage, but like the rest of the flooded cities they recover rapidly, and economic activity does not move to safer areas. Only in more recently populated urban areas, flooded areas show a larger and more persistent decline in economic activity. Our findings have important policy implications for aid, development and urban planning in a world with rising urbanization and sea levels.

Keywords: urbanization, flooding, climate change, urban recovery
JEL codes: R11; Q54

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1 Introduction

Does economic activity within cities readjust in response to major shocks, which are potentially recurrent, and which disproportionately threaten specific neighborhoods? We examine this question in the context of floods, which are among the costliest and most recurring natural disasters.

According to media reports collated by the Dartmouth Flood Observatory, from 1985-2014 floods worldwide killed more than 500,000 people, displaced over 650,000,000 people and caused damage in excess of US$500 billion (Dartmouth Flood Observatory 2014). Other datasets tell of even farther reaching impacts: according to the International Disaster Database (EM-DAT – see Guha-Sapir, Below and Hoyois, 2015), in 2010 alone 178 million people were affected by floods and total losses exceeded US$40 billion. To these direct costs we should add longer term costs due to disruptions of schooling, increased health risks, and disincentives to invest.

If there were perfect housing markets one might argue that these risks must be balanced by gains to be had from living in flood-prone areas. But as Kydland and Prescott (1977) show in their Nobel-prize winning contribution, flood plains are likely to be overpopulated, because the cost of building flood defenses tends to be borne in part by people who reside in safer areas. This problem is exacerbated by the fact that reconstruction costs in the aftermath of floods are usually also partly borne in part by non-residents. This situation creates potential for misallocation of resources, and forces society to answer difficult distributional questions. Our paper examines how prevalent it is for economic activity to concentrate in flood-prone areas, and whether cities adapt to major floods by relocating economic activity to safer areas.

To frame our analysis, we outline a simple model, which considers how a large flood may affect an individual's decision to locate in safe or risky locations. The model predicts that flooding may cause people to relocate away from risky areas because of either Bayesian updating on the probability of a flood, or because the floods reduce the cost of moving relative to staying.

In our empirical analysis we study the local impact of large-scale urban floods. We use new data from spatially disaggregated inundation maps of 53 large floods, which took place from 2003-2008. The floods that we study affected 1,868 cities in 40 countries around the globe, but mostly in developing countries. These floods were all consequential, displacing over 100,000 people each. We study the economic impact of the floods using satellite images of night lights at an annual frequency.

Our data show that the global exposure of urban areas to large scale flooding is substantial, with low elevation urban areas flooded much more frequently. Globally, the average annual risk of a large flood hitting a city is about 1.3 percent for urban areas more than 10 meters above sea level, and 4.9 percent for urban areas less than 10 meters above sea level. These estimates likely represent a lower bound on urban flood risk since we do not have detailed flood maps for all the large flood events in the period we study. Of course, this average risk masks considerable variation across locations. Local flooding risk results from a complex combination of local climate, permeation, and topography, among other factors. Some urban areas – even if located at low elevation – will flood rarely, if ever, while others are exposed to recurrent flooding. For example, even in our relatively short sample period (January 2003 to May 2008), a substantial number of cities were flooded repeatedly in our data. Out of 34,545 cities in the world a little over 5 percent (1,868 cities) get flooded at least once in our data. Conditional on being flooded, about 16 percent were flooded in more than one year. This is consistent with systematically higher risk of flooding in these locations.

In spite of their greater exposure to large flood events, we find that across the globe, urban economic activity, as proxied by night light intensity, is concentrated disproportionately in low elevation areas. This disproportionate concentration of economic activity in flood-prone areas is found even for areas that are prone to extreme precipitation.

When we analyze the local economic impact of large floods, we find that on average they reduce a city's economic activity, as measured by night time lights, by between 2 and 8 percent in the year of the flood (the larger estimates come from using measures of extreme precipitation, rather than flooding). For low elevation areas – those less than 10m above sea level – these effects are even stronger.

Our results also show that recovery is relatively quick – lights typically recover fully within a year of a major flood, even in the hardest hit low elevation areas. This suggests that there is no significant adaptation, at least in the sense of a relocation of economic activity away from the most vulnerable locations. With economic activity fully restored in vulnerable locations, the scene is then set for the next round of flooding.[1]

A possible motivation for restoring vulnerable locations is to take advantage of the trading opportunities – and amenity value – offered by water-side locations. But we find that economic activity is fully restored even in low elevation locations that do not enjoy the offsetting advantages of being near a river or coast. Our results are also robust to excluding cities that are entirely less than 10m above sea level, where movement to higher ground within the existing urban area in response to a flood is not an option.

One exception to our general finding that cities do not adapt in response to large floods, can be found in the subset of recently populated parts of cities. These areas, which we define as unlit during the first year that we observe night lights (1992), account for just 13 percent of the urban areas that we study. We find that in these recently populated urban areas, flooded areas show a larger and more persistent decline in night light intensity, indicating a stronger and more persistent relocation of economic activity in response to flooding. These results might be due to information updating or fewer sunk investments, in line with the predictions of our theoretical model.

Our results are important for a number of reasons. First, the trend towards increased global urbanization is ongoing; presently, just over half of the world's population lives in urban areas, and this is expected to rise (United Nations 2008). As urbanization progresses, it is important to know whether cities have ways to adapt and avoid dangerous areas. Our results suggest that flooding poses an important challenge for urban planning because adaptation away from flood-prone locations cannot be taken for granted even in the aftermath of large and devastating floods.

Second, floods disproportionately affect poor countries. Given the scale of human devastation, and its potential to affect the formation of human capital (for example disruptions to study or

[1] We cannot rule out adaptation in the form of new or improved flood defenses. But most of the world's flooded urban areas are too poor to finance substantial flood defenses. Even where such defenses are built, they typically represent a publicly funded solution, rather than private adaptation.

health damages) this is an important issue for growth and development. Specifically, in developing countries planning and zoning laws and their enforcement are weak. Consequently, slums and other informal urban settlements tend to develop on cheap land with poor infrastructure, which includes flood-prone land (Handmer, Honda et al 2012). More than 860 million people live in flood prone urban areas worldwide. Annual increases of 6 million a year were observed between 2000 and 2010. Our finding that low elevation areas concentrate much of the economic activity even in poor urban areas with erratic weather patterns highlights the tragedy of the recurring crisis imposed by flooding.

Third, global warming and especially rising sea levels are expected to further exacerbate the problem of flooding. The threat of rising sea levels is not confined to developing countries and small island nations. Based on the extent of sea level rise that we now expect given cumulative emissions through 2015, Strauss, Kulp and Levermann (2015) identify 414 US municipalities that would see over half of their population-weighted area below future high tide levels. For continued, business-as-usual emissions scenarios, by 2100 this estimate rises to some 1,540 municipalities, which currently are home to more than 26 million people. Hallegatte et al. (2013) find that global average annual flood losses of US$6 billion in 2005 could reach US$52 billion by 2050. Under a scenario characterized by climate change and subsidence but no adaptation this amount could increase to US$1 trillion or more per year. Understanding the extent to which people relocate away from stricken areas is vital for assessing the costs of increases in floods (Desmet et al 2015, Desmet and Rossi Hansberg 2013, Kahn and Walsh 2014). Our findings on the resilience of cities suggest that the degree of responsiveness is rather low, and consequently the costs of increased flooding risk may be higher than currently anticipated.

Fourth, recovery assistance after flooding is an important part of international aid. Our findings suggest that part of the aid and reconstruction efforts should be targeted at moving economic activity away from the most flood-prone areas, in order to mitigate the risk of recurrent humanitarian disasters, and reduce the costs of bailing out future flood victims.

Finally, our results are relevant for discussions of the costly effects of path dependence (Bleakly and Lin 2012, Michaels and Rauch 2013). Our findings suggests that cities and parts of cities, which are built in flood-prone areas, may be locking in exposure to flood risk for a long time, even when circumstances and the global climate change.

The remainder of the paper is structured as follows. We present a simple model of how an individual may respond to a flood in Section 2, discuss related literature in Section 3, describe the data in Section 4, present our main results in Section 5 and conclude in Section 6.

2 Theory

To frame our empirical investigation, we outline a simple framework that allows us to consider how individuals may respond to a large flood. We consider a discrete-time model, where a person has to choose between two locations, one to which we refer as "Risky" (indexed by R) and another which we will for simplicity consider "Safe" (indexed by S).

The person in question resides initially in the risky location, and considers whether to relocate to the safe location. The period utility of the person from the risky location is

$$U_R = C_R - P_F(D_F - T_F), \tag{1}$$

where C_R is the consumption value of residing in the risky location; P_F is the assessed probability of a flood, which we discuss below; D_F and T_F are the damage from a flood and the transfers received in the aftermath of a flood.

The period utility from the safe location is

$$U_S = C_S, \tag{2}$$

but in order to move the person has to pay relocation costs M, which capture the cost of moving. We also assume that once a flood has hit the person has to pay the cost M regardless of whether they move or stay, since the flood implies paying costs of renovating over and above those captured by D_F. The point of this simplifying assumption is that when a flood hits, the cost of moving (compared to staying) is lower than in the absence of the flood.

The choice over relocation represents an infinite horizon problem, with discount rate θ. Given the simple structure of the model, however, our individual relocates from the risky to the safe location if:

$$C_S - C_R + P_F(D_F - T_F) > M. \tag{3}$$

An important factor in this model is how the person assesses the probability of a flood. Following Turner (2012) we model flooding through a Beta-Bournoulli Bayesian learning model.[2] We assume that the risk of a flood (by which we mean a large flood) in a given year is x. Our resident's prior is that x is distributed according to a Beta distribution: $x \sim \beta(\alpha, \beta)$. The probability distribution function is:

$$f(x|\alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1}(1-x)^{\beta-1}, x \in [0,1], \alpha > 0, \beta > 0, \tag{4}$$

where the normalization constant is the Beta function:

$$B(\alpha, \beta) = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}\, dx. \tag{5}$$

The prior probability of a flood is therefore

$$P_F = E[x] = \frac{\alpha}{\alpha + \beta}. \tag{6}$$

[2]As we explain below this is a simplification, since this probability can rise with climate change, or decline with public investment in climate change.

After observing t years, during which a flood has occurred S_t times, the updated posterior is:

$$E[x|t, S_t] = \frac{\alpha + S_t}{\alpha + \beta + t}. \tag{7}$$

In other words, for an individual who has information on flood events in the past t years, the expected probability of a flood next year increases by $1/(t+\alpha+\beta)$ if a flood took place in year t compared to the case where it did not. As t approaches infinity there is no updating. The model captures the intuition of Bayesian learning: as t approaches infinity there is no more updating, since the degree of risk is known.

