

Climate, urbanisation and conflict:

The effects of weather shocks and floods on urban social disorder*

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Abstract:

In this paper, we test the effect of different weather shocks on urban social disorder, for a panel of large cities in developing countries. We focus on a particular mechanism, namely the displacement of population into (large) cities. In line with previous literature, we find that rainfall anomalies affect the rate of urbanisation and city growth in developing countries. However, we also identify diverse effects across different world regions; in Sub-Saharan Africa, *lower* than expected rainfall is associated with faster growth of large cities. In Asia, on the other hand, *higher* than expected rainfall leads to higher growth of (large) cities. We explain this latter (novel) finding with respect to the effects of flooding in Asia. We test this hypothesis explicitly using a novel dataset on floods – distinguishing those that affected large cities directly from those that occurred outside of our sample of large cities. Floods are therefore associated with faster growth of the population in the city, and in turn with a higher likelihood (and frequency) of urban social disorder events. Our evidence suggests that the effects of floods on urban social disorder occur (mainly) through the displacement of population, and the “push” of people into large cities. Our findings have important implications for evaluating future climate change, as well as for policies regarding adaptation to climate change and disaster resilience.

Key words: climate change; rainfall; floods; migration; urbanisation; conflict; social disorder

JEL Codes: D9, I3, J6, O1, Q00, Q01, Q5

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1. Introduction

In this paper, we test the effect of weather shocks on urban social disorder, with a particular focus on the role of floods that occur outside of large cities, in “pushing” population into large cities, potentially resulting in social tensions and conflict in urban areas. Natural disasters and weather shocks regularly cause displacement of population, including rural to urban migration (see e.g. Barrios et al. 2006, Marchiori et al. 2012, Henderson et al. 2014). Floods, in particular, displace large numbers of people every year – in the past 30 years, they have displaced 650 million people worldwide, according to data from the Dartmouth Flood Observatory (Brakenridge 2018). While floods impact on all world regions, the magnitude of effects is particularly pronounced in Asia (see Section 3.2, Figure 1, and Appendix Table A1, below). The risk of flooding is also anticipated to increase rapidly in coming decades, due to a combination of increasing exposure -- due to ongoing socio-economic trends (including population and economic growth, and continuing urbanisation) -- and increasing hazard because of climate change on rainfall patterns and continuing sea level rise (Hallegatte et al. 2013; Jongman et al. 2014).

This displacement of population has potentially important economic and social consequences. A changing configuration of the spatial distribution of population and economic activity has direct effects on economic performance and development, as now widely acknowledged by the literature (Henderson 2003; Brühlhart and Sbergami 2009; Castells-Quintana 2018). Migration – both temporary and permanent – have also long been used as risk-coping mechanisms in the face of weather shocks, natural disasters and other income or productivity shocks (Gray and Mueller 2012, Henderson et al. 2017).

At the same time, the displacement of population comes with the potential to create social tensions where resources are scarce and overcrowding, or excessive demand for public services, occurs (Castells-Quintana et al. 2018). As an example, Collier et al. (2008) point to problems with access to land for newly arrived rural-to-urban migrants. Disorderly or reactive

migration in response to weather shocks may lead to disruptions to economic activity and even conflict (see Waldinger 2016, and citations therein, for further discussion).

While there is a growing literature on urbanisation and conflict (for example Buhaug and Urdal 2013; Ostby 2016), the findings in this literature have been mixed to date. Arguably, not all urbanisation is equal. Urbanization is mainly determined by rural-urban migration and natural population growth. Traditionally, rural-urban migration has been associated with a process of structural change, higher productivity growth, and economic development. However, nowadays in many poor countries urbanisation is not necessarily associated with economic development. Rural-urban migration in many poor countries seems more the outcome of “push” rather than “pull” factors; deteriorating agricultural conditions - worsened by climate change, high volatility in agricultural prices, natural disasters, and even violent conflict in rural areas, “push” people to urban areas, without any increase in productivity (see for instance Lipton 1977; Bates 1981; Bairoch 1988; Barrios et al. 2006; Swanson and Buckley 2013). Furthermore, a particular methodological issue with this literature is to identify exogenous sources of variation in urban population or in rates of inflows from rural to urban areas. We propose to use weather shocks, and in particular flood events that occur outside of major cities, as an exogenous push factor driving rural-urban migration, and potentially leading to conflict (i.e., social disorder) in adjacent urban areas. Weather shocks and floods can impact conflict directly by increasing the competition for limited resources, but also by altering other socio-economic dynamics. One of these is the concentration of population in urban areas. Developing countries experience today a very rapid process of urbanisation. In many cases this translates in a growth of urban agglomerations (cities) that can now reach the 10, 20 or even 30 million inhabitants. Natural disasters and changes in climatic conditions increasingly represent an important “push” factor. As more people get “pushed” to (large) cities, unplanned urbanisation and city growth brings with it important challenges for sustainable development, like the provision of basic urban services like sanitation, electricity or transportation, and employment creation (Collier et al. 2008, Castells-

Quintana et al. 2018). These challenges that come with rapid and unplanned city growth can in turn fuel conflict in urban areas.

The aim of this paper is precisely to analyse the potential effects that weather shocks, in particular floods, can have on patterns of economic development through the displacement of population from rural to urban areas. In particular, we aim at testing the effects of rural-urban migration on social disorder within cities, with weather shocks as the impulse for this population movement. We do this by analysing data for more than 138 (large) cities in 138 countries (one city per country), from 1960 to 2015.

Our paper relates to at least three strands in the literature: i) papers studying the connection between weather shocks and conflict, ii) papers studying the connection between weather shocks and urbanisation, and iii) papers focusing on conflict in urban areas (see Section 2 for a brief overview of this literature). While the literature suggests a potential connection between weather shocks, urbanisation, and conflict in urban areas, to the best of our knowledge, there is no paper empirically testing this connection in a global panel of countries/cities. Our paper aims to fill this gap.

In line with previous literature, we find that rainfall anomalies affect the rate of urbanisation in developing countries. However, we also identify diverse effects across two different world regions; in Sub-Saharan Africa (SSA), lower than expected rainfall is associated with more urbanisation, while in Asia that is not the case. Differently to what happens in Sub-Saharan Africa, in Asia higher than expected rainfall leads to higher growth of (large) cities. We explain this latter (novel) finding with respect to the effects of flooding in Asia. We test this hypothesis explicitly using a novel dataset on floods – distinguishing those that affected large cities directly from those that occurred outside of our sample of large cities. The latter events are strong predictors of population in the city, and in turn of the likelihood (and frequency) of urban social disorder events. Our evidence suggests that the effects of floods on urban social disorder occur (mainly) through the displacement of population, and the “push” into large cities. Our

findings have important implications for evaluating future climate change, as well as for policies regarding climate and disaster resilience.

