Global warming and urban structure: New evidence on climate change and the spatial distribution of population and economic activity

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Abstract:

We study the relationship between changes in weather patterns and the spatial distribution of population and economic activity within countries. Our unique global dataset combines climatic and census data for the period 1950-2015 with satellite data on built-up areas, and light intensity at night for the 1990-2015 period. We establish a global non-linear effect of climate on urbanisation. In particular, we find that deteriorating climatic conditions are associated with more urbanisation. This happens across the whole urban structure, with urbanisation increasing in both smaller and larger cities. But we also find that weather variation can alter the national urban structure, including the pattern of urban concentration, as well as the size, density and spatial structure of large cities.

Key words: climate change; urbanisation; spatial development patterns; urban structure; urban form

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1. Introduction

The global population is currently undergoing a rapid process of urbanisation. Each year, cities around the world host tens of millions of new inhabitants, with these increases heavily concentrated in low and middle income countries (United Nations, 2018). Traditionally, urbanisation has been associated with a process of structural change and economic development. But today, poor countries urbanise faster and at a much earlier stage of development (see for instance Glaeser, 2014, and Jedwab and Vollrath, 2015), which suggests that the drivers of urbanisation have changed. This has pushed a whole research agenda trying to explain rapid urbanisation in today's developing countries (see for instance Cobbinah et al., 2015; Gollin et al., 2017; Jedwab et al., 2017; and Jedwab and Vollrath, 2019) as well as the phenomenon of 'urbanisation without growth' (Kojima, 1996; Fay and Opal, 2000; Bloom et al., 2008; and Castells-Quintana and Wenban-Smith, 2019).

In this context, urbanisation and city growth are increasingly seen as an outcome of "push" rather than "pull" factors: people get displaced to cities as much as attracted by them (Lipton, 1977; Bates, 1981; Bairoch, 1988; Barrios et al., 2006; and Maurel and Tuccio, 2016). One of the push factors that has gained attention in recent years is the climate. A changing climate translates into significant disruption to living conditions, as a result of numerous changes to environmental conditions. These include slow-onset events, like for instance desertification, worse disease environments, the distortion of fundamental natural cycles and the collapse of entire ecosystems, as well as shocks, like hurricanes and flooding.[4] These climate-related events already cause millions of people worldwide to move every year (Kaczan and Orgill-Meyer, 2020). In 2016 only, over 24

[4] Consequently, although the climate economics literature tends to rely on temperatures and rainfall, these two variables should be understood as capturing a changing climate, where even small changes in average temperature (or average rainfall) can correspond to dramatic and varied changes in environmental conditions relevant for social or economic outcomes of interest (see for instance https://climate.nasa.gov/effects/, and the discussion in Hsiang, 2016). With "only" 1º C. of global warming in the last decades, we already see notable effects on weather patterns and variability, particularly in terms of the frequency of more extreme weather events, as we show in Section 2 (and in Appendix B) using our data.

million people were displaced by sudden-onset climate events, with an additional unknown number of people moving in response to slow-onset hazards such as drought (Opitz Stapleton et al., 2017). As highlighted in the climate literature, a common adaptation to climate change is to move (Raleigh et al., 2008; Laczko and Aghazarm, 2009; Castells-Quintana et al., 2018), with most climate-induced migration occurring within countries, from rural to urban areas, as rural and agricultural-dependent locations are the areas where the impacts of climate change to date are being felt most strongly (Yohe and Schlesinger, 2002; Cattaneo et al., 2019).[5] Climate change therefore, as an ongoing reality and a looming threat, not only has the potential to displace populations from rural to urban areas (see Kaczan and Orgill-Meyer, 2020), but also to accelerate (and shape) the already rapid urbanisation underway in many developing countries, with important policy implications.[6]

In this paper, we study how climate can impact the spatial distribution of population and economic activity within countries. Specifically, we exploit the random variation in historical weather conditions experienced by a given country from one 5-year period to the next, to identify the effects of climate on urbanisation.[7] In contrast to the existing literature, we study not only the evolution of aggregate urban rates but several other dimensions of urbanisation, including measures of urban concentration, city growth, density and form. To do so, we build a unique global dataset on the location of

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5 With rising sea levels and potentially increasing storm intensities, coastal cities are also vulnerable to the effects of further warming. To date the evidence suggests that urban populations displaced by large scale flooding, typically return to the same urban areas within a year of the flood (Kocornik-Mina et al., 2020).

6 As the economic geography literature has shown, the spatial distribution of populations and economic activity has important implications for development. At the country level, the rates, speed, form, and characteristics of the process of urbanisation, are all relevant for economic performance (see for instance Henderson, 2003; Bertinelli and Strobl, 2007; Brülhart and Sbergami, 2009). At the city level, the absolute size, density and form of cities, have also been shown to influence outcomes such as economic growth (Frick and Rodriguez-Pose, 2018), income inequality (Castells-Quintana, 2018) and pollution (Ahlfeldt and Pietrostefani, 2019). Spatial fragmentation of cities is known to limit the benefits of agglomeration and is often associated with bad living conditions (Lall et al., 2017).

7 While it is often argued that weather and climate are not the same, Hsiang (2016) shows that the marginal effect of the climate is exactly the same as the marginal effect of the weather, if both are evaluated relative to an initial climate. Or in other words, "[the] total effects of climatic changes … are also computed correctly in studies where marginal effects of weather are allowed to change based on underlying climatic conditions" (Hsiang, 2016, p.57), which is precisely the empirical set up that we implement in this paper.

population and economic activity, including aggregate census data, satellite data on built-up areas, and data on light intensity at night, complemented with global climatic data, aggregated at the country level.

Our paper closely relates to the literature that studies the connection between weather shocks and rural-urban migration, on the one hand, and urbanisation and city growth, on the other. Several papers in this literature use migration data to show how disasters and weather shocks regularly cause the displacement of populations: the works of Marchiori et al. (2012) for Sub-Saharan Africa (SSA), Jessoe et al. (2018) for Mexico, Strobl and Valfort (2013) for Uganda, Joseph and Wodon (2013) for Yemen, and Bryan et al. (2014) for Bangladesh, collectively underline the global nature of this phenomenon. Peri and Sasahara (2019) provide further global evidence on the migration response (within countries) to increasing temperature, in particular in middle-income countries.[8] On the other hand, other papers have identified climate change as a major underlying driver of urbanisation and city growth in SSA (see e.g. Barrios et al., 2006, Henderson et al., 2017).

While all these papers suggest that climate change can influence rural to urban migration, and therefore urbanisation, to the best of our knowledge, there is no paper that tests the effects of weather variation on various dimensions of the overall spatial distribution of population and economic activity within countries using a long-run global panel of countries.[9] Our paper aims to fill this gap. We contribute to the literature by providing evidence of the impact of climate on the spatial distribution of population and economic activity i) taking a global view and allowing for non-linear effects of climate, ii) studying heterogeneities, including by world regions, by baseline climate, and by socio-

[8] There is also evidence of climate change inducing international migration (see Cattaneo and Peri, 2016, for a global analysis, and Nawroztki et al., 2013, for migration from Mexico to the US), as well as studies on the expected international spatial economic impact of global warming (see Desmet and Rossi-Hansberg, 2015).
[9] Empirical evidence has mostly focused on aggregate urbanisation and the effects of (lack of) rainfall in SSA. Peri and Sasahara (2019) look at temperatures worldwide, but focus on rural-urban migration, and do not explore in depth other dimensions of the spatial distribution of population and economic activity within countries.

economic characteristics such as income and economic structure, and iii) by going beyond the aggregate urban rate to study other dimensions of the urban structure of countries, including urban hierarchy (between cities) as well as urban size, density and form (within cities).

We find that weather variation – both rainfall and temperature – affects urbanisation, and that the marginal effects depend strongly on baseline climate. In particular, higher temperatures in places that are already hot, and lower rainfall in places where it is already scarce[10], are associated with more urbanisation. In short, we identify a global non-linear relationship between climate and urbanisation. We find that these effects occur across the whole national urban structure (i.e., increasing urbanisation in both smaller and larger cities, and even in the largest city of the country). But we also show that weather variation can change the national urban structure, including the pattern of urban concentration, as well as the size, density and spatial structure of large cities, with primary cities becoming larger and denser but also more fragmented in response to deteriorating weather conditions. Our findings hold for our full global sample, although the effects are most pronounced for developing countries.

The remainder of our paper proceeds as follows: In Section 2, we present our data and provide a descriptive analysis of the co-evolution of our climatic variables and different measures capturing the spatial distribution of populations within countries. Section 3 presents the results of our econometric analysis: at the national level, both for aggregate urban rates (Section 3.1) and changes in the national urban structure (Section 3.2), and at the city level (Section 3.3). Finally, in Section 4 we discuss our results and conclude with policy implications and avenues for further research.

[10] As a short-hand, we sometimes refer to these circumstances as "deteriorating climatic conditions". This corresponds closely to the findings in Burke et al. (2015) that country level productivity is increasing in temperature (for colder countries) up to the optimum, and decreasing in temperature for warming beyond that point (in hotter countries).

2. Data

To study how the spatial distribution of population and economic activity within countries has reacted to changes in the climate, we build a unique global dataset for 151 countries (and cities) worldwide over several decades, combining information from different sources, including aggregate census data, satellite data on built-up areas and pixel-level data on light intensity at night, along with global climatic data. Next, we provide descriptive statistics of our climate and urban variables, while Table A.1 in Appendix A contains a list of variable definitions and sources.[11]

2.1 Climate data:

Our climate variables are based on historical weather data, including temperature and rainfall observations, and are derived from monthly global gridded data, which have been aggregated to country means. In our baseline specifications, we use simple area-weighted country means of our climate variables.[12] In particular, we construct two main climatic variables: *ave_rain* and *ave_temp*, which measure mean annual average rainfall (in meters per year) and temperatures (in degrees Celsius), respectively, at the national level, over 5-year time periods from 1950 to 2015.