This simple model guides our empirical investigation in the following ways. First, we investigate the link between risk and low elevation locations. Anticipating and quantifying flood risk in the real world is a complicated endeavor, but we ask specifically how much more susceptible to large scale flooding are low elevation locations, compared to high elevation ones. This informs us about the approximate magnitude of P_F.

Second, we ask whether people generally reside in riskier low elevation urban areas. In the model, the benefits to living in risky areas (if $C_R > C_S$), or moving costs, M, might make it prohibitively expensive to relocate. One set of advantages for risky areas could be that living near coasts or rivers makes seaborne activities, such as trade and fishing, less costly. At the same time, living in flood prone areas may be the legacy of historical lock-in (Bleakly and Lin 2012; Michaels and Rauch 2013).

Third, we examine whether the presence of higher risk of flooding due to climatic factors shifts people towards safer areas. In our model, an increase in P_F holding all else constant, shifts people away from risky low elevation areas.

Fourth, floods may cause people to leave the riskier areas because of either Bayesian updating, or because floods reduce the cost of moving to safer areas (relative to staying in the riskier ones). Our paper examines the extent to which large floods move economic activity away from risky areas towards safer ones.[3]

Fifth, because updating decreases in t, we expect that there will be more updating in newly populated urban areas. In the empirical analysis we examine whether there is more relocation from riskier to safer areas in the aftermath of a flood in urban areas that concentrated no (measurable) economic activity until recently.

Going beyond what we can test directly, the model raises a number of additional issues. In particular, climate change and rising sea levels may make areas riskier than they were historically. In general, this may affect the riskiness both of areas that are currently perceived as safe as well as those perceived as risky. But it seems plausible to assume that at least in the near future, it is in the low elevation areas that rising sea levels will have a greater effect.

[3]In reality even if people update and move away from risky areas in the aftermath of a flood, uninformed newcomers might take on the risk and move into abandoned (or cheap) flooded areas. In general, if floods make risky areas less attractive, the price reduction could draw in more people. In an extreme case, if the supply of housing in both risky and safe locations is fixed, then floods would not change the relative population density of both locations. But if housing supply is somewhat elastic, then safe areas may become relatively denser.

Our analysis also touches upon a number of normative considerations. As Kydland and Prescott (1977) note, flood protection may exacerbate the moral hazard problem of living on the flood plains. By spending public money to reduce the risk borne by those living in flood prone areas, such flood protection involves a cost. At the same time, as our paper shows, people may be reluctant to relocate away from risky areas. As sea levels rise and the world becomes richer, the tradeoffs between flood protection and the relocation of economic activity to safer areas are likely to become an important issue for public debate (see Strauss, Kulp and Levermann, 2015).

Another normative issue is how much ex-post transfers should victims receive, and in what form. In the model, a larger value of T_F makes movement away from risky areas less likely. From the perspective of a donor, if a property is frequently flooded, the costs of repeatedly paying compensation might be high. In developing countries where institutions are weak, finding private flood insurance may be a difficult challenge, especially for the poor. Ex-post disaster relief, including from large scale floods, is therefore a task that governments and non-government organizations around the world engage in from time to time. The main policy issue that we raise is whether it should be possible, in certain circumstances, to concentrate public reconstruction efforts towards safer areas, in order to avoid the high risk of recurrent disasters.

3 Related Literature

This paper contributes to a number of active strands of literature in urban economics, economic development, and the economics of disasters and climate change.

First, our paper speaks to the literature on the economic impact of floods and other natural disasters. Closely related to our study is Boustan, Kahn, and Rhode (2012), who look at the migration response to natural disasters in the US during the early twentieth century. They find movement away from areas hit by tornadoes but towards areas prone to flooding, possibly due to early efforts to build flood mitigation infrastructure. In a more modern setting, differences in migration responses by disaster type were also observed in research by Mueller, Gray and Kosec (2014) on determinants of out-of village migration in Pakistan. They find that heat stress, and not high precipitation or flooding, is associated with long-term migration. Also closely related is Hornbeck and Naidu (2014), who examine the Mississippi Flood of 1927, which led to out-migration of African Americans and a switch to more capital intensive farming. Our paper differs from most of these studies in its scope (we examine areas around the world, especially in developing countries), its timing (we examine much more recent floods), and its focus on urban areas and recurrent shocks. Our findings are also different, indicating that persistence of economic activity in risky areas is a concern.

A related strand of literature examines the updating of beliefs and changes in risk perceptions in the aftermath of natural disasters. Turner (2012) presents a model of Bayesian learning, where individuals update their risk assessments based on recent experience of disasters. Using data on US county level population, Turner finds evidence that population declines are more pronounced following a larger than previously experienced hurricane. Related papers include Cameron and Shah (2010) who find evidence of increased risk aversion among individuals in rural Indonesia who had over the past three years experienced first-hand a flood or an earthquake. Similarly, Eckel et al. (2006) note, based on interviews with a sample of Hurricane Katrina evacuees, that psychological factors such as levels of stress in the aftermath of an event influence individual risk aversion. Other case studies of floods include papers on the effect of Hurricane Katrina on the development of New Orleans and its residents (Glaeser 2005, Basker and Miranda 2014, Deryugina, Kawano and Levitt 2014), on the consequences of the Tsunami of 2004 (de Mel, McKenzie and Woodruff 2012), and Typhoons in China (Elliott et al. 2015). Also related are studies of the effect of flooding on house prices in the Netherlands (Bosker, Garretsen et al. 2015). Global studies include Hsiang and Jina (2014), who study the effect of cyclones on long run economic growth worldwide, and Cavallo et al (2013), who study the effect of natural disasters on GDP. Floods are generally more difficult to locate with great precision than, say, earthquakes or tropical storms.[4] Our innovation is to combine detailed inundation maps with information on elevation, which is well measured globally and at high resolution. This approach allows us to conduct precise within-city analysis at the global level - the first such analysis for floods that we are aware of.

Second, our study is related to the broader analysis of urban responses to large scale shocks. Two other recent papers that analyze the adaptation which takes place within cities to large scale shocks are Hornbeck and Keniston (2014), who analyze the recovery of Boston from the fire of 1872, and Ahlfeldt et al. (2015), who analyze the reorganization of Berlin in response to its division and reunification. Both are important case studies of large once-off shocks, whereas the shocks we study are more recurrent. Several other papers investigate urban destruction and recovery in the aftermath of wars, epidemics and other calamities (Davis and Weinstein 2002, Brakman et al 2004, Miguel and Roland 2011, Paskoff 2008, Beeson and Troesken 2006). Our study adds both a global perspective, since we analyze shocks around the world, but also a more localized perspective, since we examine what happens within cities. Whereas most of this literature has interpreted the recovery from shocks in a positive way, our finding that there is no shift in economic activity towards higher ground is not necessarily such a positive message.

Third, our study relates to a growing literature on urbanization in developing countries (Barrios et al. 2006, Marx et al 2013, Henderson et al 2014, and Jedwab et al 2014). We contribute to this literature by highlighting the causes of some of the costs of cities in poor countries. Our paper also relates to a literature on the use of night lights data for empirical analyzes of economic growth (Henderson et al 2012, Michalopoulos and Papaioannou 2014). The night lights data allow us to measure economic activity at a fine spatial scale, and to do so even in countries where data quality is poor. A limitation with the use of night lights is that the effect of disasters on power plants may be hard to distinguish from the destruction of buildings and infrastructure. This problem is mitigated in our study, since we focus primarily on the differential effect of treatment by elevation within flooded cities. While measurement error could attenuate our estimates, we still find that low elevation areas are hit more often and harder than other areas.

Finally, our paper also relates to the literature estimating the costs of climate change and sea level rise (Hanson et al 2011, Hallegatte et al 2013, Desmet et al. 2015, Tessler et al. 2015). Coastal cities feature prominently in this large literature, given their current and future exposure

[4]Of course, flooding is sometimes the result of tropical storms – as is the case for 10 of the 53 large flood events included in our sample. These storms include hurricanes, cyclones, and typhoons, which are different names given to the same type of tropical storm that occurs in different parts of the world. While wind field models, combined with detailed storm track data, can allow precise estimation of the location and intensity of winds associated with tropical cyclones (see e.g. Strobl 2011), this method may not identify the precise extent of associated flooding.

to flooding in particular. One important factor in assessing the long term impact of flooding is adaptation, or the degree to which people move away from environmentally dangerous locations. Our study suggests that adaptation responses may be inadequate, and consequently the costs of increases in future flooding may be higher than anticipated.

4 Data

The dataset that we compile for our empirical analysis comprises data on flood locations, physical characteristics of locations (including elevation and distance to rivers and coasts), precipitation, urban extents, population density and night light intensity, all mapped onto an equal area one kilometer-squared grid covering the entire world (using the Lambert cylindrical equal area projection). The data are drawn from a number of sources as detailed below.

Floods

The primary data for our analysis are the flood maps that we use to identify flooded locations. These come from the Dartmouth Flood Observatory (DFO 2014). The DFO database includes information on the location, timing, duration, damage, and other outcomes for thousands of flood events worldwide from 1985-2015. These data were compiled from media estimates and government reports. While we use this database to derive general statistics about floods, our paper is focused mostly on a subset of floods for which DFO provides detailed inundation maps (which we discuss in more detail below). These maps were produced predominantly for the period 2003-2008, and even for that period they do not cover all large floods (see below).[5]

In this paper we focus on the most devastating flood events, which (according to DFO) displaced at least 100,000 people each, to which we sometimes refer in short as “large floods”.[6] Our focus on large floods with available inundation maps, left us with a sample of 53 large flood events that affected 1,868 cities in 40 countries worldwide from 2003-2008. This sample represents a majority (55 percent) of displacement-weighted events, which took place during this period, according to the DFO database (see Table 1). Table 1 also provides a count of events displacing more than 100,000 people per year, based on the complete DFO database. The table suggests that the period of our main sample (2003 - 2008) was one with a particularly high number of large flood events. The higher frequency of large floods during our period of analysis compared to other periods could reflect an actual change in flood devastation over time and/or more intensive documentation by DFO, as suggested by the availability of detailed inundation maps for this period.

The locations of the large flood events in our sample are illustrated on the world map in Figure 1. The map shows all urban areas in the world (in light grey). City sizes are inflated – even more so

[5]Some maps for earlier and more recent events exist on the DFO website, which were less detailed and/or not fully processed and were therefore not directly comparable.