The remainder of our paper proceeds as follows: In Section 2, we briefly review the three strands of related literature already mentioned. In Section 3, we present our data, providing a descriptive analysis of the coevolution of weather shocks and floods, urbanisation and city growth, and social conflict in urban areas. Section 4 performs some econometric analysis and presents our main results. Finally, Section 5 concludes, highlighting policy implications from our results and avenues for further research.

2. Climate, urbanisation and conflict: a review of the literature

(i) Weather shocks and conflict

Recent decades have seen an increase in the interest in the relationship between natural resources and conflict. A body of literature argues that the abundance of natural resources, in particular minerals and oil, is positive correlated to political violence. The abundance and easy access to these resources can be used to fund rebel organizations and can lead to frictions over their allocations. At the same time, the state dependence on these commodities can weaken state capacity (Hendrix 2010). Other authors have supported the idea that it is the scarcity of vital resources, like water and food, that can lead to conflict (see below). In this context, the scarcity of resources can generate grievances and fuel conflict over distribution.

Several researchers have tried to test the causal relationship between income, natural resources, natural disasters, and conflict. They have relied on the consensus that low levels of income are correlated with high levels of conflict and look at land and water resources to determine the link between scarcity and conflict. As income is endogenous to conflict, they have used rainfall as a source of exogenous variation of income. Miguel et al (2004) instrument GDP growth in SSA with rainfall growth, and find that lower economic growth increases the probability of civil war. Bohlken and Sergenti (2010) run a similar analysis for India,

instrumenting for state-level GDP with rainfall. They also find that low rainfall growth increases the number of riots that a state experiences in a given year. The idea behind using rainfall as a plausible candidate instrument is that low levels of rainfall result in crop failure, thereby depressing rural income. However, the critical assumption underlying the use of rainfall as an IV is that rainfall affects conflict only through its impact on income.

Other authors have found a weaker relationship. Couttenier and Soubeyran (2014) argue that the relationship between rainfall and civil war is driven by aggregate shocks, in particular global climate shocks. Using a country-specific drought measure and a difference in difference specification, the authors find a weaker relationship between droughts and civil war than had previously been measured. Ciccone (2011) revisits Miguel et al.'s (2004) analysis of civil war in SSA and shows that there is actually a positive correlation between twice-lagged rainfall levels and current conflict. This author develops this point later (Ciccone 2013) and looks at the effect of transitory shocks on civil conflict risk to test whether income shocks lower the opportunity cost of participating in violence, and finds again that negative income shocks lower the risk of civil conflict. In contrast with these two groups of authors, Hendrix and Salehyan (2012) demonstrate the existence of a curvilinear relationship between rainfall and social conflict for African countries: very high and very low rainfall years increases the likelihood of all types of political and social conflict

In terms of the mechanisms that relate weather shocks, and in particular rainfall deviations, with civil war and conflict, the literature has suggested at least five different mechanisms.¹ A first body of literature focuses on access to water. During rainfall shortages water stores decline, and consumers may come into conflict within their own society over access to wells and riverbeds (Kahl 2006) or over water rights and access (Eriksen and Lind 2009). A second group of authors focuses on the effect of droughts and floods on food prices, leading to

¹ The literature emphasizes the importance of extreme events, since deviations from normal rainfall disrupt the expectations societies develop about normal rainfall patterns, and plan crops and coping strategies accordingly (Reardon and Taylor, 1996).

disputes between rural producers and urban consumers. Alexandratos (2008), for example, have shown that the rising price of staples crops in 2008 and 2011 led to massive protests and riots when urban consumers started to demand relief from food price inflation. A third mechanism relates to the effect on government revenues through a reduction of the tax base or an increase in the demand for services and assistance to respond to weather shocks. This is particularly true in countries where agriculture and other water-intensive sectors are central for the national economy, as is the case in many African countries. As Benson and Clay (1998) have shown for African economies, extreme weather events have had a particularly pronounced effect on public finances. A fourth mechanism relates to the effects on overall growth (Miguel et al 2004, Barrios et al 2008, Jensen and Gleditsch 2009). Rainfall anomalies can lead to displacement or crop failure, which at the same time affect economic productivity. General economic discontent may in turn lead to public disorder and conflict. Finally, rainfall deviations may also affect livelihoods, forcing many to migrate to urban areas in search of better opportunities. Migration to cities increases the supply of labour, leading to more intense competition over jobs. Similarly, more migrants in cities affect the demand for housing and other basic services such as sanitation, electricity, police protection, and roads (Neuwirth 2005). Our paper focuses on this last mechanism, which to the best of our knowledge, has not been explicitly tested in the literature to date.

(ii) Weather shocks, urbanisation and city growth

The literature on climate change and urbanisation has focused on the effect of rainfall on urbanisation, mainly in Africa. For example, Barrios et al (2006) estimate that shortages in rainfall have acted to increase rates of urbanisation on SSA countries. But they do not find evidence of a similar effect for the rest of the developing world. Moreover, they find that this effect has been reinforced after colonial independence of SSA, which in many cases was associated with legislation that lifted the prohibition of the free internal movement of native Africans. Henderson

et al (2014, 2017) confirm the strong link between climate change and urbanisation and city growth. More severe and persistent climate changes, measured with respect to rainfall, will likely increase the challenges faced by farmers and further accelerate migration to cities. This occurs primarily in arid countries in SSA. By lowering farm incomes, shortages in rainfall encourages migration to nearby cities, while wetter conditions slow it. Similarly, Bruckner (2012) uses rainfall as an instrument for agricultural GDP share in Africa and finds that a decrease in this share leads to increased urbanisation.

(iii) Migration to cities, urbanisation and conflict

The literature that links migration and conflict has focused mainly on rural-urban migration as a potential driver of grievances and opportunities for violent mobilisation. Rural-urban migration can influence both grievances and opportunities for social disorder. The explanations that the literature has used include relative deprivation and radicalisation of migrants, reduced opportunity costs, enhanced social communication, and ethnic frictions. The influx of rural-urban migrants tends not to be accommodated by public or private sectors, and migrants are likely to experience rising relative deprivation, which in turn increases the likelihood of their engaging in social disorder (Gizewski and Homer-Dixon 1995). Migrants may also have problems adjusting to life in the cities, in particular the disruption of the old customs and habits. As a result, migrants may tend to be more easily recruited into radical movements (Gizewski and Homer-Dixon 1995). In urban environments, there is also a more intense competition for access to services and jobs among migrants and local urbanites (Reuveny 2007). Cities can also be ethnically and religiously diverse, and this mixing may represent a further destabilising factor (Beall et al 2010).

Despite the several theoretical reasons to expect a link between rapid urbanisation (and city growth) and conflict in urban areas, there is a relatively limited literature that has empirically tested the link between the two. Buhaug and Urdal (2013) find no support for the “urbanisation bomb”, the idea that urban population growth should lead to an increase in political violence.