For robustness, we also construct a gridded weather dataset, merged with gridded population data, and urban area identifiers, from which we derive a number of alternative aggregations of the weather data.[13] These include national level aggregates, weighted by population, including weather variation in all grid-cells or, alternatively, in rural (non-

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[11] Figure A.1 in Appendix A maps the countries included in our sample divided into 8 world regions.

[12] The country-level datasets that we use were obtained from the World Bank's Climate Change Knowledge Portal (CCKP): https://climateknowledgeportal.worldbank.org/download-data (last accessed on 18 June 2020). These are simple area-weighted country means, based on gridded data from the University of East Anglia's CRU dataset (see Harris et al. 2014).

[13] The gridded weather data are drawn from the CRU TS version 4.03 dataset from the University of East Anglia, which we merge with gridded population data from the Global Population of the World v4. Urban areas are identified based on urban extents data from the Global Rural Urban Mapping Project v1.

urban) grid-cells only (as used in e.g. Dell et al. 2012).[14] For the city-level analysis reported in Section 3.3, we further construct city-specific versions of our climate variables based on weather variation in the proximity of the city, and based on national level weather variation weighted by distance to the city. We also consider other climatic measures commonly used in related papers: we construct rainfall and temperature *anomalies* (as used in e.g. Barrios et al., 2006, and Hendrix and Salehyan, 2012), and *decennial changes* (as used in Peri and Sasahara, 2019). Finally, we consider potential interdependencies between rainfall and temperatures (in line with e.g. Matiu et al., 2017) and construct a *moisture* index that captures potential evapotranspiration (as used in e.g. Henderson et al., 2017). Appendix B provides formal definitions and details on the construction of all our climatic variables. Table 1 shows descriptive statistics, for the full panel of country level 5-year periods used in our analysis, and distinguishing between low-, middle and high-income countries.[15] Descriptive statistics by world region are presented in Table B.2 in Appendix B.

Table 1: Summary stats for main weather variables, world and by income level

	Long-run average (1950-2015)				Long-run changes (1950-2015)			
	World	Low	Middle	High	World	Low	Middle	High
Ave Rain	1.0293	1.1038	1.0816	0.8664	-0.0045	-0.068	-0.011	0.032
	(0.7402)	(0.6617)	(0.8229)	(0.6550)	(0.133)	(0.134)	(0.111)	(0.113)
Ave Temp	18.18	23.05	18.81	13.67	0.88	0.84	0.86	0.91
	(8.44)	(5.52)	(7.65)	(9.19)	(0.44)	(0.44)	(0.46)	(0.43)
Rain Anom	0.04	0.02	0.01	0.10	-0.05	-0.51	-0.19	0.25
	(0.55)	(0.62)	(0.54)	(0.49)	(0.82)	(0.95)	(0.79)	(0.69)
Temp Anom	0.25	0.09	0.21	0.43	1.57	1.80	1.67	1.40
	(0.78)	(0.82)	(0.76)	(0.76)	(0.61)	(0.61)	(0.62)	(0.57)
Rain_dec_ch	1.05	0.79	1.21	3.65	-11.84	86.20	-28.52	-44.54
	(137.26)	(114.81)	(139.70)	(137.89)	(259.24)	(136.61)	(230.87)	(292.09)
Temp_dec_ch	0.13	0.08	0.12	0.17	0.32	0.20	0.39	0.30

[14] In practice (and as noted by Dell et al. 2012) these different aggregation methods produce very similar measures at the national level (see summary stats in Appendix Table B.1). In all cases, the pattern of results we obtain is qualitatively very similar, regardless of the method used to aggregate climate data to the national level.

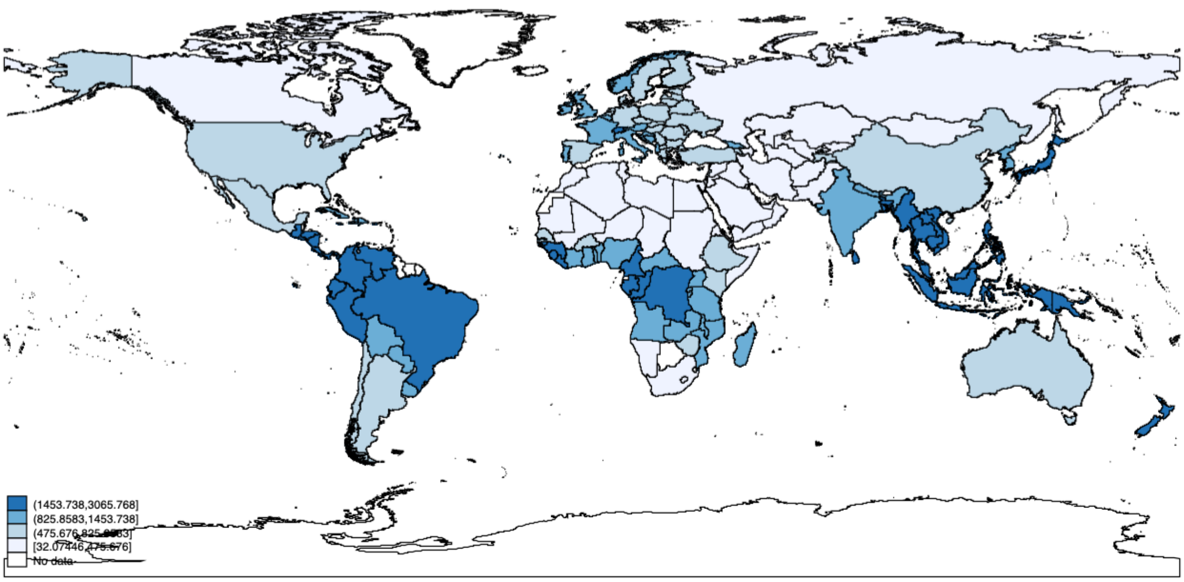
[15] Low/middle/high-income countries are classified based on real GDP per capita in the given year. Countries with a log value smaller than 7 are classified as low-income, those with a value between 7 and 9 are classified as middle-income and those with a value higher than 9 as high-income. These values are chosen following international distinctions and what is done in related papers. Using different thresholds does not alter the results presented in the paper. In our analysis, we also distinguish between developed vs. developing countries based on World Bank classification.

	(0.49)	(0.40)	(0.48)	(0.55)	(0.55)	(0.71)	(0.54)	(0.52)

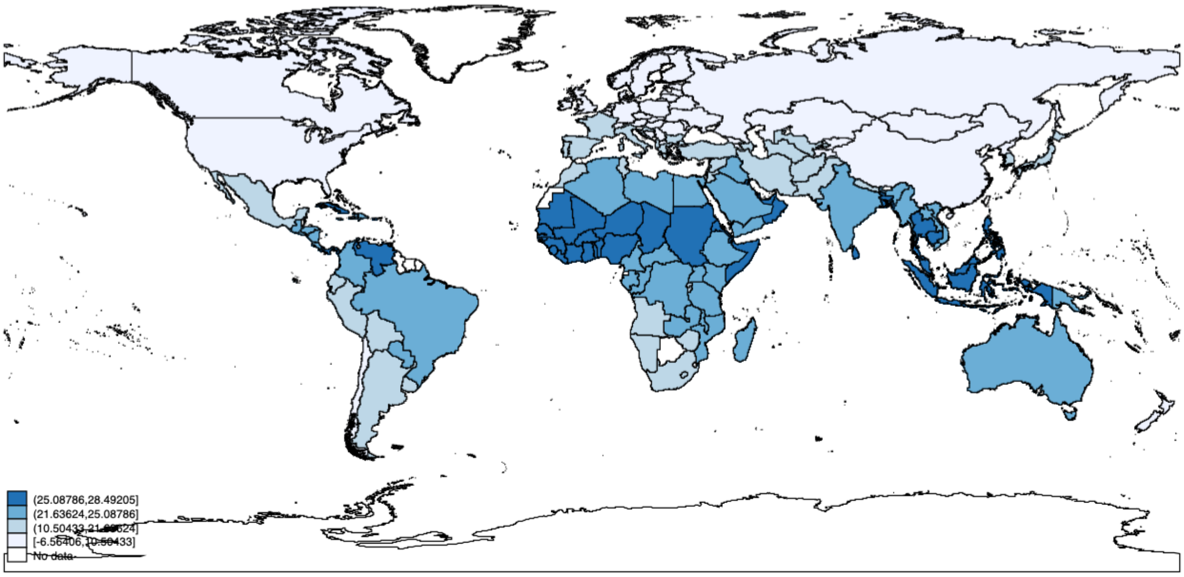
Note: The table shows mean values for each variable by income group (the first four columns) and long-run changes in these variables by income group (in the last four columns). Standard deviations in parentheses. Variables are as defined in the text and in Appendix B.

As Table 1 shows, mean annual rainfall in our sample is around 1 meter per year, while mean annual temperature is around 18 degrees Celsius (first column).[16] We also see the long-established negative correlation between average temperatures and income, further illustrated below in Figure 1. Given the global nature of our analysis, it is important to note the wide variation in baseline climate (or average weather conditions) across our global sample, as illustrated by Figure 1, panels A and B, which show, respectively, the cross-sectional variation in average temperatures and rainfall in our sample.