[6]For comparability we used displaced as indicator of intensity instead of the traditional 1 in 10 year flood, 1 in 100 year flood, etc. Our choice is motivated by our interest in floods that are devastating to human lives in an absolute sense, and not just relative to local precipitation patterns. We also note that DFO ‘displaced’ figures are an attempt to estimate the number of people who were evacuated from their homes due to floods. These estimates are not exact, and may cover both temporary displacement and events where people’s homes were permanently destroyed.

for flooded cities – in order to make them more clearly visible on a map of the entire world. The map shows locations that were affected by large floods, with darker shades representing higher frequencies of flooding. The number of floods in the legend refers to the number of years during our main sample period (2003-2008) in which each city was affected by a flood that displaced a total of 100,000 people or more. As the map illustrates, large urban floods are especially common in South and East Asia, but they also afflict parts of Africa and the Americas.[7]

The patterns that the map reveals are not coincidental. Large-scale flooding usually involves heavy precipitation, so it mostly occurs in tropical or humid sub-tropical areas. Of course other areas are not immune from large floods due to tropical storms (e.g. hurricane Sandy in the New York Area in 2012) and Tsunamis (the 2011 Tsunami in Japan), which fall outside our period of analysis. Large-scale urban flooding also typically occurs more often in densely populated areas, such as the basins of the Ganges, Yangtze, and Yellow rivers. Finally, large-scale flooding more commonly occurs in developing countries, where flood defences are weaker (or non-existent). But again the examples mentioned above, and the large flooding events in Louisiana and Florida (shown on our map) show that rich nations are by no means immune.

The DFO flood maps are constructed from satellite images. Flood outlines based on satellite imagery are translated by DFO into Rapid Response Inundation maps showing the extent of area that is flooded – often for different days during a given flood event. It is very likely that the DFO maps understate the true extent of flooding in each event, in part due to cloud cover obstructing the view from the satellites, or in part because the extent of flooding is not documented for every point in time. Furthermore, as explained above, some large flood events do not appear on any inundation maps. For this reason, cities that never appear in the database might nonetheless be flooded in a given year, and we restrict most of our analysis to cities that appear as flooded in at least one inundation map. Since we are concerned that the documented high water marks of floods within cities might understate the actual one, we do not use information on the extent of flooding within cities. Instead, we define a city as flooded in a given year if at least one gridpoint within it is flooded (by a large flood) in that year. An example of one of our flood maps, in this case the flooding associated with Hurricane Katrina in the city of New Orleans and its environs in 2005, is given in Panel A of Figure 2.[8]

Several types of extreme events caused the 53 large floods that we analyze: heavy precipitation (42 events, of which 12 are due to monsoonal rain), tropical storms (10 events), and a tidal surge (the 2004 Tsunami). Since tropical storms can cause damage from wind as well as flooding, we discuss regression results showing that precipitation, rather than wind damage, is likely the main driver of our results. Taken together, DFO estimates suggest that the 53 flood events displaced almost 90 million people, of which 40 million were displaced in the 2004 floods in India and

[7]Europe and Australia are also not immune from large floods, but during the period that we examine they were not affected by large floods covered by DFO inundation maps.

[8]This and other DFO inundation maps are available as image files from `http://floodobservatory.colorado.edu/Archives/MapIndex.htm`. Different color codes are used in these images to indicate flood extents at different points in time (and also across flood events). Our approach to digitizing these images captures the mainly red and pink hues used by DFO to show the flooded areas. Specifically, we use the following code to capture flood extents: $((``MAP_{id}.jpg - Band_1" > 240)\&(``MAP_{id}.jpg - Band_2" < 180)\&(``MAP_{id}.jpg - Band_3" < 180))|((``MAP_{id}.jpg - Band_1" > 80)\&(``MAP_{id}.jpg - Band_2" < 10)\&(``MAP_{id}.jpg - Band_3" < 10))|((``MAP_{id}.jpg - Band_1" > 245)\&(``MAP_{id}.jpg - Band_2" < 215)\&(``MAP_{id}.jpg - Band_3" < 215))$. We georeferenced each map in ArcGIS to identify its precise location, enabling the creation of a digital shape file identifying locations affected by each of the events included in our sample.

Bangladesh.

Night-time light data

To identify the economic effects of floods at a fine spatial scale, we use data on night lights as a proxy for economic activity. These data are collected by satellites under the US Air Force Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS). The satellites circle the earth 14 times each day, recording the intensity of Earth-based lights. NOAA's (National Oceanic and Atmospheric Administration) National Geophysical Data Center (NGDC) processes the data and computes average annual light intensity for every location in the world. An average 39.2 (s.d. 22.0) nights are used for each satellite-year dataset. Light intensity can be mapped on approximately one-kilometer squares and are thus available at much higher spatial resolution than standard output measures. The data are available annually from 1992 - 2013. For some years more than one dataset is available. Where this is the case, we chose datasets so as to minimize the number of different satellites used to collect the data.[9]

While these data are well suited for studying local economic developments on a global scale, they are not without limitations. One concern is that the use of different satellites for different years may result in measurement error. We address this concern by including year fixed effects in all our specifications. Another limitation is that the lights data range from 0-63, where 63 is a top-coded value. While imperfect, we note that most of the floods that we analyze affect developing countries where much of the light activity is below the top-coded level, and this point emerges clearly from the descriptive statistics.[10] For our main sample of cities affected by at least one of the large floods the proportion of top-coded cells varies from just 1.4 percent to 5 percent over the period 2003-2008. Lastly, we note that the lights datasets also include light related to gas flares. Our data processing included the removal of gas flaring grid points from the data (as in Elvidge, Ziskin, Baugh et al. 2009).[11]

An example of a light intensity map for the city of New Orleans and its environs is provided for the years 2004, 2005 and 2006 in Panels B, C and D of Figure 2. The three panels illustrate how light intensity in the city looked in the year prior to the flood caused by Hurricane Katrina (2004 - Panel B), in the year of the flood (2005 - Panel C) and in the year following the flood (2006 - Panel D). One can see a distinct dimming of the lights in the year of the flood (2005 - Panel C), relative to the previous year (2004 - Panel B). This pattern is particularly pronounced in the North-Eastern parts of the city, corresponding to the worst affected areas, according to the DFO flood map in Panel A of Figure 2. The light intensity map in Panel D of Figure 2 (2006) appears to show a restoration of light intensity in the city to levels that are fairly close to those observed prior to the flood. The example of Hurricane Katrina also demonstrates that despite the top-coding and any measurement error, even in a rich country such as the US, the effects of floods are visible from light activity. Nevertheless, we should emphasize that New Orleans is atypical of our data; the vast majority of the large flood events that we analyze take place in poorer countries.

[9] We use data from Satellite F10 for 1992-1993; from Satellite F12 for 1994-1999; from Satellite F15 for 2000-2007; from Satellite F16 for 2008-2009; and from Satellite F18 for 2010- 2012.

[10] Aside from top-coding, the specification of the light intensity measure involves low levels of light set to zero. This might be a further source of measurement error, although is less likely a concern for our analysis, given the focus on urban areas. In our data there are only about 5.5 percent of observations coded zero, which is not surprising given how urban extents are identified in the GRUMP data (see subsection).

[11] Only 0.0057 of gridpoints fall in this category.

Urban extents

We focus our analysis on urban areas, as defined by the Global Rural-Urban Mapping Project (GRUMP) urban extent grids from the Center for International Earth Science Information Network (CIESIN) at Columbia University, for the year 1995 (GRUMPv1, 2015). To keep the analysis tractable, we treat these boundaries as fixed. Urban extents are defined either on the basis of contiguous lighted cells using night-time light data or using buffers for settlement points with population counts in 1995 greater than 5,000 persons (CIESIN 2011). For our analysis we split urban areas that span multiple countries into distinct units, so that we can assign each urban area to the country in which it lies. This gives us a total of 34,545 urban areas. However, for our main specifications, we restrict our analysis to urban areas that were hit at least once by a large flood in our data - a sample of 1,868 cities. We also take population density data at one-kilometer square resolution from the same source.[12]

Other data

In our analysis we also use data on elevation (in meters above sea level), which are taken from the US Geological Survey (USGS), and data on distance to (nearest) coasts and rivers (in kilometers) from the same source. The elevation data come from the GTOPO30, a global digital elevation model.[13] The data on elevation are spaced at 30-arc seconds and cover the entire globe. As with all our data these are projected from geographical coordinates to an equal area projection (Lambert cylindrical equal area) and fitted onto our 1 square kilometer grid.

We also obtain monthly precipitation data on a 0.5 x 0.5 degree cells resolution from the Climatic Research Unit (CRU) at the University of East Anglia (Jones and Harris, 2013).[14] We use these data to construct extreme precipitation indicators for locations that experience monthly precipitation in excess of 500mm (or 1000mm) at least once in a given year.[15] Although extreme precipitation is by no means a perfect predictor of flooding for a particular location, it has the advantage of being an exogenous source of variation in flood location and timing. We use these extreme precipitation indicators as alternative explanatory variables to mitigate against endogeneity concerns with respect to our flood indicator.

5 Results

We begin with a cross-sectional analysis of flood exposure and the concentration of economic activity, by location, using the full sample of all urban areas in the world.

[12]We use population density data adjusted to match UN total estimates ("ag") not national censuses ("g").

[13]GTOPO30 is the product of collaboration among various national and international organizations under the leadership of the U.S. Geological Survey's EROS Data Center. See `https://lta.cr.usgs.gov/GTOPO30`.

[14]A 0.5 x 0.5 degree cell measures approximately 60km x 60km at the equator. At higher latitudes the East-West dimension of these cells becomes smaller. For example, the highest latitude city in our main sample is located at about 39 degrees North. At this latitude, a 0.5 x 0.5 degree cell measures roughly 42km (East to West).

[15]These are relatively rare events. About 15 percent of urban gridpoints in the world have experienced monthly precipitation exceeding 500mm at least once during the period 1992-2012, while only 1.2 percent of urban gridpoints in the world experienced monthly precipitation exceeding 1000mm at least once during the period 1992-2012.

We first examine the nature of global urban flood risk, using information from our inundation maps. In Table 2 we test how exposure to large urban flooding (events that displace at least 100,000 people) depends upon location characteristics. We regress a measure of the frequency of flooding on an indicator for low elevation (being no more than 10 meters above sea level) and controls, for the full sample of all urban areas. The regressions reported in Table 2 are of the following form:

$$FloodFreq_{ik} = \beta_{11} + \beta_{12}(Elev < 10m)_i + \beta_{13}River_i + \beta_{14}Coast_i + Country_k + \epsilon_{ik}. \quad (8)$$

The left hand side represents the frequency of flooding for a given location, measured as the number of years during our main sample in which each location is hit by at least one large flood event, divided by the length of the sample.[16] The sample here is all urban gridpoints in the world, based on the 1995 GRUMP definitions, discussed above. The right hand side includes dummy variables for locations that are less than 10m above sea level ($Elev < 10m_i$), less than 10km from the nearest river ($River_i$) or coast ($Coast_i$). Columns (5) to (8) include country fixed effects. To account for spatial correlation, we cluster the standard errors by country, which is a more conservative approach than that taken in most of the literature.