Ostby (2016) investigates the relationship between in-migration and political violence with city-level data in Africa and Asia, and finds that the movement of rural people into the cities creates social disorder through mechanisms such as poverty, unequal educational opportunities, and the socioeconomic marginalization of rural-urban migrants. Our analysis is in line with research that argues there may be a link between climate, urbanisation and (urban) conflict. In this article, we examine the effects of flooding on conflict in urban areas, testing more explicitly city growth as the mechanism between these links. In addition, while most of the literature has focused on one region, mainly Africa, or short periods, we test our hypothesis over a period of 50 years for a large world sample. This allows us to study differentiated effects across world regions (mainly differences between Africa and Asia). Our analysis is in line with the work of Bhavnani and Lacina (2015) in India, who test the causal effect of migration on social disorder by instrumenting migration with abnormal rainfall in migrant-sending states, and conclude that migration, on average, leads to rioting in the host area.

3. Data and descriptive analysis

To study the potential effects of weather shocks on urbanisation and city growth, and through these on social disorder in urban areas, we build a large dataset considering 138 countries over the 1960-2010 period. Our dataset includes several variables for our three key dimensions, namely weather shocks, urbanisation and city growth, and conflict in urban areas. For weather shocks, we consider rainfall anomalies and average temperatures (constructed from monthly gridded data), and the number of people displaced by floods. For urbanisation and city growth, we consider urbanisation rates and population in largest cities. For conflict in urban areas, we consider different measures of social disorder. Below we explain our key variables and sources.

3.1 Data sources and main variables

Weather shocks data

Our variables to capture weather shocks come from two main sources. Historical weather data, including temperature and rainfall observations, are derived from monthly global gridded data, which have been aggregated to country means.² Our main measure of rainfall, *rain_anom*, captures annual deviations in rainfall for a particular country, relative to the variability of year-to-year rainfall for that country (as used in e.g. Barrios et al. 2006 and Hendrix and Salehyan, 2012), and is defined as $Rain_anom_{it} = (ann_rain_{it} - mean_rain_i) / sd_rain_i$.³ We also include observations of annual average temperatures, from the same source.

Our data on flooding come from the Dartmouth Flood Observatory (DFO) archive (Brakenridge 2018). The DFO database includes information on the location, timing, duration, damage, and the number of people killed and displaced, for thousands of flood events worldwide from 1985-2015, compiled from media estimates and government reports. The DFO archive includes information about the location of each event. Particularly useful for our purposes are a set of shapefiles that define the areas affected by each flood event in the archive. While these shapefiles often cover fairly broad areas (these are not inundation maps), for the purposes of our city-level analysis they allow us to distinguish floods that have impacted directly on the cities in our data from those that have affected other areas within the same country.⁴ This is particularly useful for our purposes. Many flood events impact directly on large cities, displacing people already living in cities. These events would not therefore be expected to increase the population of those cities. By contrast, flood events occurring outside of major cities, and displacing population, may cause (some of) those displaced to move to the city. Using GIS software, we overlap the flood shapefiles obtained from DFO, with coordinates of the cities in our data (one city per country), to distinguish flood events that overlap with the city from those that affect

² The country-level datasets that we use were obtained from the World Bank's Climate Change Knowledge Portal (CCKP): http://sdwebx.worldbank.org/climateportal/index.cfm?page=downscaled_data_download&menu=historical (last accessed on 7 November 2018). These data are derived from the University of East Anglia's Climate Research Unit (CRU) time-series (TS) dataset of high resolution gridded monthly climatic observations (see Harris et al. 2014).

³ The *rain_anom* variable is standardised, such that the mean in our sample is close to 0, the standard deviation approximately 0.5 and the range of values in the sample is from roughly -2 to +2 (see Table 1, which includes summary stats for our main variables).

⁴ As per the DFO website, Archive Notes: "Polygons representing the areas affected by flooding are drawn in a GIS program based upon information acquired from news sources. Note: These are not actual flooded areas but rather the extent of geographic regions affected by flooding." (accessed November 2018).

other areas within the same country. Based on this categorization, we are able to construct our main flood variable, which is the sum of the number of people displaced⁵ by flood events occurring in country i in the period t , which did not overlap with the largest city in that country.

Urban data:

For urbanisation and city growth we focus on two sets of variables. On the one hand, we use urbanisation rates, defined as population living in urban areas as percentage of total population. On the other hand, we use population in the largest city. The focus on the largest cities rests on the fact that the pattern of urbanisation in many developing countries shows a high degree of urban concentration, with one or few cities of disproportionate size. For urban population, we use data from the World Urbanisation Prospects⁶, which includes observations of city population every five years from 1950-2015. In line with the urban economics literature, cities are considered not as administrative units but as functional urban areas. This means that we consider population in the whole urban agglomeration.

Urban conflict data:

For conflict in urban areas, we use data from the Urban Social Disorder Data.⁷ This dataset gives information on the number of conflict or disorder events in urban areas, including demonstrations, riots and armed conflict (battles or terrorist events), a proxy of the intensity by giving an estimate of the number of people involved in each incident and the number of fatalities

⁵ The definition of “displaced”, as used in the DFO archive is as follows: “Number Displaced - This number is sometimes the total number of people left homeless after the incident, and sometimes it is the number evacuated during the flood. News reports will often mention a number of people that are 'affected', but we do not use this. If the only information is the number of houses destroyed or damaged, then DFO assumes that 4 people live in each house. If the news report only mentions that "thousands were evacuated", the number is estimated at 3000. If the news reports mention that "more than 10,000" were displaced then the DFO number is 11,000 (number plus 10%). If the only information is the number of families left homeless, then DFO assumes that there are 4 people in each family.” – DFO website, Archive Notes, available at <http://floodobservatory.colorado.edu/Archives/ArchiveNotes.html> (last accessed November 2018).

⁶ We also have urban data from the Urban Platform of the EU Commission, providing data for more than 10,000 cities around the world – over half of which are in Asia. However, the relative lack of temporal variation in this data, and the limited number of cities for which we have obtained urban social disorder data, restricts our analysis for the moment to the largest urban agglomeration in each country. Future developments of this research project will involve extending the analysis to other urban areas beyond the primate city.

⁷ Available from <https://www.prio.org/Data/Armed-Conflict/Urban-Social-Disorder/> (accessed November 2018).

(if any). We code this information, for integration with our climate and urban data, by counting the number of events per city-period (summing over 5 year intervals), taking one city per country (as discussed above) – as our measure of the intensive margin of urban disorder events. We also create a binary indicator for whether a given city experienced any disorder events in a 5-year period – our measure of the extensive margin of urban disorder. Both measures are generated for all events, and separately for events that involved fatalities and those that did not involve any fatalities, according to the USD data.