Figure 1: Global maps showing variation across countries in long-run average climate (1901-2015)



[16] This is high relative to scientific estimates of global temperatures, reflecting the nature of averaging over country-level observations, where small warm countries carry the same weight as large cold countries.



Note: Top panel above is rainfall (in mm per year) and bottom panel is temperature (in degrees Celsius), as described in the text.

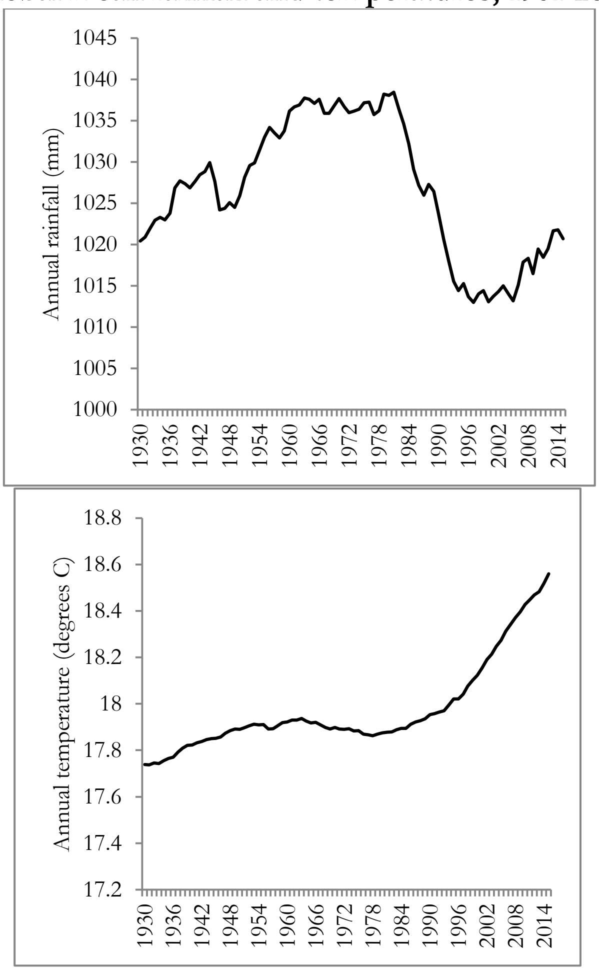
Global Warming

The effects of climate change on weather patterns are also evident in our data. Over our sample period (from 1950-2015), average temperatures increased by 0.88 degrees Celsius (see column 5 of Table 1), which fits well with scientific observations of global warming, while average annual rainfall declined by about 5mm, or by about 1% when comparing changes at the country level to country average rainfall. Distinguishing by income levels, warming has been slightly higher in high-income countries (0.91 degree Celsius). Global trends in average temperatures and rainfall over the 20th century are illustrated for our sample of countries in Figure 2. Regionally, the strongest warming in our data is observed for countries at higher latitudes (usually richer countries), again in line with scientific observations (see Figure B.2 in Appendix B). This means that colder countries have experienced faster rates of warming than hot countries. However, a given amount of warming is likely to have differential effects for socio-economic outcomes, depending on initial or baseline climates.[17] We test this idea explicitly in our analysis by allowing the

[17] It has been estimated that the optimal temperature for economic productivity is around 13 degrees Celsius, with warming for relatively cold countries found to be productivity-improving, while for hotter countries further warming reduces economic productivity (see Burke et al., 2015).

marginal effects of weather variation on urban trends to vary with baseline climate. The strongest drying trends (relative to average rainfall) in our data are observed in places that are already relatively dry, such as North Africa and the Middle East (-11%), and SSA (-7%), as depicted in Figure B.2 (in Appendix B). By income levels, this translates into an increase in average rainfall in high-income countries vs. a decrease in low and middle-income ones. Beyond averages, it is important to note that the amount of warming observed over the 20th century has also had a notable effect on the frequency of relatively large deviations from average weather conditions. For example, the frequency of years with temperatures more than one standard deviation above country-specific means increased 34-fold, and more than two standard deviations above country means increased 256-fold, over the course of the 20th century (see Figure B.3 in Appendix B).

Figure 2: Global mean rainfall and temperatures, 1901-2015



Note: The figures show rolling 30-year averages of annual average rainfall (in mm per year – left panel) and temperature (in degrees Celsius – right panel) for the countries in our data, such that the first data point in each figure (labelled 1930) represents the average over the preceding 30 years (1901-1930), and so on. The figures illustrate the pronounced warming (and drying) trends globally over the latter half of the 20th Century.

2.2 Urban variables:

To study the effects of changes in the climate on various urban outcomes, we examine not only what happens at the national level but also at the city level, something which, to the best of our knowledge, has not been done before in the literature using a global sample. To this end, we combine national-level census data on the urban hierarchy with city-level structural information about the primary city, gained from satellite data on night-time lights as well as built-up areas.

In particular, we rely on the World Bank - World Development Indicators database and the United Nations' World Urbanization Prospects (WUP), which includes urban and rural population every five years from 1950–2015, for all countries in the world. We study the urbanization rate (defined as population living in urban areas as percentage of total population) and distinguish between urbanisation in large cities (i.e., cities of more than one million inhabitants in 2018, as defined by WUP) vs. urbanisation in small and medium-sized cities (i.e., cities below one million inhabitants). The WUP dataset also includes data on population for all cities in the world with more than 300 thousand inhabitants in 1990. We consider urban primacy, defined as the share of urban population living in the largest city, a commonly used measure of urban concentration (see Ades and Glaeser, 1995; Henderson, 2003). Finally, to consider the absolute size of cities, we also construct measures of average city size (following Castells-Quintana, 2018).[18]

To study outcomes at the city level, we look at primary cities. To be able to

[18] For every country-year pair in our data set, our average city size variable gives the average population size of urban agglomerations in the country that had at least 300,000 inhabitants in 1990 using WUP data.

analyse not only changes in total population in the city, but also the within-city spatial distribution of population and economic activity, we rely on several data sources. We follow the growing strand of the literature within economic geography that makes use of geo-located data to study socio-economic dynamics (recent examples include Lessmann and Seidel, 2017; Henderson et al., 2018; Düben and Krause, 2019; Harari, 2020). We use WUP data, but also novel data from the European Commission's Global Human Settlement Layers - GHSL (Florczyk et al., 2019), which combines Landsat satellite imagery on built up area with census information (Pesaresi and Freire, 2016). For the years 1975, 1990, 2000 and 2015, the GHSL data classify each pixel in a global grid according to the urban structure it belongs to. For each primary city, this allows us to distinguish between the high-density areas (more than 1500 people per sq km) and relative low-density areas belonging to the urban agglomeration.

Finally, we also rely on satellite data on night-time lights to compute additional measures for the urban structure of primary cities. We use data from the Defence Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), operated by the National Oceanic Administration Agency (NOAA), and available at the pixel level (30 arc seconds, corresponding to less than 1 square kilometre at the equator) as a yearly panel from 1992 to 2013.[19] This data has become established as a proxy for local economic activity in recent years (see Henderson et al., 2012; Donaldson and Storeygard, 2016; Candau and Gbandi, 2019). However, it has hardly been applied to study dynamics within cities, because within large cities many pixels reach the end of the scale and many parts appear equally bright. We overcome this problem by working with the lights values by Bluhm and Krause (2018), who apply a top-coding correction to the original data so

[19] Because of their gradual changes, we assign the first year of the lights data, 1992, to 1990 as well as the last year, 2013, to 2015, to match the quinquennial structure of our data (1990, 1995, 2000, 2005, 2010, 2015). Dropping the first and last period does not significantly alter our results.

they more adequately represent the brightness of large cities.[20] Using these data, we compute i) light per capita (by dividing the sum of lights within the city boundaries by population data),[21] ii) the spatial Gini coefficient of inequality in light within the city, and iii) Moran's I, measuring spatial autocorrelation by indicating whether bright (dim) cells are surrounded by similarly bright (dim) cells (Moran, 1950); a high Moran's I suggests a monocentric structure, while a low Moran's I points to more fragmentation (see Tsai, 2005; Bluhm and Krause, 2018).[22]

Table 2 presents descriptive statistics for our main urban variables considered to describe the spatial distribution of population and economic activity within countries. As before, we look at cross-country averages for our world sample, as well as averages by income group (i.e., low, middle and high income). Table C1 in the Appendix provides the corresponding statistics for each world region.

Table 2: Descriptive Statistics of Urban Variables by Income Group

	Latest available year (2010/2015)				Long-run changes			
	World	Low	Middle	High	World	Low	Middle	High
Panel A: Country-Level variables								
Urb Rate	58.38	29.88	47.32	77.53	22.05	19.85	22.42	22.84
	(23.04)	(10.41)	(16.97)	(13.19)	(12.67)	(6.75)	(10.67)	(15.52)
Urb > 1m	18.79	7.32	15.09	26.32	6.21	5.25	6.74	5.94
	(18.53)	(7.48)	(12.67)	(22.89)	(8.09)	(5.87)	(7.15)	(9.57)
Urb < 1m	39.49	22.56	32.23	51.21	15.93	14.60	15.68	16.90
	(19.98)	(10.39)	(15.21)	(19.45)	(11.47)	(7.10)	(10.81)	(13.20)
Urb Largest	19.15	12.29	15.38	25.69	5.96	8.51	6.55	4.79
	(16.49)	(6.23)	(10.50)	(21.08)	(8.16)	(5.33)	(6.18)	(10.33)
Urb Non-Largest	39.06	17.59	31.94	51.83	16.10	11.34	15.87	18.05
	(19.49)	(6.52)	(13.72)	(17.73)	(10.40)	(5.18)	(9.42)	(12.03)

[20] The top-coding correction applied by Bluhm and Krause (2018) involves the use of a geo-referenced replacement algorithm, in which top-coded pixels get assigned value from the Pareto distribution. See further discussion in Appendix C.
[21] The maximal urban extents are given by the GHSL data from the year 2015 (end of sample). In each year, we count the lights that fall within these boundaries and divide them by the yearly population data from the WUP to obtain lights per capita.
[22] In computing Moran's I, we take the precise location of each pixel within a city into account. Using the inverse distance matrix as the spatial weights matrix, the index captures whether similar light intensities cluster together in space. Further details on the calculation of Moran's I are included in Appendix C.