We find that globally, urban flooding risk by this measure is around 1.3 percent per year for areas at least 10m above sea level (based on the intercept of Column 1). low elevation areas are substantially more likely to be in a city affected by flooding. For urban areas less than 10m above sea level, the annual risk of being hit by a large flood rises to about 4.9 percent[17], i.e. an annual probability of almost one in 20 of being hit by a flood that displaces at least 100,000 people. That is likely an underestimate of global flood risk, since there may on (rare) occasions be more than one event per city per year, and also because that we only have inundation maps for fewer than half the events in our sample period (January 2003 - May 2008). At the same time, it is possible that the period we study may have been especially bad. From the information in Table 1 it does appear that 2003-2008 was a period with a relatively high number of large flood events.

Looking beyond the means, cities close to coastlines or rivers do not appear to face significantly higher flood risk than other urban areas, according to our data, although the estimates for rivers are non-trivial in magnitude and marginally significant; see Columns (2)–(4), and (6)–(8) of Table 2. We also note that the estimated effect of elevation is a bit less precise when we control for country fixed effects, although the magnitude is fairly similar to the estimates without fixed effects.

We next investigate whether economic activity concentrates disproportionately in flood-prone urban areas – specifically locations that are low elevation, and those that are exposed to extreme precipitation, or both. To investigate this question, we regress light intensity at each gridpoint (in 2012) on an indicator for low elevation (being less than 10m above sea level), an indicator for being exposed to high levels of precipitation in a single month, an interaction of the two, and

[16] In practice, we only have data on floods up to May 2008, so that our sample spans five years and five months. To capture the likelihood of flooding per year for a given location, the dependent variable here is generated by dividing the number of years (2003-2008) in which a location is hit by a large flood, by the length of the sample, i.e. five years and five months (or 65/12).

[17] Summing the intercept and the coefficient on the low elevation indicator, i.e. $0.013 + 0.036$.

controls, for the full sample of all urban areas. The precise specifications reported in Table 3 are of the following form:

$$ln(Y_{ilk}) = \beta_{21} + \beta_{22}(Elev < 10m)_i + \beta_{23}Precip_l + \beta_{24}Precip_l \times (Elev < 10m)_i + Country_k + \epsilon_{ilk}, \quad (9)$$

where the left hand side is the natural log of mean light intensity (in 2012) at each gridpoint i (located in grid cell l, in country k).[18] The right hand side includes the low elevation indicator, an indicator for areas that have experienced extreme precipitation in a single month at least once in the period 1992-2012, and the interaction of these two indicators. Each specification also includes country fixed effects. Columns (4), (7) and (10) add city fixed effects. Columns (3), (4), (6), (7), (9) and (10) add river and coast dummies, defined above. We include three different versions of the extreme precipitation indicator: These indicate locations that experience more than 1000mm (500mm) of precipitation in a single month at least once in the period 1992–2012, or monthly precipitation of 500mm or more at least twice during that period.

The results reported in Table 3 show that low elevation areas are more lit relative to country averages – as indicated by the coefficients on the elevation dummy (in the first row), which are all positive (and significant in Columns 1–3, 5–6 and 8–9). These results suggest a greater concentration of economic activity in low elevation areas. These areas are also, as we might expect, more vulnerable to large floods – i.e. they get hit more frequently – as demonstrated in the previous analysis (described above and reported in Table 2). Even in the specifications that include city fixed effects (Columns 4, 7 and 10), the coefficients on the elevation dummy are positive, although only in one of them (Column 4) is the estimate precise at conventional levels.

Looking at the interactions between the low elevation indicator and the extreme precipitation indicators (in Columns 2–10), we find again that even in areas that experience monthly precipitation exceeding 500mm at least once, low elevation areas are still more lit relative to country averages (Columns 5 and 6), and no less lit than city averages (Column 7). For areas that experience monthly precipitation exceeding 500mm at least twice, low elevation areas are again found to be more lit relative to country averages (Columns 8 and 9), and no less lit than city averages (Column 10). For areas exposed to monthly precipitation exceeding 1000mm at least once, low elevation areas are no less lit than country or city averages (Columns 2–4). All of these findings are also robust to including controls for proximity to the nearest river or coast (Columns 3, 4, 6, 7, 9 and 10).

Taken in the aggregate, the results in Table 3 indicate that globally, urban economic activity is concentrated disproportionately in low elevation areas, which are more prone to flooding, and this is even true in regions that are prone to extreme rainfall.

We also experiment with variations of the specifications presented in Table 3 to investigate if certain types of countries are better at avoiding concentrating economic activity in low elevation, flood-prone locations. Specifically, we examine the effects of national income and democracy on the location of economic activity, as proxied by the intensity of night lights. The results are reported in Table A1, and they suggest that democracies (classified as having a Polity IV score

[18] Precipitation is measured at the grid cell level, where cells measure 0.5 x 0.5 degrees.

in 2008 greater than or equal to five) are better at avoiding concentrating economic activity in flood-prone locations. On the other hand, we find that richer countries are not significantly different from poorer ones in avoiding flood-prone areas.

We next move to the panel analysis of the local economic impacts of large urban floods. Here the dataset consists of a panel of gridpoints (i) located in city (j) in country (k) with time dimension (t). In order to focus the analysis on changes over time within areas that are prone to large-scale flooding, we restrict the sample to gridpoints in cities that are affected by a large flood at least once in the sample, excluding other cities, many of which may be qualitatively different and may never flood.

In our analysis, we use variation over time in the occurrence of flooding (and later, also extreme precipitation), by estimating equations of the form:

$$ln(Y_{ijkt}) = \beta_{31} + \beta_{32}Flood_{jt+s} + Gridpoint_i + Year_t + Country_k \times Trend_t + \epsilon_{it}, \qquad (10)$$

where Y_{ijkt} is mean light intensity in gridpoint i (located in city j, in country k) in year t and $Flood_{jt+s}$ is a flood dummy, indicating whether or not city j was hit by a large flood in year $t+s$. We include gridpoint and year fixed effects and country-specific trends.[19] As a robustness check, we re-estimate our regressions with dynamic panel specifications, which include a lagged dependent variable, instrumented by a second lag (Arellano and Bond 1991).

Estimation results of equation 10 are reported in Table 4. Column (1) of Table 4 shows that a flooded city darkens in the year in which it is flooded. This effect is also present when controlling for the instrumented lagged dependent variable, in Column (4). The magnitude is similar in both specifications, at -0.021 and -0.023, respectively, and statistically significant at the five percent level in both cases. This can be interpreted as a 2.1 (or 2.3) percent reduction in average light intensity of urban gridpoints in the year of the flood. Although we note that this represents the average effect for all gridpoints in a flooded city, including areas that are likely unaffected by the flood. Flooded gridpoints are likely to experience greater changes in light intensity, but the quality of our flood maps only allows us to use variation in flooding at the city level – and later interact it with measures of flood-proneness due to low elevation.

How should we interpret the magnitude of these estimates? Henderson, Storeygard and Weil (2012) relate the change in lights to changes in economic activity. Their main estimate of the GDP to lights elasticity is approximately 1 in developing countries. Based on that estimate, the percentage reductions in light intensity associated with floods that we estimate could be interpreted as percentage reductions in economic activity, although the relationship between lights and economic activity estimated by Henderson et al. (2012) could of course be different at the local level.

Our estimates of the effects of flooding focus on the reduction in economic activity captured by the night lights. These do not include the costs of rebuilding houses and other infrastructure. In fact, if reconstruction efforts temporarily increase night time lights – and these efforts occur in the same year as the flood – this could mask the true economic impact of the flood, which could be larger than we estimate.

[19] These country trends account for the differences across the world in the changes in lit areas.

Some readers may be concerned about possible endogeneity of our flood indicators, with respect to economic activity, given that we identified large floods as those that displaced at least 100,000 people. To mitigate such concerns, Table 4 also includes results using extreme precipitation indicators, in place of the flood dummy. The extreme precipitation indicators, $Precip_{ljt}$, indicate whether or not grid cell l in city j experienced monthly precipitation exceeding 500mm (or 1000mm) in year t. These are not common occurrences; about 15 percent of urban gridpoints in the world have experienced monthly precipitation exceeding 500mm at least once during the period 1992-2012, while only 1.2 percent of urban gridpoints in the world experienced monthly precipitation exceeding 1000mm at least once during the period 1992-2012.

The results of these specifications are reported in Columns 2–3 and 5–6 of Table 4. The effect of an episode of monthly precipitation exceeding 500mm is similar in magnitude to that of a large flood, at between -0.025 and -0.027 (Columns 2 and 5). The rarer event of monthly precipitation exceeding 1000mm has a substantially larger effect on light intensity in affected cities, leading to average dimming of between -0.080 and -0.083 (Columns 3 and 6). The coefficients on the extreme precipitation indicators are statistically significant at the one percent level in each of these specifications.[20]

We also repeat our main analysis at the city-wide level, aggregating the data to city level, with observations weighted by city population. At the city level the specification becomes:

$$ln(Y_{jkt}) = \beta_{41} + \beta_{42} Flood_{jt+s} + City_j + Year_t + Country_k \times Trend_t + \epsilon_{jt}. \tag{11}$$

which is essentially the same as 10 but with city fixed effects now replacing gridpoint fixed effects.

The estimation results for this specification, now across rather than within cities, are reported in Table A2. We find a similar pattern of results as before. The effect of a large flood on city-wide light intensity is still statistically significant at the five percent level, albeit slightly smaller in magnitude at between -0.017 and -0.019 (Columns 1 and 4). Episodes of extreme precipitation also reduce light intensity at the city-wide level, with the effects significant at the one percent level in each case (see results in Columns 2–3 and 5–6 of Table A2).

We next investigate patterns of recovery of urban economic activity in the aftermath of floods. In Table 5 we report the results of estimating versions of Equation 10 including lagged versions of the flood indicator (up to $t-4$) – i.e. testing the effects of large floods on light intensity at up to four years after the flood. Columns (1) and (6) of Table 5 repeat Columns (1) and (4) of Table 4 for ease of comparison. The remaining Columns of Table 5 show that the statistically significant impact of the flood on light intensity in the year of the event disappears at $t-1$ and does not reappear at futher lags. These results indicate that urban economic activity is fully restored just one year after a large flood strikes a city. This pattern of rapid recovery is also found for cities affected by episodes of extreme precipitation (see results in Tables A3 and A4).

[20] We do not use extreme rainfall to instrument for flooding, because extreme rainfall can adversely affect a city's economic fortunes even if far fewer than 100,000 people are displaced. In technical terms, this amounts to a violation of the exclusion restriction. This problem, coupled with the relative rarity of large floods (a small first stage), implies that 2SLS estimates of the effects of large floods using extreme rainfall as an instrument are much larger than the OLS estimates that we report in the paper. We therefore prefer to focus on the OLS estimates, which we find more credible.