3.2. Descriptive analysis and Stylised facts

Before performing econometric analysis, we can look at our data for our three key dimensions (weather shocks, urbanisation and city growth, and conflict in urban areas). Table 1 presents some summary statistics for our main variables for our world sample. Figures 1.a to 1.f present the evolution of rainfall, floods, urban growth and conflict in urban areas. The figures show the average across countries for our world sample, for Asian countries only, and for SSA countries only. Table A.1, in the appendix, presents summary statistics by world region.

[INSERT TABLE 1: Descriptive Statistics, main variables APPROXIMATELY HERE]

[INSERT FIGURE 1: Trends, main variables APPROXIMATELY HERE]

Looking at Table 1 and Figure 1, we can highlight some relevant stylised facts. In terms of weather shocks, our data shows a clear decreasing trend from 1960 until 1990 in SSA, both in terms of annual rainfall and rainfall anomalies. Decreasing, and more erratic, rainfall in many SSA countries has been highlighted as a cause of rapid urbanisation and lower economic performance in the last decades of the 20th century (e.g., Barrios et al 2006; 2010). In Asia, by contrast, rainfall levels are not only significantly higher than in SSA (and our world sample average), but also show

much lower anomalies. When looking at data on flooding, substantial differences across world regions (and specifically between SSA and Asia) is also evident; in Asia, the average across countries in the number of people displaced by floods is much higher than in SSA or any other region of the world (even when weighting by population of the largest city, as shown in Figure 1). The number of people displaced by floods in Asia shows a substantial increase between 1990 and 2000, when, on average, more than 5 million people in a 5-year period were displaced by country.⁸

In terms of urban growth, there is a clear upward trend, especially in SSA. However, the urban rate in SSA countries remains lower than in the rest of the world. On average, there is still at least a 10-percentage points difference between SSA and Asian countries. Something similar is evident when we look at the size of the largest cities; while in SSA the average across countries in size of the largest city is still below 3 million inhabitants, in Asia that figure is now around 7 million. In absolute terms, the highest increase in Asia happened between 1995 and 2005, when the figure went from 5 to 6.2 million inhabitants.

Finally, in terms of conflict in urban areas, there is also a clear upward trend in the number of urban disorder events. In Asia, the number of events is especially high, and it shows a significant rise between the year 2000 and 2005. Interestingly, for Asia, the trends of our key variables show i) a substantial increase in the number displaced people by floods from 1990 to 2000, ii) an acceleration in the size of the largest cities right after (between 1995 and 2005), and iii) a significant increase in the number of urban disorder events after 2000.

To (descriptively) explore the potential connection between our key dimensions (weather shocks, urbanisation and city growth, and conflict in urban areas), Figures 2.a to 2.d show the association between some of our main variables. Table A2, in the appendix, shows the correlation coefficients between our main variables. As shown, people displaced by floods shows a positive association with urban disorder events, especially in Asia. People displaced by floods also shows a

⁸ As shown in Figure 1, on average, the number of displaced people by floods in one year in one country can represent more than

positive association with the size of the largest city. This association is stronger when considering only floods that have not affected the largest city.⁹ Finally, the size of the largest city is also positively associated with the number of urban disorder events.

[INSERT FIGURE 2: Associations, main variables APPROXIMATELY HERE]

4. Empirical analysis

Our analysis involves a panel dataset covering the period 1960-2015 (1985-2015 for the floods data), for 138 (large) cities in 138 countries (one city per country). At the city level, we observe population and urban conflict events. Our main explanatory variables of interest – weather shocks and floods – are defined at the country level, given that we expect weather shocks outside of cities to “push” population into (large) cities.¹⁰ Similarly, (most of) our control variables – e.g. GDP per capita and total population -- are observed at the national level.

Our sample of cities represents the largest city in each country (in terms of population in the urban agglomeration) – and based on the availability of the USD conflict data, which is generally only observed for one city per country. Where USD data for more than one city in a given country are available, we restrict our attention to the single largest city (usually, but not always, the capital city).

In estimation, our sample size is sometimes restricted due to the availability of our key variables. For example, while we have 138 cities in our sample, in specifications with urban disorder events as the outcome, the sample is restricted to those countries in the USD data, leaving us with a sample of 85 cities with data on urban social disorder events. Similarly, in terms of time coverage, our data spans from 1960-2015 (based on availability of the USD data). However, in regressions using flood data, we are restricted to the period 1985-2015, given the

20 per cent of the population of the largest city of that country, as was the case in 1995-2000 period.

⁹ By contrast, rainfall anomalies show no association with urbanisation (and size of the largest city) in the whole sample, but are negatively associated in SSA (in line with the literature).

coverage of the flood events for which we have obtained maps (shapefiles) of affected areas, from the DFO archive (as detailed above).

Estimation strategy

To test the effect of weather shocks (including floods) on the evolution of city size, we run regressions of the following form:

$$CitySize_{it} = \alpha_1 + \beta_1 WeatherShocks_{it} + \beta_2 \mathbf{X}_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (1)$$

where $CitySize_{it}$ is the size, in terms of total population, of the largest city (in logs) in country i in period t (where $t = 1960, 1965, 1970 \dots$ etc.). Alternatively, we also consider the log of the urbanisation rate (the ratio of urban to rural population) in country i .¹¹ City size and urbanisation rates are observed every five years (i.e. in 1960, 1965, 1970... etc.). Our main explanatory variables of interest are $WeatherShocks_{it}$. Depending on the specification, these are either rainfall anomalies (as defined above), and temperatures, or the log of the number of people displaced by floods (again, as discussed above). The \mathbf{X}_{it} are a set of time-varying country-level controls, including the log of GDP per capita and total country population.¹² We also include year fixed effects, γ_t , and city (country) fixed effects, θ_i . The standard errors, ϵ_{it} , are clustered at the city (country) level.

In a similar vein to equation (1), we test the “reduced-form” of our main hypothesis, to examine if the number of people displaced by flooding outside of major cities is associated with urban disorder within those cities:

$$Disorder_{ijt} = \alpha_1 + \beta_1 Floods_{it} + \beta_2 CitySize_{it} + \beta_3 \mathbf{X}_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (2)$$

where $Disorder_{ijt}$ represents a measure of the number of “disorder” events, of type j , in city i in period t (as observed in the USD data). We distinguish in the data between events that involved

¹⁰ Within-country population movement is much more likely (and easier) than cross-border. For that reason, and for simplicity of the analysis, we do not consider the possibility of cross-border movements of population.

¹¹ We take the log of the urbanisation rate to replicate the empirical set-up in Barrios et al. (2006), as a starting point for our empirical analysis.

fatalities and those that did not.¹³ $Floods_{it}$ is defined, as discussed above, as the log of the number of people displaced by flood events that occurred in country i in period t , which did not overlap with the largest city (where the disorder events are observed).