Primacy	32.92	40.81	32.44	32.06	-2.48	-0.53	-2.19	-3.90
	(17.63)	(13.37)	(14.78)	(20.82)	(12.56)	(19.00)	(11.17)	(11.43)
Ave. City Size	1268.84	1148.38	1273.05	1333.77	1015.91	1090.99	1133.20	913.52
	(874.51)	(506.50)	(637.95)	(1150.21)	(774.96)	(482.06)	(618.73)	(971.22)
Panel B: Variables for the primary city								
Pop	4216.05	1674.78	4611.56	4664.93	3368.64	1593.88	4137.76	3232.74
	(5771.8)	(1067.15)	(5825.59)	(6547.66)	(4765.43)	(1012.51)	(5296.05)	(4893.57)
Density	3082.23	3142.49	3096.55	3029.74	-521.31	-331.74	-306.53	-442.03
	(2389.9)	(1130.95)	(1140.66)	(3377.27)	(3020.02)	(1055.75)	(1701.50)	(3514.04)
High-density share	85.79	95.50	87.29	81.64	2.66	6.61	2.99	1.07
	(15.54)	(5.91)	(14.03)	(16.68)	(15.99)	(16.46)	(16.09)	(15.46)
Light per capita	52.05	8.14	24.24	95.62	4.14	0.36	5.05	3.92
	(88.92)	(7.02)	(18.74)	(123.36)	(39.11)	(5.72)	(11.43)	(59.32)
Light Gini	30.78	27.52	30.15	32.68	-7.55	-23.74	-8.56	-1.97
	(9.37)	(5.49)	(10.70)	(8.85)	(13.20)	(10.04)	(12.58)	(10.23)
Moran's I	82.23	76.18	81.73	84.58	-0.46	-2.58	-0.89	0.70
	(9.30)	(5.97)	(10.75)	(8.11)	(5.83)	(6.73)	(5.92)	(5.51)

Note: The table presents summary statistics of urban variables at the national city-level for the primary city. Values in parenthesis show standard deviations. The long-run changes for the national variables are computed over the period 1950/60 to 2010/15 (depending on data availability). The long-run changes for the city level variables were computed over the period 1950 to 2015 (population), 1975 to 2015 (density and high-density share) and 1990 to 2015 (lights-based measures).

Changes in Urban Structure

As we can see in Table 2, urbanization rates are higher in richer countries, but low and middle-income countries have been catching up in recent decades. Urbanization in both large (>1m) and small and medium-sized cities (<1m) has increased in all countries; however, the increase in large cities has been most pronounced in North as well as Latin America, while urbanization in smaller cities has increased most strongly in SSA and the Middle East/North Africa. In contrast to urbanization rates, primacy rates are higher in low-income countries, but have been on the decline. This decline is particularly pronounced in SSA, which, nevertheless, still has the highest primacy rates. In terms of average city size, we see a huge increase in the last decades, in particular in South East Asia (SEA).

Turning to the city-level data, primary cities have grown most strongly in population in middle-income countries, driven mostly by SEA. But it is low-income countries, often on the African continent, that have particularly dense primary cities: in low-income countries 95% of the city area is on average classified as high-density, a share which has increased by 6.6 percentage points since 1975. Night lights per capita in primary cities are particularly high in richer countries, as expected, and the difference with counterparts in low-income countries is now actually higher than in 1990. But inequality in lights within the primary city has decreased across the world, in particular in low and middle-income countries (with improved electrification being one potential driver). Finally, Moran's I, as a measure of spatial autocorrelation within the primary city, exhibits some interesting features: first, it is higher the richer a country is, pointing towards more regular, monocentric, and, in general, well-planned cities. Second, primary cities in poorer countries, particularly SSA ones, are more fragmented – and are becoming even more so, as their decreasing Moran's I index shows. The decline in light-inequality (i.e., Gini) and in monocentricity (i.e., Moran's I) suggests a process of spatial fragmentation, especially pronounced in the large cities of the developing world.[23]

3. Empirical analysis

In this section, we present results of our empirical analysis that tests the effects of weather variation and gradual changes in weather patterns on the spatial distribution of population and economic activity. For simplicity, and to more easily connect with the literature, we proceed in three steps: first we test the effects of climate on the aggregate national urban rate (Section 3.1). Second, we test the effects of climate on other measures of the national urban structure, including urbanisation in large versus small and medium-sized cities, as well as measures of urban concentration (Section 3.2). Finally, we zoom in to the city level, to test the effects of climate on the size and spatial structure of cities (Section 3.3).

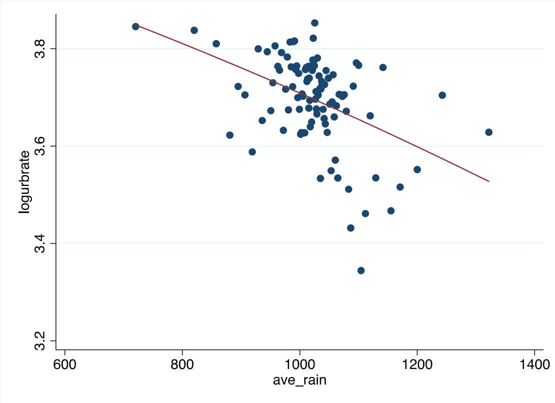
[23] The UN-Habitat Report (2016) has highlighted the fragmented nature of large cities in many developing countries, especially in SSA. In very poor countries, fragmentation is expected due to deficient infrastructure and high commuting costs, making work and living places coincide. There is ample empirical evidence of persistently high transport costs and poor basic services in many cities in SSA (see for instance Castells-Quintana, 2017; Bluhm and Krause, 2018). In richer cities, and as transport systems improve and commuting costs fall, monocentricity is predicted to develop (Ogawa and Fujita, 1980; Proost and Thisse, 2019).

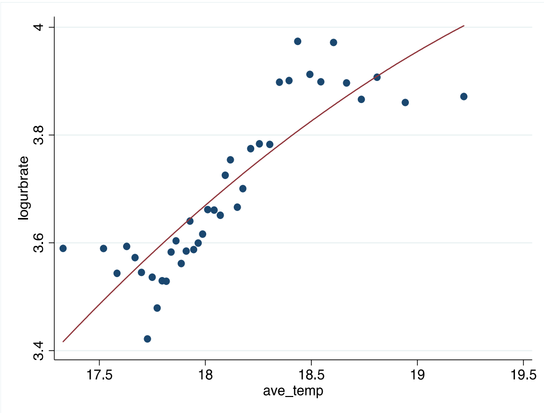
3.1. Climate and urbanisation:

Comparing countries based on their average temperature in 1950, we find that those with higher base-line temperatures (and rainfall) increased their urbanisation rates more over the 1950-2010 period. Being closer to the Equator, developing countries are, on average, warmer than their developed counterparts. But as shown before, warming has been stronger at higher latitudes, and the increase in urbanisation rates has been, on average, lower in countries that experienced higher warming over the 1950-2010 period. What about the relationship between warming and urbanisation controlling for base line climate? In Figures 3.1 and 3.2, we show this connection between urbanisation (i.e., the urban rate) and the climate, controlling by country fixed effects. In this way, Figures 3.1 and 3.2 capture the connection between urbanisation and the climate considering only the within-country evolution over time (what we are after). Both figures suggest a relevant association: According to Figure 3.1, higher annual rainfall is associated with lower urban rates. According to Figure 3.2, higher temperatures are associated with *higher* urban rates.[24]

Figures 3.1 and 3.2: Average annual rainfal and temperatures and the urban rate

[24] Without controlling for country-fixed effects the relationship is actually negative, in line with the idea that countries that have warmed the most are, on average, those that have urbanised the least. This means that the observed association in Figure 3.2 is not driven by warming and urbanisation happening faster in the same countries.





Note: The Figures show binscatters, where each point represents 40 observations in the dataset. Climate variables are measured in the preceding 5-year period compared to the urban rate. In these figures rainfall is measured in mm per year, and temperature in degrees Celsius. The scatters control for country-fixed effects.