We also test for recovery at the city-wide level, running versions of Equation 11 with lags of the flood indicator (results presented in Table A5). Again, we find a similar pattern, with the effect of the flood on city-wide light intensity disappearing after just one year.

We next consider heterogeneity of floods' effects within cities. In particular, we are interested in the differential effect of large floods by elevation. We test this by interacting the flood indicator with an elevation band indicator. Returning to the panel of gridpoint-years, the regression specification now becomes:

$$ln(Y_{ijkt}) = \beta_{51} + \Sigma_h \beta_{52h} Flood_{jt+s} \times Elevation_h + Gridpoint_i + Year_t + Country_k \times Trend_t + \epsilon_{it}, \quad (12)$$

where $Elevation_h$ is a dummy for elevation band h. In practice we interact the flood indicator with an indicator for urban locations that are less than 10m above sea level (and an indicator for areas that are 10m or more above sea level). The results of these specifications are reported in Table 6. As before, these regressions include year and gridpoint fixed effects, as well as country-specific trends (in Columns 1–6). In Columns (7) to (8) we replace the country-specific trends with city-specific trends, to account for different city-specific changes in light intensity over time. We also re-estimate our main regressions using the dynamic panel specification described previously (results reported in Columns 4–6).

The results in Columns (1) and (4) show that low elevation areas within cities are hit harder than other areas when a city is struck by a large flood. The effect on light intensity for areas less than 10m above sea level is estimated at between −0.027 and −0.028. This effect is even slightly stronger (−0.030) when accounting for city-specific trends in Column (7). These effects are statistically significant at the one percent level. The estimated effects for areas more than 10m above sea level are smaller in magnitude, and not statistically significant in Columns (1) and (4). Similar specifications, where instead of elevation we interacted floods with indicators for distance to nearest river or coast, found no such significant pattern of heterogeneity.[21]

The effects at low elevation are even stronger when using extreme precipitation to identify affected locations. Specifically, the results in Table A6 show that light intensity for locations less than 10m above sea level is reduced by up to −0.122 in years with episodes of monthly precipitation in excess of 1000mm.[22]

The interaction of the flood indicator with an indicator for low elevation areas captures the impact of floods on the riskiest parts of cities. As we might expect the effects identified for low-elevation areas are both stronger in magnitude and more precisely estimated than the average effects reported in Table 4. However, as pointed out previously, the effects we report are still average effects across all gridpoints (in this case, all gridpoints less than 10m above sea level) in affected cities. The effects for gridpoints experiencing the worst actual flooding could well be stronger again than those reported here.

The heterogeneous impacts by elevation that we identify here show that it is unlikely that the effects we find can be attributed solely to the destruction of power plants or power lines. Such

[21] These alternative specifications are not reported in this version of the paper. Results available on request.

[22] A similar analysis for episodes of monthly precipitation in excess of 500mm did not find any significant heterogeneity by elevation. Results not reported here, but available on request.

effects would reduce light in the entire city, in both its higher and lower elevation neighborhoods. The heterogeneous impact is suggestive that lights within cities indeed correlate with local economic activity.

Table 6 also shows the pattern of recovery following a flood event for urban locations at different elevations. Again the effects of the flood disappear just one year after the event, even for the harder hit low elevation areas (those less than 10m above sea level) – as demonstrated by the results in Columns (2), (5) and (8) of Table 6. The positive and significant coefficients on the interaction of the $flood_{t-2}$ indicator with the $elev < 10m$ indicator in Columns (3), (6) and (9) of Table 6 indicate some over-shooting in the recovery of low elevation areas. Two years after a flood event, the light intensity in the hardest hit areas of flooded cities is above its (country-specific or city-specific) trend. A similar specification, where instead of the flood indicator we interacted elevation with an indicator of extreme precipitation, found a temporary increase in light intensity one year after experiencing monthly precipitation of 1000mm or more. However, this increase disappears in the following year, which might have to do with aid and reconstruction efforts [23]

The pattern of results presented in Table 6 – both the heterogeneous impacts by elevation and the rapid recovery of even the harder hit low elevation areas – is robust both to the exclusion of locations within 10km of rivers and coasts (see Table A7) and to the exclusion of cities that are entirely less than 10m above sea level (see Table A8). The rapid recovery of low-elevation areas, even when excluding locations within 10km of rivers and coasts, suggests that this recovery process is not simply being driven by the attractiveness of water-side locations. Similarly, the finding that the rapid recovery of low-elevation areas is found even when we exclude (the small number of) cities that are entirely less than 10m above sea level – where relocating economic activity to higher ground (within the city) is unfeasible. In other words, people in flooded areas typically have the option to move to higher ground even within their metro area, but either cannot afford the move or choose not to do so. This result supports our conclusion that this process is being driven by an important economic problem, and not simply a technical or geographic constraint on adaptation.

Finally, we also test for differential effects of floods within cities by newly populated versus existing locations. These specifications are similar to Equation 12, but instead of an elevation dummy, here we interact the flood indicator with a dummy for newly populated areas (locations that were dark, with $lights = 0$ in 1992) and a dummy for existing areas (those that were not dark in 1992). The results of these regressions are reported in Table 7.

The results show larger and more persistent impacts of flooding on newly populated areas, with the negative effect of the flood on lights persisting, and intensifying, for about three to four years after the event. These findings are in line with the predictions of our model; because updating decreases in t (where t is the length of the sample of information that an individual has on past flooding), we expect that there will be more updating in newly populated urban areas.

The persistent negative effect of floods in areas that were not lit in 1992 stands in contrast with the return to pre-existing conditions elsewhere in cities. The negative effect of floods in new areas is (from the year after the flood) roughly an order of magnitude larger than in the areas that were settled in 1992. And the negative effects are significant at the 5-10 percent levels for

[23] This alternative specification is not reported in this version of the paper. Results are available on request.

four years. Even five years after the flood, and despite the limitations of our short panel and conservative inference, the point estimate of the flood is still larger than in the year of impact. These results suggest that there is some adaptation to floods, but only in areas that are newly populated, where the risk of flooding may not have been fully realized, and substantial sunk investments may not yet have been made.

6 Discussion and conclusions

In this paper we study the effect of large floods on local economic activity in cities worldwide. In particular, we examine (i) whether economic activity concentrates disproportionately in flood-prone urban areas; (ii) whether higher risks of extreme precipitation affect the concentration of economic activity in areas with higher risk of flood; and (iii) whether large floods cause economic activity to shift to safer urban areas or safer parts within the same urban area.

Our analysis indicates that urban areas globally face substantial flooding risk. In particular, in our data, low elevation urban areas – those less than 10m above sea level – on average face a one in 20 risk of a large scale flood, displacing at least 100,000 people, hitting their city. This is likely an underestimate of the true risk, given that we have incomplete coverage of the events that meet this criterion during our main sample period (January 2003 to May 2008).[24] We also find that large scale flooding represents a recurrent risk for certain urban locations. Of the 1,868 cities affected by a large flood in our data, about 16 percent get hit in more than one year during our brief sample period. In spite of the greater vulnerability of low elevation areas to flood risk, we find that global urban economic activity is disproportionately concentrated in these areas.[25] This concentration of urban economic activity in flood-prone areas is found to hold even in regions that are prone to extreme precipitation.

Urban flood risk is likely to increase with trends such as population growth and urbanization, which are more intensive in areas currently most at risk – e.g. South Asia and sub-Saharan Africa – along with the potentially exacerbating effects of climate change and rising sea levels.

When we analyze the local economic impact of large floods, we find that on average they reduce urban economic activity by between 2 and 8 percent in the year of the flood, depending on the method used to identify affected locations. These effects are even stronger (up to a 12 percent reduction) for low elevation areas. Our results also show that recovery, even in the harder hit low elevation areas, is relatively quick, with economic activity fully restored within a year of the flood. These results – which are consistent across our various specifications and robust to excluding areas within 10km of the nearest river or coast, and to excluding cities that are entirely less than 10m above sea level – indicate a lack of adaptation, in the sense of a movement of economic activity away from the most vulnerable locations within cities. One exception to this appears to be in newly populated areas, where the decline in economic activity is both stronger and more persistent.

[24] Although this may have been an especially destructive period, as suggested by the data in Table 1.

[25] This concentration in vulnerable locations also appears to have intensified over time. Looking at changes in light intensity from 2000-2012, we find that low elevation areas have grown more rapidly relative to average country trends (but less rapidly relative to city trends). Looking at city averages, low elevation cities have also grown faster relative to country trends. Results of this analysis available on request. See also Ceola, Laio and Montanari (2014).

Projections of future losses rest heavily on assumptions about the degree of adaptation we can expect in response to changing risk profiles. While the potential for human and economic systems to adapt may be high, our findings indicate that the elasticity of human location with respect to changes in locational fundamentals is in reality rather low. This suggests that in the face of intensifying patterns of risk and exposure, future costs may be higher than anticipated. While defensive investments, involving the building of more robust infrastructure and flood protection schemes, may mitigate some of the risks associated with extreme precipitation and coastal flooding, they are not costless.[26] Moreover, it is often the case that money and effort are more readily expended in disaster recovery than prevention.[27] Motivating the latter faces political challenges. Aside from the issue of political myopia, it has also been shown that voters are more likely to reward highly visible recovery efforts than preventive actions (Healy and Malhotra, 2009).

We make two specific contributions to the literature that attempts to estimate future costs of anticipated climate change. First, we provide empirical evidence on the degree of adaptation we can expect in response to changing flood risk profiles. Second, we present a novel methodology for estimating the local economic impacts of urban flooding and the first global estimates of these costs that we are aware of. Of course the direct effects on urban economic activity that we identify here – losses of between two and eight percent of economic activity in the year of a large flood – exclude a number of additional costs, which should be taken into account in calculating the full economic cost of urban flooding. For example, our estimates do not include the value of aid flows (domestic, international, government and NGO) that helped cities to recover and the costs of replacing buildings and infrastructure damaged or destroyed by floods.[28] Our estimates also do not account for the costs to human capital in the form of interrupted or lost years of schooling, and damage to health and physical development. These human capital effects may be substantial and long-lasting.[29]

Our findings highlight the costs associated with the path dependence of urban locations, and stress the existence of barriers to change in the spatial distribution of economic activity across cities. From a policy perspective, this suggests that incorporating flood risk (and adaptation) into development and urban planning is an important challenge. Making progress on this front is most urgent in developing countries where rapid population growth and urbanization, combined with weak planning and zoning laws, contribute to the high levels of flood risk.

[26]Nor are fiscal costs of natural disasters low. When non-disaster government transfers are added to disaster-specific aid fiscal costs of exogenous shocks in US counties increase almost three-fold (Deryugina 2013).