Equation (2) is estimated using count models when $Disorder_{ijt}$ is measured as a count of events for a given city-period observation.¹⁴ This approach tests the *intensive* margin of the effect of floods (and city population) on the frequency of disorder events. Alternatively, equation (2) can be estimated using a probability model when $Disorder_{ijt}$ is measured as a binary indicator for city-period observations with zero or non-zero counts of disorder events of a particular type.¹⁵ In this case equation (2) would test the *extensive* margin of the effect of floods (and city population) on the likelihood of (a particular type of) urban disorder. The remaining variables on the RHS of equation (2) are defined as in equation (1), with the difference that here we include $CitySize_{it}$ alongside our main explanatory variable. We also considered additional control variables relevant for explaining social disorder in urban areas, such as an indicator for country-periods with ongoing armed conflict, and an indicator of democracy.¹⁶ We first estimate versions of equation (2) without including city size on the RHS, to test for any significant effect of floods on urban social disorder. We then include city size, to test the idea that the effect of floods on urban social disorder is operating (primarily) through the displacement of population and movement of people into the city.

Our primary hypothesis is as follows: floods occurring outside of cities displace population, leading to an increase in city population, resulting in increased urban social disorder. This general hypothesis leads to two testable hypotheses, based on estimating equation (2):

¹² Where these controls are included alongside $WeatherShocks_{it}$, the controls are lagged in order to avoid weather shocks (or floods) having a contemporaneous effect on these controls.

¹³ We are also exploring differences in the type of event – e.g. distinguishing between demonstrations, riots and armed conflict (including battles or terrorist actions). Analysis with disorder events disaggregated in this way to be added later.

¹⁴ Given over-dispersion in the urban disorder events data, we report the results of estimation using a negative binomial model as our baseline, although we have also experimented with a poisson model, with (qualitatively) similar findings. Further results with robustness checks (model specs, additional controls etc.) to be added.

¹⁵ Where we estimate equation (2) using a probit model, the specification includes Random Effects, as opposed to Fixed Effects. If we include country fixed effects (or country dummies), the relative lack of variation in the binary outcome at the country level results in many countries being dropped (due to collinearity) with a substantial decrease in the number of observations and precision of the findings. This is particularly an issue for the shorter panel where we use floods data (1985-2015).

H1: $\beta_1 > 0$, where $CitySize_{it}$ is not included in equation (2)

H2: $\beta_2 > 0$ & $\beta_1 = 0$, where $CitySize_{it}$ is included in equation (2)

In words, H1 predicts that the number of people displaced by floods that occur outside a city is positively associated with social disorder events in the city. H2 predicts that this effect is mediated via the effect of floods on city population, and the consequent effect of city population on urban social disorder. H2 predicts that the *only* effect of floods on urban social disorder is via the effect of floods on city population (i.e., city size). A weaker version of H2 would be that the magnitude of the coefficient on floods (β_1) would decrease (and/or become less statistically significant), when $CitySize_{it}$ is added to equation (2), indicating that some (but not all) of the effect of floods on urban social disorder is happening via the effects on city population.

Finally, we test the effects of city size on urban social disorder directly, by running regressions of the following form:

$$Disorder_{ijt} = \alpha_1 + CitySize_{it} + \beta_2 X_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (3)$$

where variables are defined as in equations (1) and (2) above. Equation (3) is also estimated for both the extensive and intensive margins, as discussed above for equation (2).

Results

We start with regressions of city size and urbanisation rates on weather shocks (as in equation 1). The first set of results, presented in Table 2, shows the effect of rainfall anomalies on city size. In general, we find a strong negative association between rainfall anomalies and city size – periods with low rainfall are associated with higher city size. This is particularly the case in SSA. However, in Asia, we find the opposite pattern – *higher* rainfall is associated with city growth.

¹⁶ These additional controls are based on PRIO conflict data, and the Polity IV data on democracy, respectively.

[INSERT TABLE 2 APPROXIMATELY HERE]

In Column (1) of Table 2, which includes the full sample and controls for (lagged) log GDP per capita, we find a significant negative association between rainfall anomalies and city size. Column (2) repeats this specification allowing for differentiated coefficients for SSA countries (cities). Column (3) allows for differentiated coefficients for Asia. While for SSA the coefficient for rainfall is negative, for Asia it is positive (both being highly significant). Columns (4), (5) and (6) repeat column (1), (2) and (3) restricting the sample to developing countries only, showing similar results.¹⁷

We also run regressions for equation (1) but considering urbanisation rates, rather than the size of the largest city. Like results in Table 2, we find that lower than expected rainfall leads to higher urbanisation in SSA, but not in Asia (see Table A3 in the Appendix). While the (negative) association between rainfall anomalies and urbanisation has been observed previously for Africa (e.g. Barrios et al. 2006), the observation of a positive association between rainfall anomalies and city growth for Asia is relatively novel. The reversal of the sign on rainfall anomalies for Asia may appear confusing. One potential explanation is that higher rainfall is associated with more economic growth and therefore faster city growth in Asia. However, we do not find such an association – in fact in results not reported here, we find that rainfall anomalies are negatively associated with economic growth in Asia.¹⁸ Instead, we believe our finding may come from what rainfall *anomalies* mean in each region, and hint to differential effects of climate change in different world regions. In (most of) Africa, rainfall is already scarce, and shows a clear decreasing trend over the last decades. A negative anomaly in our data means lower-than-expected rainfall -- a negative productivity shock to agriculture -- potentially pushing people from

¹⁷ In further robustness checks not reported here, we repeated the specifications in Table 2 excluding outliers in terms of city population (Tokyo), and including both interaction terms (with SSA and Asia) in the same regression. In all cases the results remain essentially unaffected. Results available on request.

¹⁸ We perform growth regressions in a similar spirit to the analysis reported in Barrios et al. (2010). For Africa, we find something similar to Barrios et al.: more rainfall, although not too much, is associated with higher economic growth. For Asia, we found the opposite: more rainfall is associated with less growth. Results available on request.

rural to urban areas. By contrast, in Asia, a positive rainfall anomaly in our data may be associated with too much rain (and therefore the risk of floods). In other specifications, not reported here, we also experimented with interactions between rainfall anomalies and an indicator for countries with high average annual rainfall. The findings from this exercise also suggest that “too much” rainfall is associated with faster growth of large cities in countries with already high levels of rainfall.¹⁹

Where flooding occurs in rural areas, the displaced population may be pushed towards cities. We test this hypothesis more explicitly in the next set of results.