To further test how climatic trends can drive urbanisation, we estimate a simple econometric model where the urban rate is regressed on our measures of climate conditions, as specified by Equation (1):

$$Urb_{it} = \alpha_1 + \beta_1 Climate_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (1)$$

where Urb_{it} is the urban rate (the population living in urban areas as a percentage of the total population in logs) in country i in period t.[25] Following the literature, and given data availability, we use 5-year periods (t = 1960, 1965, 1970… etc.). Our main explanatory

[25] Our empirical set up follows closely the specifications used in the existing literature that relates urbanisation to weather variation at the national level (e.g. Barrios et al., 2006; Bruckner, 2012; Henderson et al. 2017; Peri and Sasahara 2019), as well as papers that relate income growth to weather variation at the national level (e.g. Dell et al., 2012; Burke et al., 2015).

variables of interest are $Climate_{it}$. In our main results, presented below, we focus on average annual rainfall (in meters) and temperature (in degrees Celsius), aggregated over the preceding 5-year period. For robustness, we also test the effects of rainfall and temperature *anomalies* and *decennial changes* in these variables, as well as alternative methods of aggregating climate data to the national level (see discussion in the data section, and results in Appendix D). As the climate-urbanisation relationship is likely to depend on each country's baseline climate, we introduce our climatic variables in linear and quadratic terms, in line with the climate literature (see for instance Burke et al. 2015; Matiu et al. 2017). We also include year fixed effects, γ_t, to control for global shocks, and country fixed effects, θ_i, to control for time-invariant characteristics of countries. The standard errors, ε_{it}, are clustered at the country level. Identification in our data rests on the assumption that inter-temporal variation in our climate measures is exogenous with respect to urban trends, conditional on country and period fixed effects.[26]

Table 3 shows our main results describing the effect of variation in annual rainfall and temperature on the urban rate. The results in column 1 show significant non-linear climatic effects – i.e. depending on the country baseline climate.[27] Results yield a U-shaped relationship between the evolution of rainfall and the urban rate; for countries with low levels of rainfall, more precipitation leads to less urbanisation, but for countries with high rainfall, more precipitation leads to more urbanisation. For temperature, the pattern is similar: for countries with low mean temperatures, an increase in mean temperature leads to less urbanisation, but for countries where temperatures are already

[26] Below, we also test the robustness of our main findings to the use of different measures of climatic variation, clustering errors at the country and time level, the inclusion of additional time-varying controls, including the log of GDP per capita and total country population, the inclusion of region-specific trends, and the inclusion of country-level linear time trends.

[27] According to McIntosh and Schlenker (2006), in a panel FE model, there are differences between a global quadratic functional form across units and a quadratic functional form within group. They propose to use a "hybrid estimator" to capture and distinguish both non-linearities (i.e., global and within). We have estimated our model in Equation (1) using this hybrid estimator. Results are only significant for the "global" non-linearities, confirming that our quadratic terms are basically capturing non-linearities *across* countries depending on their baseline climate (even when the main identification is within-country over time).

high, higher temperatures lead to more urbanisation. These results are consistent with the literature on rural-urban migration (see for instance Cattaneo et al, 2019; Kaczan and Orgill-Meyer, 2020), as well as the observed global non-linear effect of temperature on economic productivity (see Burke et al. 2015). For low rainfall and temperatures, an increase in any, or both, means better rural conditions. But when rainfall and temperatures are high, an increase means *worse* rural conditions, which creates an incentive to move to urban areas.

Table 3: Main results, urban rate

	(1) full sample	(2) developed	(3) developing	(4) low income	(5) middle income	(6) high income
Dependent variable:	log(urb)	log(urb)	log(urb)	log(urb)	log(urb)	log(urb)
ave_rain	-0.6352***	-0.2806*	-0.5626***	-1.0226**	-0.4576**	-0.2202
	(0.1766)	(0.1449)	(0.1983)	(0.4277)	(0.2156)	(0.1683)
ave_rain^2	1.16e-04***	2.63e-05	1.16e-04***	2.41e-04**	8.27e-05*	6.26e-05
	(4.05e-05)	(3.11e-05)	(4.40e-05)	(1.19e-04)	(4.48e-05)	(4.36e-05)
ave_temp	-0.2462***	0.0162	-0.2803***	-0.0581	-0.2450***	-0.0643*
	(0.0400)	(0.0216)	(0.0787)	(0.4546)	(0.0713)	(0.0381)
ave_temp^2	0.0066***	-0.0011*	0.0076***	-0.0021	0.0062***	0.0009
	(0.0011)	(0.0006)	(0.0018)	(0.0096)	(0.0018)	(0.0009)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1606	396	1210	327	761	485
No. of countries	146	36	110	44	105	63
R-Square (within)	0.637	0.652	0.695	0.789	0.725	0.514

Note: This table reports results of specifications based on Equation (1) and as described in the text. The dependent variable in each column is the log of the urban rate. Robust standard errors (clustered by country) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As shown by columns 2 and 3 of Table 3, the results are driven primarily by effects in developing countries. This finding fits with expectations given that developing countries i) have a higher share of population living in rural areas, ii) are regions where the effects of climate change are being felt the strongest, and iii) is where populations have lower adaptive capacity. Furthermore, according to columns 4, 5 and 6, the reaction to changes in rainfall is strongest in low-income countries, consistent with previous findings for SSA (see for instance Barrios et al 2010). For temperatures, the effect is strongest in middle-income countries, in line with results in Peri and Sasahara (2019).[28]

Figures D.1, D.2 and D.3 (in Appendix D) show marginal effects for rainfall and temperatures on the urban rate, for the full sample, for developed countries, and for developing countries, respectively. For developing countries, the estimated marginal effects show that for rainfall, it is low rainfall that is associated with higher urbanisation.[29] According to our results, for countries with average annual rainfall below 500mm (per year), a 100mm reduction in average annual rainfall over a 5-year period results in a 5% increase in the urbanisation rate. For temperatures, we see the marginal effect taking opposite signs depending on the baseline temperature. In hot countries, higher temperatures are associated with more urbanisation, whereas in cold countries lower temperatures are associated with more urbanisation, again reflecting the expected effects of worsening climatic conditions.[30] To illustrate the magnitude of estimated effects, for a relatively hot country, with average annual temperature around 25 degrees Celsius, a 1 degree increase in average temperatures over a 5-year period would result in a 10% increase in the urbanisation rate.

Robustness

In Tables D.1 to D.4 in Appendix D, we present various robustness checks on our main findings. In Tables D.1 and D.2, we replicate the results in Table 3 for alternative measures of weather variation used in related literature. In Table D.1, we use *population-weighted* average rainfall and temperatures, as in Dell et al. (2012), to capture the fact the

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[28] At the household level, according to Peri and Sasahara (2019) often it is not those with the lowest income that migrate first; low-income individuals may be constrained and therefore less likely to move given worse climatic conditions in rural areas, which in turn represent a negative income shock (see for example Gray and Mueller, 2012; Bryan et al., 2014). By contrast, the constraints to move are less likely to be binding at middle-income levels.

[29] The marginal effect turns positive at high levels of rainfall, although this effect is not statistically significant.

[30] The negative marginal effect of temperature on urbanisation appears for initial temperatures below around 15 degree Celsius, while the positive marginal effect appears for initial temperature above around 25 degrees Celsius. This would be the case of some countries in LATAM, SEA, and most countries in MENA and SSA.

effect of weather variation will be stronger in more populated areas. In Table D.2, we use *decennial changes*, as used for instance in Cattaneo and Peri (2016), and *anomalies*, as used for instance in Barrios et al. (2006).[31] Results using population-weighted average temperature and rainfall, decennial changes and anomalies show similar results to those in Table 3, confirming the idea that when climatic conditions deteriorate urbanisation rates increase (although for decennial changes the coefficient for rainfall loses significance).[32] In Table D.3, we check for a different clustering of residuals by country and time, for whether the effects depend on the degree of openness (following theoretical insights in Matsuyama, 1991), and controlling for additional time-varying controls, including the log of GDP per capita and total country population (at the expense of losing observations). Our results hold, and are significant for country-periods with high as well as low openness. Finally, in Table D.4, we consider the fact that rainfall and temperatures are not independent from each other (Matiu et al., 2017). First, we consider an interaction between temperature and rainfall. Second, we consider a *moisture* index (as used in e.g. Henderson et al., 2017). Finally, we consider the principal component of temperatures and rainfall. In all cases, we find highly significant coefficients, which are also robust to different specifications, including controlling for region- or country-specific linear trends. All these robustness checks reinforce our main results suggesting that when climatic conditions deteriorate urbanisation increases.

Heterogeneity – By initial distribution of cities

In Tables D.5 and D.6 in Appendix D, we perform a set of heterogeneity analyses. In Table D.5, we begin by testing the effects of climatic conditions on urbanisation

[31] When looking at *changes* or *anomalies* we drop the quadratic term, following the specifications in the cited papers. Note that anomalies already capture the baseline climate by looking at deviations from the country's long-run mean and therefore capturing country-specific shocks. However, results hold if we consider a quadratic specification.
[32] If anything, for temperature the results using the population-weighted versions of our climate variables show a slightly stronger and more precisely estimated effect.

depending on the initial number of cities per unit area in each country.[33] In response to worsening climatic conditions, rural dwellers considering a move to urban areas likely face a trade-off between better employment opportunities (which should be increasing in city size) and cost of moving (which should be increasing in distance), with bigger cities, on average, likely to be further away.[34] A higher number of cities per unit area is therefore expected to increase the propensity for rural-urban migration, especially for budget-constrained rural dwellers. In low-income countries, where the budget constraints to move play the strongest role, we find that the effect of higher temperatures on urbanisation is greatest for countries with a higher number of cities in 1960.[35]

Heterogeneity – By baseline climate, agricultural share and world regions

In Table D.6, we present heterogeneity effects by baseline climate, by agriculture's share of GDP, and by world region. We show that the effects of rainfall and temperature anomalies on urbanisation are strongest in countries that are relatively hot (column 1) or wet (column 2), corresponding to the non-linear effects previously identified, as well as in countries with high agricultural share of GDP (column 3), as expected. With their livelihoods dependent on potentially small variations in temperature and precipitation, rural farmers are threatened by climatic shocks in a more immediate way than individuals not directly dependent on agriculture. It is known that, by lowering farm incomes, negative climatic trends - both one-off events and a succession of disasters - encourage

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[33] Defined as the number of cities (based on UN WUP data) per 1,000km^2 (based on World Bank data for land area) for each country in 1960. We find significant differences across countries: while countries in SEA have a relatively high initial number of cities per area (0.077), countries in SSA have a relatively low initial number of cities (0.025), compared to the average in our data (0.056). Also, countries in SSA, as well as in Latin America, tend to very high degrees of urban concentration in few cities, and there is a debate whether secondary cities are catching up (Christiaensen and Kanbur, 2017; Bluhm and Krause, 2018; Castells-Quintana and Herrera-Idarraga, 2019).