[27]It has been estimated that $7 of international aid flows are spent on disaster recovery for every $1 spent on prevention (Kellett and Caravani, 2014). Following the 2014 floods in the UK, Prime Minister David Cameron stated that "money is no object in this relief effort" ("Flood simple: the UK flooding crisis explained", Guardian, 13 February 2014, `http://www.theguardian.com/uk-news/2014/feb/13/uk-floods-essential-guide` accessed on 29 April 2015.

[28]International aid flows in response to flooding averaged around US$188 million per year during our main sample period (2003-2008), according to data from `aiddata.org`. We do not have global information on the value of domestic transfers in response to disasters.

[29]According to one study, the long-run human capital costs of disasters represent a multiple of immediate damages and death tolls (Antilla-Hughes and Hsiang, 2013).

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Figure 1: Map of all urban areas in the world showing the locations of cities affected by our sample of large flood events. City sizes are inflated in order to make them visible on a map of the entire world. Smaller dots correspond to cities not affected by any of the floods in our sample. The number of floods in the legend refers to the number of years from 2003-2008 during which each city was affected by a flood that displaced a total of 100,000 people or more. This map uses the Mercator (WGS 1984) projection. The rest of the analysis in the paper uses equal area projections.

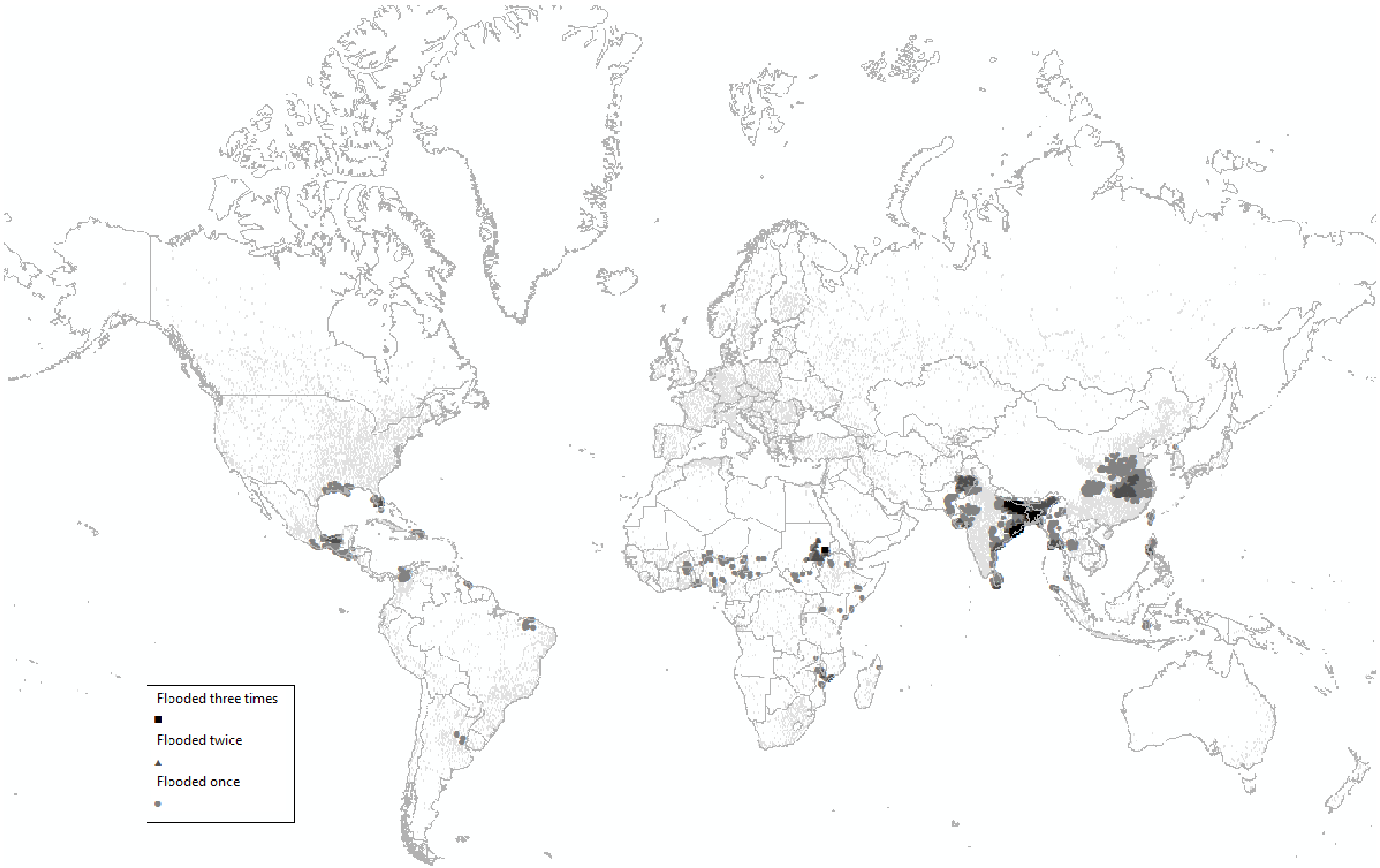

Figure 2: Inundation and light intensity maps for Hurricane Katrina, New Orleans. Panel A shows a detail from one of the inundation maps associated with Hurricane Katrina, concentrated on the area around the city of New Orleans. The map displays in red and pink the areas that were inundated during the flooding. Panels B, C and D show the average annual light intensity in 2004, 2005, 2006 respectively, for the city of New Orleans. There is a notable dimming of lights city-wide in 2005. This is particularly pronounced in the eastern parts of the city, which were worst affected by the flood. In Panel D a recovery of light intensity is apparent. We are unable to observe any decline in light intensity in the range above the top coded light intensity level of 63. However, New Orleans is rich compared with the rest of our sample, where top coding tends to be less frequent.

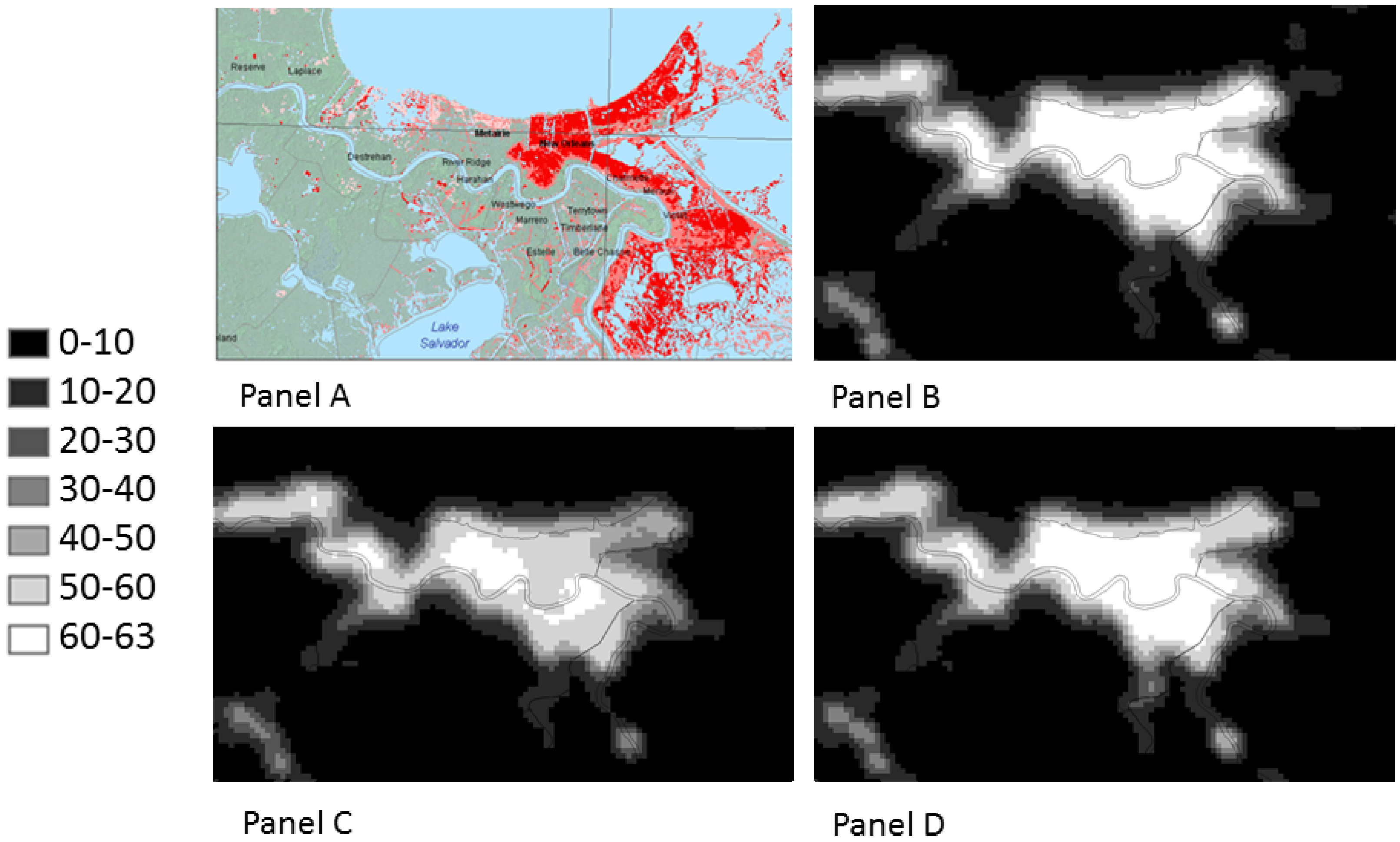

Table 1: Flood events displacing at least 100,000 people, by year (1988-2014)

Year	Number of events	(in our sample)	Millions of people displaced	(in our sample)
1988	22		19.1	
1989	20		8.0	
1990	18		14.2	
1991	21		16.9	
1992	12		12.6	
1993	16		34.2	
1994	15		7.8	
1995	24		47.4	
1996	18		12.1	
1997	21		5.6	
1998	23		41.7	
1999	22		56.4	
2000	20		49.2	
2001	13		9.4	
2002	16		19.0	
2003	16	(13)	20.6	(19.9)
2004	19	(15)	50.0	(49.1)
2005	30	(8)	21.8	(5.8)
2006	25	(7)	16.7	(5.2)
2007	30	(9)	33.2	(8.2)
2008	24	(1)	20.7	(1.5)
2009	17		7.8	
2010	17		19.8	
2011	14		6.9	
2012	12		5.1	
2013	14		6.2	
2014	9		3.1	
Total	508	(53)	565.6	(89.6)

Notes: Data from the Dartmouth Flood Observatory (DFO) database. Our sample refers to the 53 flood events from the DFO database for which we have detailed inundation maps, as discussed in the text.