In Table 3 we test the effect of flooding on city growth.²⁰ We limit our attention to people displaced by flood events which did not overlap with a country’s largest city (see discussion of this above in the data section). Here we find that the numbers displaced by floods occurring outside of our large cities, is associated with (changes in) the population in the city – indicating that people displaced by floods are “pushed” towards the largest urban areas. We find no evidence of significant regional variation in this case – the interactions with the SSA or Asia dummies are not significant. The effects of flooding on population in cities is similar for the full sample (in Columns 1-3) and when we restrict to “developing” countries only (Columns 4-6).²¹

[INSERT TABLE 3 APPROXIMATELY HERE]

Next, we turn to estimating equation (2) – the core of our empirical analysis – for the reduced form effects of floods on urban social disorder. The results in Tables 4 and 5 suggest that the numbers displaced by floods occurring outside major cities are strongly associated with

¹⁹ Results available on request.

²⁰ Note the sample size drops considerably here – mainly due to the more limited time coverage in the flooding data, which is only available since 1985.

²¹ In Appendix Table A4, we report regressions like those in Table 3, but using urbanization rates rather than city size. Floods affect positively the urbanization rate in SSA, but not in Asia. As with Table 2, we also run further robustness checks not reported here, repeating the specifications in Table 3, excluding outliers in terms of city population (Tokyo), and including both interaction terms (with SSA and Asia) in the same regression. In all cases the results remain essentially unaffected. Results available on request.

(the evolution of) the number of disorder events occurring in those cities (the “intensive margin” – Table 4), and with the probability of observing disorder events in a given city (the “extensive margin” – Table 5), as anticipated in H1. In Table 4, the results show that floods are positively related to the count of all disorder events at the city-level (Column 1), and the count of fatal disorder events (Column 3), while the estimated coefficient on floods is positive but not statistically significant for non-fatal events (in Column 5). Similarly, the results in Table 5 show that floods are positively associated with the probability of observing urban disorder events (total – Column 1; fatal – Column 3; and non-fatal – Column 5).

[INSERT TABLES 4 AND 5 APPROXIMATELY HERE]

In Tables 4 and 5 we also test H2 – that the effects of floods on urban disorder operate (mainly) via city growth – by adding city population as an additional control (in Columns 2, 4 and 6 of Tables 4 and 5). In each case, we see the magnitude of the coefficient on floods declines, and become less statistically significant, when we add city population, indicating that (most of) the effect of floods on urban disorder is indeed operating via the effects of flooding on city growth. The coefficient on city population is positive and significant in all cases. These findings would seem to support the expectation expressed in H2. The findings reported in Tables 4 and 5 are robust to the inclusion of indicators for country-periods with ongoing armed conflicts, and for democracy.²²

Finally, we test directly for the effects of city growth on the frequency (and probability) of urban disorder events. In Table 6, we report the estimated effect of (log) city population on the count of disorder events at the city-level (in Columns 1-3) and on the probability of observing disorder events (in Columns 4-6). We find that increases in city population are significantly associated with higher counts of disorder events (Column 1), of fatal events (Column 2), as well

as non-fatal events (Column 3). Turning to the extensive margin, results in Columns 4-6 suggest that city growth is associated with a higher probability of urban disorder events (again, total, fatal and non-fatal).²³

[INSERT TABLE 6 APPROXIMATELY HERE]

5. Conclusions, discussion and next steps

In the analysis presented in this paper, we begin by replicating an existing finding from the literature – that lower than expected rainfall is associated with higher urbanisation and city growth in countries in Sub-Saharan Africa. However, we also establish a new finding related to rainfall anomalies: in Asia, *higher* (rather than lower) than expected rainfall appears to be associated with faster growth of large cities. We interpret this finding with reference to an overabundance of rainfall in Asia. For arid countries – including many in Sub-Saharan Africa – low rainfall likely represents a negative productivity shock to agriculture, potentially pushing people from rural to urban areas. For wetter regions, including many Asian countries, the opposite may be the case – too much rainfall results in a negative productivity shock for agriculture (possibly associated with flooding), driving people from rural to urban areas.

We test this hypothesis explicitly by drawing on novel data related to flooding. In particular, we distinguish between floods that impact directly on major cities, and those that occur outside of our sample of large cities. We find that the latter are strongly associated with the evolution of population in the major (developing) world cities that we study. We next turn to the central hypothesis of our paper – that the displacement of population by flooding leads to increased risk of urban disorder, due to increasing congestion in urban areas as population is “pushed” into cities as a result of floods elsewhere. We find evidence to support the direct effect

²² The results are also robust to the exclusion of outliers in terms of city population (Japan), numbers displaced by flooding (India and Indonesia) and frequency of urban disorder events (Iraq). Results available on request.

²³ The coefficients on city population here are similar to those in Tables 4 and 5, but are estimated more precisely here, given the larger number of observations (we can take advantage of the full sample period – 1960–2015 – in Table 7, since we are not including floods data in these regressions).

of floods on urban social disorder (both the count of events – the “intensive” margin -- and the probability of observing a disorder event – the “extensive” margin), and evidence to support the hypothesised mechanism.

Our findings have important policy implications, especially for evaluating future climate change, as well as for policies regarding climate and disaster resilience, considering the connection between weather shocks and natural disasters, the spatial reallocation of population, and the tensions and conflict that can come with it.

Our findings should also call for further research. As suggested by our differential findings for Africa and Asia, heterogeneities across countries in regards to baseline climate (arid vs humid countries), type of weather shocks expected, and potentially other country/city characteristics – e.g. share of agriculture in GDP – should be studied in more detail to understand the potential impact of climate change specific to each country. Exploring alternative datasets could also allow for more localised (spatially refined) analysis. Finally, a more explicit causal analysis of the different mechanism linking weather shocks, urbanisation and city growth and disorder in urban areas could be explored, for instance by looking at data on local labour market outcomes, development of local infrastructure, income distribution, and other urban dynamics.

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Figures and Tables:

*** FIGURES ***

FIGURES 1a. -- 1.f: Evolution of main variables



Note: Trends show the average across countries for Asia, SSA and the world sample, respectively. In Fig. a, annual rainfall is measured in mm (per year). In Fig. c, people displaced by floods are expressed per year and relative to the size of the largest city. In Fig. e, population is measured in millions. In Fig. f, numbers give number of events (average across countries per period).