[34] Mallick (2014) found that 25 percent of households affected by Cyclone Aila in Bangladesh in 2009 moved to neighbouring cities. Of those who moved to cities, 78 percent chose relatively large cities within the region, where they pursued jobs in the service industry (as cited in Ober, 2019). See also Raleigh et al. (2008) and Rigaud et al. (2018).

[35] Results in column 1 of Table D.5 show the opposite pattern – urbanisation responds most strongly to higher temperatures in places with low initial cities per unit area, likely reflecting the correlation between this measure and national level income. The interpretation of the result for low-income countries (column 4 of Table D.5) is further supported by insights from the case study presented in Appendix G, which highlights the diverse urban development patterns across developing countries with different initial urban structures.

migration to cities (Brückner, 2012; Saldaña-Zorrilla and Sandberg, 2009; Neumann et al., 2015). However, agriculture is not necessarily the only mechanism linking climate and population movement; as mentioned before, changes in the climate translate into higher frequency and intensity of extreme events (like droughts and flooding), which displace millions of people every year (see for instance Eckstein et al, 2018). Climate shocks have also been linked to conflict at the subnational level (see Harari and La Ferrara, 2018; Bosetti et al, 2018), which might act as a further channel linking climate shocks with migration to cities.

Finally, in column 4 of Table D.6, we test for regional differences in terms of the climate-urbanisation relationship and find some interesting variation across world regions. According to our results so far, the effect of changes in the climate depend on initial climatic conditions. As noted in Section 2.1, world regions differ substantially in their average climatic conditions. In SSA, where rainfall is already scarce, and shows a clear decreasing trend over the last decades, we find that periods with low rainfall and/or high temperatures are associated with higher urbanisation. However, in other regions (for instance in SEA, where rain can become excessive) we find a different pattern.[36] These contrasting findings hint to differential effects of climate change in different world regions with different baseline climate, as reflected also by the quadratic effects already noted in Table 3.

3.2. Climate and the national urban structure:

So far, we have shown that when climatic conditions worsen this leads to more urbanisation, and we have shown the global reach of this phenomenon, once one allows

[36] The effect of rainfall in SEA is positive (i.e. higher rainfall associated with more urbanisation), albeit not significant at conventional levels (p=0.23). This is something that we further explore in the next section, taking into account that millions of people are displaced each year by "sudden-onset" events (disasters), with floods and storms accounting for roughly two-thirds of this displacement globally, and these events are particularly concentrated in South East Asia (IDMC, 2018, as cited in Ober, 2019).

for a non-linear effect of climate. But, is this "climate-driven urbanisation" evident and similar across the whole urban structure? Or do changes in the climate lead to more urbanisation in specific urban areas, and therefore affect the national urban structure beyond the urban rate? These questions, to the best of our knowledge, have not been addressed in the literature to date, but are of increasing interest given that climate change is becoming a major factor displacing population, and given the relevance of the national urban structure in the process of development of countries.[37]

We test the effects of climatic conditions on the urban structure using a similar specification as the one given in Equation (1), but changing the dependent variable. Results are presented in Table 4. In columns 1 and 2 we distinguish urbanisation in large cities (i.e., over one million inhabitants) vs. urbanisation in small and medium-sized cities (i.e., below one million).[38] In columns 3 and 4 we distinguish urbanisation taking place in the largest city vs. urbanisation in the rest of the urban areas of the country. In all cases, we see a similar pattern as in Table 3 where we considered the overall urban rate: i.e. a U-shaped association between both rainfall and temperature, and urbanisation. These results imply that the urbanisation-increasing effect of worsening climatic conditions is evident in cities above one million inhabitants as well as in cities below one million, and in the largest city as well as in the rest of the urban hierarchy. However, comparing the magnitude of the coefficients across the four columns, we also find significant differences between urbanisation in large cites (column 1) vs urbanisation in smaller cities (column 2), and between urbanisation in the largest city (column 3) vs urbanisation elsewhere (column 4). For rainfall, worsening climatic conditions (a decrease in rainfall when rainfall is already low) increases urbanisation in large cities more than urbanisation

[37] Climatic factors are of course not the only source of urbanization and changes in the national urban structure. A variety of other factors also play a role, including economic development, political characteristics of countries (Ades and Glaeser, 1995; Davis and Henderson, 2003; Henderson and Wang, 2007; Candau and Gbandi, 2019), trade, manufacturing development (Krugman and Livas, 1996), and (historical) infrastructure (Bonfatti and Poehlhekke, 2016), to mention some.

[38] We focus on countries with at least one urban agglomeration over one million inhabitants in 2018 (following the definition in the World Development Indicators). This mainly excludes very small countries.

in small and medium-sized cities. By contrast, for temperatures, we see substantially larger effects on urbanisation in small and medium-sized cities compared with urbanisation in large cities (with urbanisation in small and medium-sized cities responding almost 5 times more to high temperatures than urbanisation in large cities). A similar pattern of findings emerges with the distinction between the largest city and the rest of the urban hierarchy in columns 3 and 4; urbanisation in the largest city responds most strongly to changes in annual rainfall, while it is urbanisation taking place outside the largest city which responds more to changes in annual temperature.[39]

Table 4: Other dimensions of the national urban structure

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	log(urb>1m)	log(urb<1m)	log(urb largest city)	log(urb outside largest city)	log(primacy)
ave_rain	-0.9483**	-0.2995	-1.0851***	-0.5537**	-0.3357**
	(0.2996)	(0.2097)	(0.2832)	(0.2366)	(0.1656)
ave_rain²	1.68e-04**	1.08e-04**	1.94e-04***	1.75e-04***	5.62e-05
	(8.11e-05)	(5.47e-05)	(7.01e-05)	(5.69e-05)	(4.47e-05)
ave_temp	-0.1794***	-0.2681***	-0.1892***	-0.3070***	0.0611**
	(0.0583)	(0.0507)	(0.0549)	(0.0465)	(0.0309)
ave_temp²	0.0038**	0.0105***	0.0036**	0.0117***	-0.0023**
	(0.0015)	(0.0024)	(0.0016)	(0.0020)	(0.0009)
Year FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
Observations	1221	1221	1601	1595	1541
No. of countries	111	111	146	146	146
R-Square (within)	0.476	0.505	0.412	0.503	0.053

Note: Column 5 restricts the sample to countries of more than a million inhabitants. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The results in Table 4 show that deteriorating climatic conditions can fuel urbanisation across the whole national urban structure, but different components may react to different changes in the climate. This means that weather variation can alter the national urban structure, including the pattern of urban concentration. In column 5 of Table 4, we explore the connection between our climatic variables and primacy rates, as a common measure of urban concentration. Results suggest that low rainfall increases

[39] Figure E.1 in Appendix E shows marginal plots for average annual rainfall and temperatures for urbanisation in large cities and urbanisation in small and medium-sized cities.

primacy rates. For temperatures, the results suggest that when temperatures become too high primacy rates decrease. The primacy-reducing effect of higher temperatures happens for mean temperatures above 20 degree Celsius (as shown in Figure E.2 in Appendix E). This level of mean temperatures is characteristic of most countries in SSA, but also of other hot regions like the MENA region and SEA. Many countries in these regions are characterised by declining primacy rates (even when the size of the largest city continues to grow, as described in Section 2.2).

The contrasting findings for rainfall and temperature, observed in Table 4, may partly reflect regional differences, particularly related to different baseline climates across regions, as suggested by the regional heterogeneity analysis presented in Appendix Table E.1. While the effects of higher temperatures appear consistent across regions, this is not the case for rainfall; we find that low rainfall is associated with urbanisation that is more strongly oriented towards larger (largest) cities in SSA, whereas in SEA, higher rainfall is associated with more urbanisation in small-to-medium (non-largest) cities. While the (negative) association between rainfall anomalies and urbanization has been observed previously for SSA (e.g. Barrios et al. 2006), the observation of a positive association between rainfall anomalies and urbanisation for SEA is novel.[40] These findings are also consistent with the idea that slow onset changes in climate (e.g. increasing aridity in SSA) may lead to more permanent (and more long-distance) movement of people, whereas sudden-onset events (such as floods in SEA), tend to be associated with temporary displacement of population and short-term movements to nearby cities (see e.g. Bohra Mishra et al., 2014, for micro-evidence from Indonesia; also Mallick, 2014, for micro evidence from Bangladesh).

[40] If higher temperatures have a bigger effect on small cities, then higher temperatures reduce primacy. Similarly, if low rainfall in SSA has a bigger effect on urbanisation of big cities, this increases primacy (a negative relation between rainfall and primacy). At the same time, if high rainfall in SEA increases population in small cities (more than in big cities), this would reduce primacy (again a negative relation between rainfall and primacy). Thus the regional heterogeneity analysis presented here also helps us to understand the findings on primacy presented in Table 4, Column 5.

3.3. Climate and the size and spatial structure of the largest city:

Finally, in this section, we study the potential impact of variations in climatic conditions on the size, density and spatial structure of the largest city in each country. As discussed previously, the size, density and spatial structure of cities has been shown to play a role in the economic performance and quality of life of urban dwellers. We do not aim at exploring in depth the growth of cities (something out of our scope here); the aim of this subsection is merely to show that, as with national-wide variables, changes in the climate can also have an impact in the growth of cities – something, to the best of our knowledge, not done in the literature to date using a global sample of cities.