Table 2: Flood odds by location characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$	$FloodFreq_{ik}$
$Elev < 10m_i$	0.036			0.041	0.033			0.034
	(0.017)			(0.018)	(0.018)			(0.019)
$River_i$		0.010		0.009		0.009		0.009
		(0.006)		(0.006)		(0.006)		(0.006)
$Coast_i$			-0.001	-0.010			0.007	-0.001
			(0.007)	(0.003)			(0.006)	(0.001)
$Constant$	0.013	0.014	0.016	0.012				
	(0.005)	(0.004)	(0.005)	(0.004)				
Observations	3,807,799	3,807,799	3,807,799	3,807,799	3,807,799	3,807,799	3,807,799	3,807,799
Country fixed effects	No	No	No	No	Yes	Yes	Yes	Yes

Notes: The regressions reported in this Table correspond to Equation 8, and include the full global sample of all urban areas. The dependent variable $FloodFreq_{ik}$ measures the odds of flooding per year for a given location, defined as the number of years during our main sample in which each location is hit by at least one large flood event, divided by the length of the sample (five years and five months).
$Elev < 10m_i$ is a dummy variable for locations that are less than 10m above sea level.
$River_i$ and $Coast_i$ indicate locations that are less than 10km from the nearest river or coast, respectively.
Robust standard errors, clustered by country, in parentheses.

Table 3: Light intensity by elevation and exposure to extreme precipitation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$	$ln(Y_{ilk})$
$Elev < 10m_i$	0.182	0.184	0.137	0.059	0.157	0.110	0.038	0.172	0.125	0.047
	(0.037)	(0.037)	(0.032)	(0.027)	(0.033)	(0.028)	(0.033)	(0.034)	(0.029)	(0.028)
$Elev < 10m_i \times Precip > 1000mm_l$		-0.034	-0.032	-0.030						
		(0.075)	(0.075)	(0.048)						
$Precip > 1000mm_l$		-0.063	-0.081	-0.021						
		(0.079)	(0.074)	(0.054)						
$Elev < 10m_i \times Precip > 500mm_l$					0.113	0.112	0.078			
					(0.044)	(0.048)	(0.064)			
$Precip > 500mm_l$					-0.043	-0.054	-0.078			
					(0.064)	(0.062)	(0.054)			
$Elev < 10m_i$ $\times Precip > 500mm(twice)_l$								0.067	0.065	0.049
								(0.026)	(0.028)	(0.038)
$Precip > 500mm(twice)_l$								-0.050	-0.066	-0.114
								(0.075)	(0.073)	(0.056)
Observations	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083	3,642,083
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	No	Yes	No	No	Yes	No	No	Yes
River & Coast FE	No	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
$Prec > 1000mm$	Mean	0.012								
$Prec > 500mm$	Mean	0.153								
$Prec > 500mm(twice)$	Mean	0.111								

Notes: The regressions reported in this Table correspond to Equation 9 and include the full global sample of all urban areas.
The dependent variable in all regressions $ln(Y_{ilk})$ is the natural log of mean light intensity (measured in 2012) at each gridpoint i (located in grid cell l, in country k).
$Elev < 10m_i$ is a dummy variable for locations that are less than 10m above sea level.
$Precip > 1000mm_l$ ($> 500mm_l$) indicates locations that have experienced monthly precipitation of 1000mm (500mm) or more at least once, and in the case of $Precip > 500mm(twice)_l$ monthly precipitation of 500mm or more at least twice, in the period 1992-2012.
Regressions with river and coast controls include dummies for locations within 10km of the nearest river or coast.
Robust standard errors, clustered by country, in parentheses.

Table 4: Main effects of flood on light, gridpoint year panel

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Flood_{jt}$	-0.021			-0.023		
	(0.010)			(0.010)		
$Precip > 500mm_{lt}$		-0.025			-0.027	
		(0.008)			(0.008)	
$Precip > 1000mm_{lt}$			-0.080			-0.083
			(0.018)			(0.018)
$ln(light_{t-1})$				Yes	Yes	Yes
Observations	1,422,018	1,422,018	1,422,018	1,392,501	1,392,501	1,392,501
No. of gridpoints	243,303	243,303	243,303	235,460	235,460	235,460

Notes: The results presented in this Table correspond to Equation 10 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt}$ is a dummy indicating whether or not city j was hit by a large flood in year t.
$Precip > 1000mm_{lt}$ ($> 500mm_{lt}$) indicates locations that experienced monthly precipitation of 1000mm (500mm) or more in year t.
All regressions include year fixed effects, gridpoint fixed effects and country-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table 5: Recovery, gridpoint year panel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Flood_{jt}$	-0.021					-0.023				
	(0.009)					(0.011)				
$Flood_{jt-1}$		-0.003					-0.021			
		(0.012)					(0.014)			
$Flood_{jt-2}$			0.017					0.017		
			(0.015)					(0.015)		
$Flood_{jt-3}$				0.005					-0.002	
				(0.004)					(0.007)	
$Flood_{jt-4}$					0.001					0.001
					(0.004)					(0.005)
$ln(light_{t-1})$						Yes	Yes	Yes	Yes	Yes
Observations	1,422,018	1,414,781	1,417,877	1,421,167	1,420,548	1,392,501	1,386,261	1,380,492	1,375,245	1,374,842
No. of gridpoints	243,303	243,292	244,256	245,077	245,018	235,460	235,421	235,302	234,838	234,962

Notes: The results presented in this Table correspond to Equation 10 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
All regressions include year fixed effects, gridpoint fixed effects and country-specific trends.
Columns (6) to (10) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table 6: Interactions with elevation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Flood_{jt} \times elev_{<10i}$	-0.027			-0.028			-0.030		
	(0.006)			(0.006)			(0.005)		
$Flood_{jt} \times elev_{10+i}$	-0.019			-0.021			-0.017		
	(0.012)			(0.013)			(0.007)		
$Flood_{jt-1} \times elev_{<10i}$		0.009			-0.014			0.003	
		(0.009)			(0.009)			(0.011)	
$Flood_{jt-1} \times elev_{10+i}$		-0.007			-0.023			-0.006	
		(0.014)			(0.018)			(0.012)	
$Flood_{jt-2} \times elev_{<10i}$			0.042			0.043			0.036
			(0.016)			(0.017)			(0.020)
$Flood_{jt-2} \times elev_{10+i}$			0.008			0.007			0.011
			(0.011)			(0.011)			(0.010)
$ln(light_{t-1})$				Yes	Yes	Yes			
Country-specific trends	Yes	Yes	Yes	Yes	Yes	Yes			
City-specific trends							Yes	Yes	Yes
Observations	1,422,018	1,414,781	1,417,877	1,392,501	1,386,261	1,380,492	1,422,018	1,414,781	1,417,877
No. of gridpoints	243,303	243,292	244,256	235,460	235,421	235,302	243,303	243,292	244,256

Notes: The results presented in this Table correspond to Equation 12 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
$Elevation_h$ is a dummy for elevation band h, where h is either less than 10m above sea level, or 10m or more above sea level.
All regressions include year fixed effects and gridpoint fixed effects. Columns (1) to (6) include country-specific trends and Columns (7) to (9) include city-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table 7: Flood impacts by newly populated vs existing locations

	(1) $ln(Y_{ijkt})$	(2) $ln(Y_{ijkt})$	(3) $ln(Y_{ijkt})$	(4) $ln(Y_{ijkt})$	(5) $ln(Y_{ijkt})$	(6) $ln(Y_{ijkt})$	(7) $ln(Y_{ijkt})$	(8) $ln(Y_{ijkt})$	(9) $ln(Y_{ijkt})$	(10) $ln(Y_{ijkt})$	(11) $ln(Y_{ijkt})$	(12) $ln(Y_{ijkt})$
$Flood_{jt} \times New_i$	-0.023						-0.026					
	(0.007)						(0.012)					
$Flood_{jt} \times Old_i$	-0.021						-0.022					
	(0.010)						(0.011)					
$Flood_{jt-1} \times New_i$		-0.065						-0.078				
		(0.025)						(0.019)				
$Flood_{jt-1} \times Old_i$		0.003						-0.016				
		(0.011)						(0.014)				
$Flood_{jt-2} \times New_i$			-0.073						-0.067			
			(0.032)						(0.021)			
$Flood_{jt-2} \times Old_i$			0.025						0.023			
			(0.014)						(0.015)			
$Flood_{jt-3} \times New_i$				-0.094						-0.074		
				(0.043)						(0.032)		
$Flood_{jt-3} \times Old_i$				0.014						0.003		
				(0.005)						(0.009)		
$Flood_{jt-4} \times New_i$					-0.072						-0.066	
					(0.040)						(0.034)	
$Flood_{jt-4} \times Old_i$					0.008						0.005	
					(0.007)						(0.006)	
$Flood_{jt-5} \times New_i$						-0.039						-0.033
						(0.025)						(0.020)
$Flood_{jt-5} \times Old_i$						0.004						0.004
						(0.007)						(0.007)
$ln(light_{t-1})$							Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,422,018	1,414,781	1,417,877	1,421,167	1,420,548	1,185,258	1,392,501	1,386,261	1,380,492	1,375,245	1,374,842	1,141,486
No. of gridpoints	243,303	243,292	244,256	245,077	245,018	244,711	235,460	235,421	235,302	234,838	234,962	233,110

Notes: The results presented in this Table are variations on Equation 12 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
New_i is a dummy for locations that were unlit ($lights = 0$) in 1992. Old_i is a dummy for locations that were lit ($lights > 0$) in 1992.
All regressions include year fixed effects, gridpoint fixed effects and country-specific trends.
Columns (7) to (12) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

7 Appendix Tables

(not necessarily for publication)

Table A1: Light intensity by elevation, democracy and income levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$	$ln(Y_{ik})$
$Elev < 10m_i$	0.182	0.309	0.272	0.053	0.390	0.364	-0.028	0.004	0.024
	(0.037)	(0.060)	(0.056)	(0.012)	(0.389)	(0.410)	(0.267)	(0.270)	(0.209)
$Elev < 10m_i \times DemocracyIndicator_k$		-0.175	-0.191	0.007				0.009	-0.225
		(0.067)	(0.076)	(0.037)				(0.029)	(0.078)
$Elev < 10m_i \times ln(GDPpercapita)_k$					-0.021	-0.023	0.009	0.005	0.028
					(0.037)	(0.040)	(0.029)	(0.029)	(0.023)
Observations	3,642,083	3,610,249	3,610,249	3,610,249	3,562,613	3,562,613	3,562,613	3,543,409	3,543,409
Country FE	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes
City FE	No	No	No	Yes	No	No	Yes	Yes	No
River and Coast FE	No	No	Yes	Yes	No	Yes	Yes	Yes	Yes

Notes: The regressions reported in this Table are variations on Equation 9 and include the full global sample of all urban areas.
The dependent variable in all regressions $ln(Y_{ik})$ is the natural log of mean light intensity (measured in 2012) at each gridpoint i (located in in country k).
$Elev < 10m_i$ is a dummy variable for locations that are less than 10m above sea level.
$ln(GDPpercapita)_k$ is the natural log of GDP per capita (in 2011) in country k (data are from the Penn World Tables v8).
$DemocracyIndicator_k$ is a dummy for countries with a Polity IV score (in 2008) greater than or equal to 5.
Regressions with river and coast controls include dummies for locations within 10km of the nearest river or coast.
Robust standard errors, clustered by country, in parentheses.
Robust standard errors are clustered by country.