FIGURES 2a. -- 2.d: Association between main variables

Fig. 2.a: floods and conflict

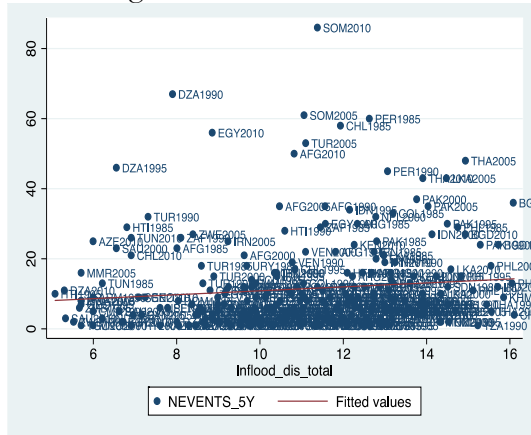


Fig. 2.a: floods and conflict, Asia

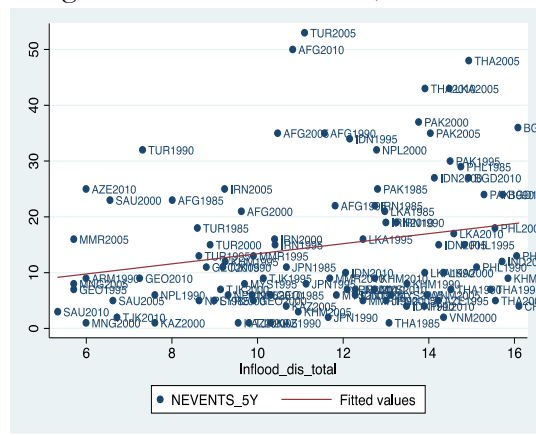


Fig. 2.c: floods and pop largest city

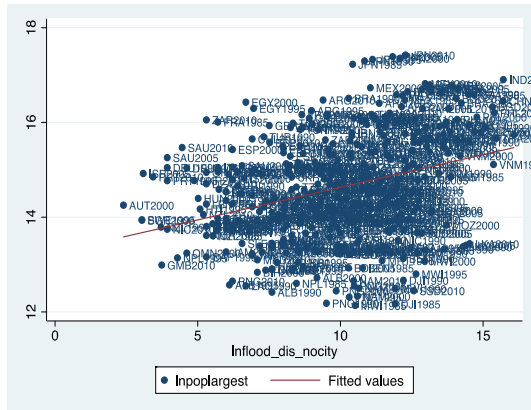
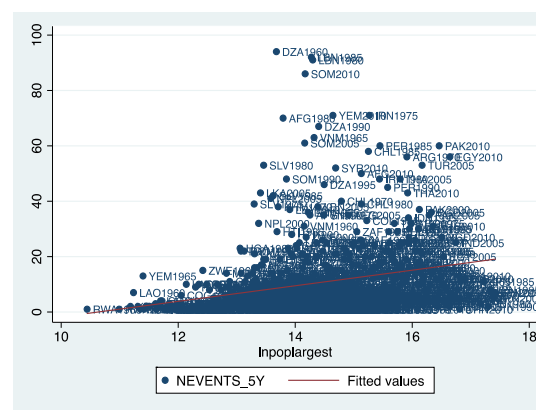


Fig. 2.d: pop largest city and urban disorder events



Note: Figures show scatters using all available observations for each pair of variables. Fig. 2.c excludes Japan as an outlier in pop of the largest agglomeration (Tokyo). Fig 2.d excludes Iraq as an outlier in urban disorder events.

*** TABLES ***

Table 1: Summary stats, full sample

Variable	Obs.	Mean	Std. Dev.	Min	Max
rain_anom	1781	0.035	0.547	-2.257	2.111
ann_rain (mm)	1781	1038.10	760.14	27.35	3331.46
ann_temp (degC)	1781	18.55	8.12	-7.38	29.14
flood_dis_total	834	744,473	5,235,825	0	9.91E+07
flood_dis_nocity	834	481,368	3,194,748	0	4.87E+07
flood_dis_city	834	263,105	2,430,352	0	5.50E+07
urbrate	1617	48.77	24.85	2.08	100
poplargest ('000s)	2114	2286.71	3887.20	2.70	38,001.02
nevents (all)	946	8.46	14.39	0	208
Fatal events	946	3.71	10.04	0	176
Non fatal events	946	4.74	6.75	0	52

Table 2: Effect of rainfall and temperature shocks on city population

VARIABLES	(1) lnpoplargest	(2) lnpoplargest	(3) lnpoplargest	(4) lnpoplargest	(5) lnpoplargest	(6) lnpoplargest
L.rain_anom	-0.049*** (0.016)	0.002 (0.015)	-0.087*** (0.019)	-0.062*** (0.021)	-0.008 (0.020)	-0.105*** (0.024)
cL.rain_anom#cL.SSA		-0.162*** (0.037)			-0.143*** (0.042)	
cL.rain_anom#cL.Asia			0.143*** (0.038)			0.154*** (0.042)
L.ann_temp	-0.045 (0.032)	-0.122*** (0.037)	-0.032 (0.039)	-0.015 (0.041)	-0.129** (0.052)	-0.013 (0.050)
cL.ann_temp#cL.SSA		0.355*** (0.109)			0.325*** (0.106)	
cL.ann_temp#cL.Asia			-0.044 (0.091)			-0.025 (0.113)
Observations	1,294	1,294	1,294	884	884	884
R-squared	0.839	0.856	0.842	0.846	0.860	0.849
Number of iso_num	134	134	134	101	101	101

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Effect of floods on city population						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	lnpoplargest	lnpoplargest	lnpoplargest	lnpoplargest	lnpoplargest	lnpoplargest
L.lnflood_dis_nocity	0.004*** (0.002)	0.003** (0.001)	0.004** (0.002)	0.005*** (0.002)	0.003 (0.002)	0.004** (0.002)
cL.lnflood_dis_nocity#cL.SSA		0.004 (0.004)			0.005 (0.004)	
cL.lnflood_dis_nocity#cL.Asia			0.004 (0.004)			0.004 (0.005)
Observations	778	778	778	486	486	486
R-squared	0.812	0.812	0.812	0.799	0.801	0.800
Number of cities	138	138	138	104	104	104

Robust standard errors in parentheses. City and time period fixed effects included in all models.

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of floods on urban disorder events, intensive margin						
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	All events	All events	Fatal events	Fatal events	Non-fatal events	Non-fatal events
L.lnflood_dis_nocity	0.033*** (0.012)	0.025* (0.013)	0.030** (0.015)	0.021 (0.016)	0.017 (0.013)	0.008 (0.014)
lnpoplargest		0.232** (0.117)		0.235* (0.143)		0.280** (0.138)
Observations	384	384	359	359	384	384
Number of cities	80	80	75	75	80	80

All models estimated using a negative binomial model with country and time period fixed effects.

Standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effect of floods on urban disorder events, extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All events	All events	Fatal events	Fatal events	Non-fatal events	Non-fatal events
L.Inflood_dis_nocity	0.063*** (0.024)	0.038 (0.025)	0.050*** (0.019)	0.035* (0.020)	0.058** (0.023)	0.031 (0.024)
lnpoplargest		0.416** (0.191)		0.255* (0.137)		0.521*** (0.182)
Observations	389	389	389	389	389	389
Number of cities	82	82	82	82	82	82

Probit random effects model, with time period fixed effects included in all models.