Climate and the growth of cities

Following the same empirical strategy adopted in Sections 3.1 and 3.2, we estimate the effect of variation in climatic conditions on the size of (large) cities, as given by Equation (2):

$$CitySize_{it} = \alpha_1 + \beta_1 Climate_{it} + \gamma_t + \theta_i + \epsilon_{it} \qquad (2)$$

where $CitySize_{it}$ is either average city size, total population living in the largest city or density (all in logs) of country *i* in period *t*, and the empirical set-up is otherwise similar to Equation (1). As before, we use 5-year periods, and consider nonlinearities in the climate-city size relationship. Results are presented in Table 5.

In column 1 of Table 5 we look at average city size, while in columns 2 and 3 we look at the size of the largest city (with column 2 using WUP data and column 3 using

GHSL data). Results show a similar pattern as observed in Tables 3 and 4: for low levels of rainfall, a reduction in rainfall leads to faster city growth. For temperature, when temperatures are low, an increase in mean temperature leads to slower city growth, but when temperatures are already high, higher temperature leads to faster city growth (Figure F.1 in Appendix F shows marginal plots for coefficients in column 2 of Table 5). Finally, in column 4, we look at density. The estimated coefficients suggest that the density of the largest city increases as temperatures get higher. In short, worsening climatic conditions lead to larger and denser cities, in line with previous findings in the literature (e.g. Henderson et al., 2017, for SSA).

Table 5: Results at the city level, looking at size and density

	(1)	(2)	(3)	(4)
Dependent variable:	log(avecitysize)	log(pop)	log(pop)	log(density)
ave_rain	-1.3606***	-1.4777***	-0.0022**	-0.0016*
	(0.3624)	(0.4247)	(0.0009)	(0.0009)
ave_rain^2	2.22e-04***	2.52e-04***	3.62e-07*	-2.95e-07
	(7.50e-05)	(8.68e-05)	(2.01e-07)	(2.01e-07)
ave_temp	-0.7234***	-0.7028***	-0.5541***	-0.3840***
	(0.1016)	(0.1053)	(0.1348)	(0.1216)
ave_temp^2	0.0198***	0.0196***	0.0136***	0.0052*
	(0.0027)	(0.0027)	(0.0032)	(0.0031)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1937	1937	584	584
No. of countries	149	149	146	146
R-Square (within)	0.788	0.763	0.496	0.093

Note: Columns 1 and 2 use WUP data for population. Columns 3 and 4 use GHSL data. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Table F.1 and F.2 in Appendix F, we perform robustness tests on our results on the size and density of the largest cities. In Table F.1, we show that results hold to restricting weather variation to the proximity of the city (i.e., 500km radius around the city), weighting by distance and population, and excluding urban grid-cells. In Table F.2, we show that results are also robust to different clustering of the residuals as well as the introduction of city-specific linear trends.[41]

Climate, city growth and the evolution of the spatial structure of cities

As suggested by results in Table 5, climatic conditions play a significant role in the evolution of the size and density of the largest city. Depending on where people settle as they arrive in cities, this *climate-driven* city growth might also affect the spatial structure of the city. Specifically, we might ask, is climate-driven city growth making cities more or less monocentric? More or less spatially unequal? Our detailed data allows us to answer these questions. To do so, we run a two-step estimation. In the first step, we predict city population size, for our sample of largest cities, using our climatic variables. In a second step, we use this prediction to estimate its impact on the city's spatial structure, as described in Equation (3):

$$CityStructure_{it} = \alpha_1 + \beta_1 \widehat{CitySize}_{it} + \gamma_t + \theta_i + \epsilon_{it} \quad (3)$$

where $CityStructure_{it}$ is alternatively our measure of monocentricity (i.e., Moran's I) or our measure for spatial inequality (i.e., Gini coefficient), both based on our night lights data. We also consider a ratio of low to high-density areas, benefiting from the detailed information in the GHSL data. $\widehat{CitySize}_{it}$ is the prediction from the first-step using our climate variables. We include country-fixed effects, so the identification comes from the within-city evolution over time. Consequently, the estimated coefficient for β_1 captures how the spatial structure of the city changes as the city grows in response to climatic drivers. Results are presented in Table 6.[42]

[41] Results are also robust to controlling for the evolution of the urban rate, and hold when we look separately at developed and developing countries, although the coefficients for rainfall lose significance when looking at developed countries only.
[42] See Table F.3 in Appendix F for first-step results.

Table 6: Results at the city level, looking at the spatial structure

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Light_Moran's I	Light_Moran's I	Light_Gini	Light_Gini	Low-to-high-density share
$\widehat{CitySize}$	-0.1121***	-0.0635***	-0.8057***	-0.5883***	-0.1137***
	(0.0203)	(0.0236)	(0.0977)	(0.1289)	(0.0375)
Year FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Observations	886	436	886	436	540
No. of countries	148	146	148	146	145
R-Square	0.391	0.442	0.105	0.103	0.121
F test on exc inst	46.18***	12.21***	46.18***	12.21***	104.22***

Note: Light_Moran's I, Light_Gini and *CitySize* all in logs. *CitySize* is estimated using ave_rainfall and ave_temperatures. Columns 1 and 3 use WUP data for population. Columns 2, 4 and 5 use GHSL data. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In columns 1 and 2 of Table 6 we look at monocentricity, while in columns 3 and 4 we look at spatial inequality. Columns 1 and 3 use the WUP data, while columns 2 and 4 use GHSL data, to measure city population. Results show that climate-driven city growth is associated with less monocentric (i.e., more fragmented) and less spatially unequal urban structures. Finally, in column 5, we find that climate-driven growth also leads to a lower share of low-density areas; the proportion of high-density areas increase as cities grow in response to worsening climatic conditions. In other words, our results suggest that as (large) cities grow in response to worsening climatic conditions nation-wide, their spatial structure changes, and they become more fragmented, with high-density areas becoming more predominant. These results are robust to our different variables capturing weather variation in the proximity of the city - i.e., estimating *CitySize* using weather variation in a 500km-radius around the city, weighting by distance and population, and excluding urban grid-cells (see Table F.4 in Appendix F).

To further illustrate the relation between climate change and urban structure, in Appendix G, we present a comparative case study of two Sub-Saharan African countries, Nigeria and Ghana, and one Asian country, Bangladesh. In line with our empirical analysis, we see, inter alia, that the relative growth of larger and smaller cities depends both on climatic factors and the initial urban hierarchy. Also in line with our global results, we see that fast city growth in large cities translates into increasing density and spatial fragmentation (as for instance seen in Dhaka).

4. Discussion and Conclusions

In this paper, we study the effects of changes in the climate on the spatial distribution of population and economic activity within countries. To do so, we construct a unique dataset that combines aggregate census data, satellite data on built-up areas and data on light intensity at night, combined with global climatic data. Whereas most of the existing literature on climate and urbanisation has tended to study the effects for individual countries or regions, we have taken a global perspective, with over half a century of data for close to 150 countries, enabling us to show the widespread nature of the effects, but also to uncover important heterogeneities in effects.

We find that deteriorating climatic conditions (i.e., higher temperatures in places that are already hot, and lower rainfall in places where it is already scarce) are associated with more urbanisation. While the existing literature has already established that weather variation and extreme weather events can contribute to urbanisation, for individual countries, and regions, we show that this finding holds for a global sample, once the non-linear effects of climate are taken into account. The effects of climate on urbanisation are also observed across the whole national urban structure (i.e., increasing urbanisation in both smaller and larger cities, and even in the largest city of the country). Looking at heterogeneities by country characteristics, we find that the effects on urbanisation depend importantly on baseline climate, and are strongest for developing countries, and where the agricultural share is higher.[43]

We also find that weather variation can alter the national urban structure, including the pattern of urban concentration, as well as the size and spatial structure of (the largest) cities. According to our results, in the face of high mean temperatures urbanisation in cities of less than a million inhabitants reacts more than urbanisation in cities of more than a million, and primacy rates fall. This suggests that in reaction to higher temperatures, people seem to move more to small and medium-sized cities (or secondary cities) than to large ones (or the primate city). We interpret these results as suggesting that global warming may be a factor contributing at the same time to rapid urbanisation, and increasing city size, but also to the process of urban "de-concentration" that many developing countries, mainly low-income countries in SSA, have been experiencing in the last decades (where secondary cities are growing faster than the largest city).

At the city level, something similar occurs: we find that worsening climatic conditions, by pushing population from rural to urban areas, increase city size and density. But this climate-driven growth also seems to foster fragmentation within the city. This suggests that as people arrive in large cities they are likely to locate in poorer areas of the city, in many cases slums. To the extent that climate-induced rural-to-urban migrants face challenges in accessing the most desirable neighbourhoods within cities, due to accommodation costs or other barriers, they are more likely to settle on the urban

[43] The global non-linear relationship between climate and urbanisation, which we identify for our full sample, is predominantly driven by effects in developing countries. However, the results of an additional test (suggested by Burke et al. 2015), where income interacted with temperature and rainfall is included alongside the nonlinear climate variables, shows that the non-linear global effects we observe are not just the result of different marginal effects for rich (cold) and poor (hot) countries. The test also shows that the non-linear relationship observed is not entirely attenuated by higher income. Furthermore, the city-level results for the effects of temperature on city population and density in particular, appear to hold across developing and developed country sub-samples, suggesting that the observed effects of climate on urbanisation (particularly in the largest cities) are unlikely to be fully offset (or adapted away) by rising incomes alone. These additional results are available on request.

fringe or in informal settlements, leading to increased urban fragmentation, which is what we observe.[44]

Our findings have important policy implications, especially for evaluating future climate change, as well as for policies regarding climate and disaster resilience. Our results indicate that climate change is likely to accelerate urbanisation in many locations worldwide, particularly in developing countries, as temperatures rise and rainfall is expected to become more concentrated (leading to more frequent extremes of both drought and flood). While some colder (typically richer) countries may experience less climate-induced urbanisation as temperatures rise, these effects are likely to be outweighed by effects in (hotter) developing countries.[45]

Our findings also indicate that climate change should be expected to alter the character of urbanisation, with potentially important implications for spatial development patterns and ultimately welfare. In particular, climate change will aggravate the current urban challenges that developing countries face (as highlighted by the UN's Sustainable Development Goals Agenda), with more people living in larger and more fragmented cities.