Table A2: Main effects of flood on light, city-year panel

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$
$Flood_{jt}$	-0.017			-0.019		
	(0.007)			(0.006)		
$Precip > 500mm_{lt}$		-0.039			-0.040	
		(0.011)			(0.015)	
$Precip > 1000mm_{lt}$			-0.057			-0.058
			(0.014)			(0.014)
$ln(light_{t-1})$				Yes	Yes	Yes
Observations	10,363	10,363	10,363	9,878	9,878	9,878
No. of urban areas	1,817	1,817	1,817	1,702	1,702	1,702

Notes: The results presented in this Table correspond to Equation 11 and use the sample of cities affected by at least one of the large flood events in our data. The dependent variable in all regressions $ln(Y_{jkt})$ is the natural log of mean light intensity for each city j (located in country k) in year t.
$Flood_{jt}$ is a dummy indicating whether or not city j was hit by a large flood in year t.
$Precip > 1000mm_{lt}$ ($> 500mm_{lt}$) indicates locations that experienced monthly precipitation of 1000mm (500mm) or more in year t.
All regressions include year fixed effects, city fixed effects and country-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A3: Recovery, gridpoint year panel, extreme precipitation (500mm) indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Precip > 500mm_{jt}$	-0.025					-0.027				
	(0.008)					(0.008)				
$Precip > 500mm_{jt-1}$		0.004					0.003			
		(0.012)					(0.011)			
$Precip > 500mm_{jt-2}$			0.002					0.003		
			(0.006)					(0.007)		
$Precip > 500mm_{jt-3}$				-0.013					-0.012	
				(0.012)					(0.012)	
$Precip > 500mm_{jt-4}$					-0.009					-0.009
					(0.010)					(0.010)
$ln(light_{t-1})$						Yes	Yes	Yes	Yes	Yes
Observations	1,422,018	1,422,018	1,422,018	1,422,018	1,422,018	1,392,501	1,392,501	1,392,501	1,392,501	1,392,501
No. of gridpoints	243,303	243,303	243,303	243,303	243,303	235,460	235,460	235,460	235,460	235,460

Notes: The results in this Table are variations on Equation 10 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
$Precip > 500mm_{jt+s}$ indicates locations that experienced monthly precipitation of 500mm or more in year $t+s$.
All regressions include year fixed effects, gridpoint fixed effects and country-specific trends.
Columns (6) to (10) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A4: Recovery, gridpoint year panel, extreme precipitation (1000mm) indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Precip > 1000mm_{jt}$	-0.080					-0.083				
	(0.018)					(0.018)				
$Precip > 1000mm_{jt-1}$		0.054					0.053			
		(0.033)					(0.034)			
$Precip > 1000mm_{jt-2}$			0.004					0.002		
			(0.020)					(0.019)		
$Precip > 1000mm_{jt-3}$				0.002					0.004	
				(0.013)					(0.012)	
$Precip > 1000mm_{jt-4}$					0.001					0.003
					(0.029)					(0.028)
$ln(light_{t-1})$						Yes	Yes	Yes	Yes	Yes
Observations	1,422,018	1,422,018	1,422,018	1,422,018	1,422,018	1,392,501	1,392,501	1,392,501	1,392,501	1,392,501
No. of gridpoints	243,303	243,303	243,303	243,303	243,303	235,460	235,460	235,460	235,460	235,460

Notes: The results in this Table are variations on Equation 10 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
$Precip > 1000mm_{jt+s}$ indicates locations that experienced monthly precipitation of 1000mm or more in year $t+s$.
All regressions include year fixed effects, gridpoint fixed effects and country-specific trends.
Columns (6) to (10) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A5: Recovery, city-year panel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$	$ln(Y_{jkt})$
$Flood_{jt}$	-0.017					-0.019				
	(0.007)					(0.006)				
$Flood_{jt-1}$		-0.003					-0.008			
		(0.014)					(0.019)			
$Flood_{jt-2}$			0.017					0.017		
			(0.016)					(0.015)		
$Flood_{jt-3}$				0.004					-0.008	
				(0.009)					(0.021)	
$Flood_{jt-4}$					0.014					0.014
					(0.009)					(0.011)
$ln(light_{t-1})$						Yes	Yes	Yes	Yes	Yes
Observations	10,363	10,281	10,315	10,352	10,338	9,878	9,869	9,833	9,785	9,796
No. of urban areas	1,817	1,814	1,820	1,818	1,819	1,702	1,707	1,707	1,703	1,712

Notes: The results presented in this Table correspond to Equation 11 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{jkt})$ is the natural log of mean light intensity in each city j (located in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
All regressions include year fixed effects, city fixed effects and country-specific trends.
Columns (6) to (10) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A6: Interactions with elevation, extreme precipitation (1000mm) indicator

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Precip > 1000mm_{jt} \times elev_{<10i}$	-0.120			-0.122			-0.100		
	(0.019)			(0.020)			(0.016)		
$Precip > 1000mm_{jt} \times elev_{10+i}$	-0.052			-0.056			-0.031		
	(0.022)			(0.021)			(0.011)		
$Precip > 1000mm_{jt-1} \times elev_{<10i}$		0.111			0.111			0.117	
		(0.015)			(0.016)			(0.017)	
$Precip > 1000mm_{jt-1} \times elev_{10+i}$		0.020			0.018			0.033	
		(0.035)			(0.035)			(0.030)	
$Precip > 1000mm_{jt-2} \times elev_{<10i}$			0.006			0.007			-0.022
			(0.009)			(0.014)			(0.011)
$Precip > 1000mm_{jt-2} \times elev_{10+i}$			0.003			0.001			-0.005
			(0.028)			(0.026)			(0.023)
$ln(light_{t-1})$				Yes	Yes	Yes			
Observations	1,422,018	1,422,018	1,422,018	1,392,501	1,392,501	1,392,501	1,422,018	1,422,018	1,422,018
No. of gridpoints	243,303	243,303	243,303	235,460	235,460	235,460	243,303	243,303	243,303

Notes: The results presented in this Table correspond to Equation 12 and use the sample of cities affected by at least one of the large flood events in our data.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Precip > 1000mm_{lt+s}$ indicates locations that experienced monthly precipitation of 1000mm or more in year $t+s$.
$Elevation_h$ is a dummy for elevation band h, where h is either less than 10m above sea level, or 10m or more above sea level.
All regressions include year fixed effects and gridpoint fixed effects.
Columns (1) to (6) include country-specific trends. Columns (7) to (9) include city-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A7: Interactions with elevation, excluding locations within 10km of rivers and coasts

	(1)	(2)	(3)	(4)	(5)	(6)
	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$	$ln(Y_{ijkt})$
$Flood_{jt} \times elev_{<10i}$	-0.030			-0.032		
	(0.007)			(0.006)		
$Flood_{jt} \times elev_{10+i}$	-0.020			-0.021		
	(0.013)			(0.014)		
$Flood_{jt-1} \times elev_{<10i}$		0.015			-0.009	
		(0.011)			(0.011)	
$Flood_{jt-1} \times elev_{10+i}$		-0.001			-0.016	
		(0.012)			(0.017)	
$Flood_{jt-2} \times elev_{<10i}$			0.037			0.038
			(0.017)			(0.017)
$Flood_{jt-2} \times elev_{10+i}$			0.017			0.017
			(0.014)			(0.014)
$ln(light_{t-1})$				Yes	Yes	Yes
Observations	814,294	810,524	812,476	795,536	792,801	790,097
No. of gridpoints	139,712	139,683	140,298	134,640	134,600	134,474

Notes: The results presented in this Table correspond to Equation 12 and use the sample of cities affected by at least one of the large flood events in our data, restricted to exclude gridpoints within 10km of the nearest river or coast.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
$Elevation_h$ is a dummy for elevation band h, where h is either less than 10m above sea level, or 10m or more above sea level.
All regressions include year fixed effects and gridpoint fixed effects and country-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

Table A8: Interactions with elevation, excluding cities entirely less than 10m above sea level

	(1) $ln(Y_{ijkt})$	(2) $ln(Y_{ijkt})$	(3) $ln(Y_{ijkt})$	(4) $ln(Y_{ijkt})$	(5) $ln(Y_{ijkt})$	(6) $ln(Y_{ijkt})$
$Flood_{jt} \times elev_{<10i}$	-0.021			-0.022		
	(0.006)			(0.007)		
$Flood_{jt} \times elev_{10+i}$	-0.019			-0.020		
	(0.012)			(0.012)		
$Flood_{jt-1} \times elev_{<10i}$		0.012			-0.006	
		(0.008)			(0.010)	
$Flood_{jt-1} \times elev_{10+i}$		-0.007			-0.022	
		(0.014)			(0.018)	
$Flood_{jt-2} \times elev_{<10i}$			0.046			0.045
			(0.016)			(0.016)
$Flood_{jt-2} \times elev_{10+i}$			0.007			0.007
			(0.011)			(0.011)
$ln(light_{t-1})$				Yes	Yes	Yes
Observations	1,379,280	1,372,088	1,375,024	1,351,484	1,345,342	1,339,592
No. of gridpoints	235,874	235,861	236,793	228,408	228,358	228,261

Notes: The results presented in this Table correspond to Equation 12 and use the sample of cities affected by at least one of the large flood events in our data, restricted to exclude cities that are entirely less than 10m above sea level.
The dependent variable in all regressions $ln(Y_{ijkt})$ is the natural log of mean light intensity at each gridpoint i (located in city j in country k) in year t.
$Flood_{jt+s}$ is a dummy indicating whether or not city j was hit by a large flood in year $t+s$.
$Elevation_h$ is a dummy for elevation band h, where h is either less than 10m above sea level, or 10m or more above sea level.
All regressions include year fixed effects and gridpoint fixed effects and country-specific trends.
Columns (4) to (6) corrected by the Arellano-Bond methodology using $ln(lights_{t-2})$ as an instrument for $ln(lights_{t-1})$.
Robust standard errors, clustered by country, in parentheses.

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