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of city population on urban disorder events, intensive and extensive margins.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	All events	Fatal events	Non-fatal events	All events	Fatal events	Non-fatal events
	Count model	Count model	Count model	Prob model	Prob model	Prob model
lnpoplargest	0.316*** (0.059)	0.255*** (0.073)	0.312*** (0.066)	0.417*** (0.106)	0.288*** (0.096)	0.415*** (0.090)
Observations	820	798	820	825	825	825
Number of cities	84	82	84	85	85	85

Columns (1)-(3) estimated using a negative binomial model with unit and time period fixed effects.

Columns (4)-(6) estimated using a probit model with random effects and time period fixed effects.

*** p<0.01, ** p<0.05, * p<0.1

Appendix Tables:

Table A1: Summary stats, by region

Variable	Obs.	Mean	Std. Dev.	Min	Max
(i) Asia:					
rain_anom	286	0.0080183	0.5482471	-2.256794	1.700054
ann_rain	286	1242.333	907.8084	114.7419	3331.46
ann_temp	286	17.28615	8.563643	-0.9312049	27.93215
flood_dis_total	156	3418932	1.15E+07	0	9.91E+07
flood_dis_nocity	156	2166922	6806468	0	4.87E+07
flood_dis_city	156	1252010	5506719	0	5.50E+07
urbrate	308	38.4289	21.96422	3.48	100
poplargest	308	4125.725	6160.853	75.908	36833.98
nevents	308	9.090909	12.34724	0	71
deathevents	308	3.448052	6.951711	0	51
nodeathevents	308	5.642857	7.421405	0	42
(ii) LA:					
rain_anom	209	0.0932131	0.5518865	-1.321491	2.110788
ann_rain	209	1671.09	704.3717	516.1188	3276.07
ann_temp	209	21.97044	4.333712	7.941677	25.93678
flood_dis_total	114	204469.6	389272.8	0	2404400
flood_dis_nocity	114	128167.9	307573.2	0	2404400
flood_dis_city	114	76301.74	240701.4	0	2010500
urbrate	209	58.88393	18.63207	15.593	94.414
poplargest	209	3450.078	4450.403	128.157	20131.69
nevents	209	8.708134	10.75675	0	60
deathevents	209	2.660287	4.362692	0	24
nodeathevents	209	6.047847	7.556684	0	52
(iii) MENA:					
rain_anom	132	-0.0787953	0.5058642	-1.230724	1.134317
ann_rain	132	200.0605	184.235	27.35337	699.2869
ann_temp	132	20.95021	4.294702	10.78404	27.89004
flood_dis_total	72	7532.917	24457.1	0	152000
flood_dis_nocity	72	6941.236	24310.9	0	152000
flood_dis_city	72	591.6806	2966.885	0	24000
urbrate	143	58.92823	20.85727	9.1	98.263
poplargest	143	2330.778	3038.784	15.966	16899.01
nevents	143	13.55944	26.25541	0	208
deathevents	143	8.20979	20.77507	0	176
nodeathevents	143	5.34965	7.733464	0	40
(iv) SSA:					
rain_anom	275	-0.0949281	0.6129314	-1.576875	1.423649
ann_rain	275	963.4508	512.5979	132.5892	2815.303
ann_temp	275	24.77563	2.891423	17.38326	29.14169
flood_dis_total	151	150510.1	430976.1	0	4109900
flood_dis_nocity	151	51124.93	117280.3	0	908900
flood_dis_city	151	99385.14	403305.2	0	4100000
urbrate	286	25.23866	13.70856	2.6	63.228
poplargest	286	1209.027	1420.122	34.319	10780.99
nevents	286	5.034965	8.332067	0	86
deathevents	286	2.520979	6.362548	0	83
nodeathevents	286	2.513986	3.591141	0	26

Table A2: Correlations

Variables	rain_anom	ann_rain	ann_temp	flood_dis_total	floods_dis_nocity	urbrate	poplargest	nevents	deathevents	nodeathevents
rain_anom	1									
ann_rain	0.0662	1								
ann_temp	-0.0972	0.3222	1							
flood_dis_total	-0.0475	0.069	0.0398	1						
floods_dis_nocity	-0.0244	0.0618	0.0214	0.948	1					
urbrate	0.086	-0.1395	-0.3587	-0.1326	-0.1281	1				
poplargest	0.0033	0.0311	-0.1141	0.2228	0.2468	0.2629	1			
nevents	-0.0665	-0.0903	-0.0489	0.046	0.0411	0.0993	0.1683	1		
deathevents	-0.0618	-0.122	-0.004	0.0053	0.0112	0.043	0.0707	0.9081	1	
nodeathevents	-0.0499	-0.0095	-0.1	0.0982	0.0765	0.1479	0.2539	0.7824	0.4496	1

Note: bold numbers are significant at the 5% level.

Table A3: Effect of rainfall and temperature shocks on urbanisation

VARIABLES	(1) lurbrate	(2) lurbrate	(3) lurbrate	(4) lurbrate	(5) lurbrate
L.rain_anom	-0.046*** (0.011)	-0.049*** (0.010)	-0.035*** (0.011)	-0.014* (0.007)	-0.071*** (0.013)
cL.rain_anom#cL.SSA				-0.086*** (0.020)	
cL.rain_anom#cL.Asia					0.067*** (0.019)
L.ann_temp	-0.036 (0.027)	-0.038 (0.024)	0.012 (0.031)	-0.096*** (0.025)	-0.013 (0.027)
cL.ann_temp#cL.SSA				0.308*** (0.073)	
cL.ann_temp#cL.Asia					-0.105* (0.057)
Observations	1,160	1,360	1,020	1,360	1,360
R-squared	0.611	0.586	0.650	0.644	0.597
Number of countries	134	136	102	136	136

Country and time period fixed effects included in all models.

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of floods on urbanisation						
VARIABLES	(1) lurbrate	(2) lurbrate	(3) lurbrate	(4) lurbrate	(5) lurbrate	(6) lurbrate
L.lnflood_dis_total	0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)			
cL.lnflood_dis_total#cL.SSA		0.003* (0.002)				
cL.lnflood_dis_total#cL.Asia			-0.001 (0.003)			
L.lnflood_dis_nocity				0.001 (0.001)	-0.001 (0.001)	0.002 (0.001)
cL.lnflood_dis_nocity#cL.SSA					0.006* (0.003)	
cL.lnflood_dis_nocity#cL.Asia						-0.003 (0.003)
Observations	641	641	641	641	641	641
R-squared	0.448	0.451	0.448	0.449	0.459	0.451
Number of countries	137	137	137	137	137	137
Robust standard errors in parentheses. Country and time period fixed effects included in all models.						
*** p<0.01, ** p<0.05, * p<0.1						