Our results call for further research, along a number of important dimensions. We have taken a global view. Research at a more disaggregated level, looking at what happens in specific countries and cities, can add further insights on the impacts of climate change on the location of population and economic activity. We present a range of heterogeneity analysis, which provides some suggestive evidence on the differing nature of climate-induced urbanisation across world regions. These differences appear to be related not just to differences in baseline climate but also to structural differences in

[44] For a discussion on rural migrants settling in slums, see Marx et al. (2013).
[45] This expectation is partly informed by the differences in our findings across developed and developing countries, but also by the apparently asymmetric effects of warming on extremes of hot and cold weather. As noted in Appendix B, warming experienced over the 20th century has already had a notable effect on the frequency of more extreme weather observations, with a more pronounced increase in the frequency of relatively hot years (compared with the decrease in the frequency of relatively cold years).

urbanisation patterns by region, including differences in the initial distribution of cities, as well as differences in response to slow-onset (e.g. droughts) vs sudden-onset climate events (e.g. floods). At the micro-level, more needs be known about households' response to weather variation, considering their vulnerability and adaptive capacity, including the option of rural-urban migration, and the trade-offs they face in terms of migration costs (distance) vs relative attractiveness of the destination, as well as potential difficulties in accessing the most desirable neighbourhoods within cities.

In a world threatened by climate change, a better understanding of how location decisions, as well as the overall spatial distribution of population and economic activity, react to global warming will be of utmost importance in informing policy-formation across a range of crucial public policy arenas, including spatial and development planning and the challenges inherent in managing increasing flows of population into cities.

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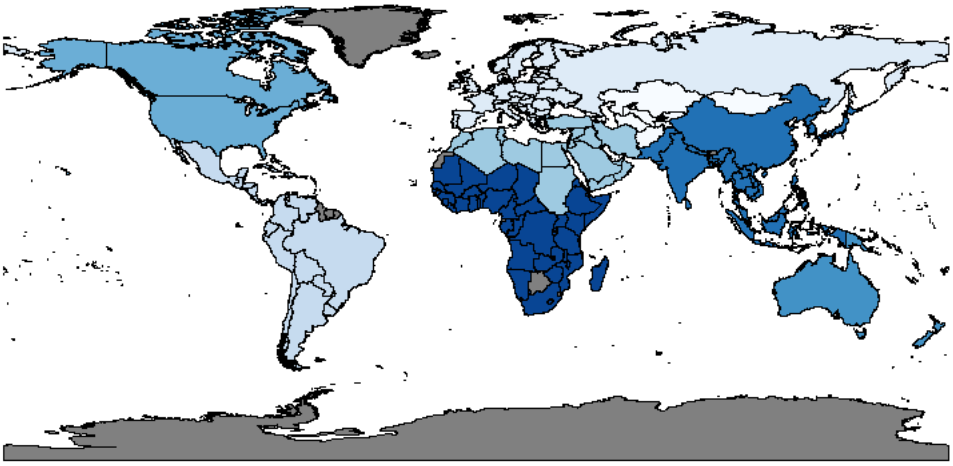
Global warming and urban structure: New evidence on climate change and the spatial distribution of population and economic activity

APPENDICES:
[Can be considered as Online Supplementary Material only]

Appendix A: Data overview [Corresponding to Section 2 in the paper]

Figure A.1: Map of countries included in the data set according the world regions



Note: Countries in grey are not included. All other countries are in different tones of blue, with each tone representing a different world region: The regions are: North America, Latin American & the Caribbean, Europe, North Africa & Middle East, Sub-Saharan Africa, Central Asia, South and East Asia, and Oceania.

Table A.1: Overview of all variables and data sources

Variable	Time Span	Source
I: Country-level variables		
I.1: Climatic variables		
Average temperature	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Average rainfall	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Temperature anomalies	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Rainfall anomalies	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Decennial temperature changes	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
Decennial rainfall changes	1901-2015	World Bank Climate Change Knowledge Portal (CCKP), country averages based on UEA's CRU-TS data
I.2: Urban variables		
Urban rate	1960-2010	World Development Indicators (World Bank)
Urban pop in cities >1 million	1960-2010	World Development Indicators (World Bank)
Urban pop in cities <1 million	1960-2010	Constructed using World Development Indicators (World Bank)
Primacy rate	1960-2010	World Development Indicators (World Bank)
Number of cities per unit area	1960	Constructed using World Development Indicators and World Urbanisation Prospects
Average city size	1950-2015	Constructed using World Urbanization Prospects (United Nations)
I.3: Other country-level variables		
GDP per capita	1960-2010	World Development Indicators (World Bank)
Total population	1960-2010	World Development Indicators (World Bank)
Agricultural Share in GDP	1965-2010	World Development Indicators (World Bank)
II: City-level variables (for primary cities)		
Population in WUP	1950-2015	World Urbanization Prospects (United Nations)
Lights per Capita	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Spatial Gini coefficient in light	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Moran's I: spatial autocorrelation	1992-2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Population in GHSL	1975, 1990, 2000, 2015	Global Human Settlement Layers
Area	1975, 1990, 2000, 2015	Global Human Settlement Layers
Population density	1975, 1990, 2000, 2015	Constructed using Global Human Settlement Layers
Share of low vs. high density	1975, 1990, 2000, 2015	Constructed using Global Human Settlement Layers

Appendix B: Climate data [Corresponding to Section 2.1 in the main text]

Climate data variable definitions:

Our climatic variables are based on historical weather data, including temperature and rainfall observations, and are derived from monthly global gridded data, which have been aggregated to country means. The country-level datasets that we use were obtained from the World Bank's Climate Change Knowledge Portal (CCKP).[46] These data are simple area-weighted country means, 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). Based on these data, we construct three distinct sets of climatic variables, as follows:

Averages:

The variables *ave_rain* and *ave_temp* measure mean annual average rainfall (in meters per year) and temperatures (in degree Celsius), at the national level, over 5-year time periods. Given that our regressions include country fixed effects, when we include *ave_rain* or *ave_temp* as explanatory variables, estimation is based on the temporal variation in these measures for each country, i.e. the variation relative to that country's long-run average climate. Average annual temperatures and rainfall have been used in global analyses of the economic effects of weather variation for example in Dell et al. (2012) and Burke et al. (2015), who also implement a quadratic specification of the weather variables, similar to the one we use here.

Anomalies:

We also construct measures of rainfall and temperature *anomalies*, based on deviations of annual observations from their long run means, divided by the long run standard deviation of that variable, for each country (as used in e.g. Barrios et al., 2006, and Hendrix and Salehyan, 2012). Formally, rainfall anomalies for country i in year t are defined as:

$$rain\_anom_{it} = (ann\_rain_{it} - mean\_rain_i) \,/\, sd\_rain_i \,,$$

[46] Available from https://climateknowledgeportal.worldbank.org/download-data (last accessed on 18 June 2020).

where *mean_rain*$_i$ and *sd_rain*$_i$ are defined over the entire available dataset from 1901-2015. Temperature anomalies are defined similarly. These annual anomalies are then aggregated to 5-year periods to match with the urban data we are using, by taking simple 5-year means of the annual anomaly measures. The anomaly variables are standardised, with mean zero. However, the data in our sample reflect anomalies over the period 1950-2015 relative to long run trends (1901-2015). For temperature anomalies, in particular, the mean value in our sample is a bit above zero, reflecting warming over the latter part of the 20th century.

Decennial changes:

Finally, we construct measures of *decennial changes* over time in rainfall and temperature, measured as the 10-year, gradual change in average temperature or average rainfall, where averages are defined over 3-year periods at the beginning and end of each 10-year interval (as used in Peri and Sasahara, 2019). Formally, we define

$$temp\_dec\_ch_{it} \text{ as } (\Sigma_{t-2 \rightarrow t}\ ann\_temp_{it}/3) - (\Sigma_{t-12 \rightarrow t-10}\ ann\_temp_{it}/3)$$

The equivalent variable for rainfall, *rain_dec_ch*$_{it}$, is defined similarly. To match with our 5-year panel, we simply take the observed values of *temp_dec_ch* and *rain_dec_ch* at each fifth year, starting in 1950.

Moisture index:

We follow Henderson et al. (2017) and calculate a *moisture index* variable that captures the interaction of rainfall and temperature that is relevant for plant growth (and thus for agricultural productivity). This measure involves dividing rainfall observations by potential evapotranspiration (a non-linear function of temperature), such that rainfall observations are essentially penalised for places that are hotter, reflecting the effects of higher temperatures on moisture availability for plant growth. Potential evapotranspiration (PET) is calculated for monthly data, then aggregated to 5-year periods to match with our data. The formula for monthly PET (as used in Henderson et al., 2017), is

$$PET_i = \left(\frac{N_i}{30}\right)\left(\frac{L}{12}\right)\begin{cases} 0, T_i < 0°\mathrm{C} \\ 16\left(\frac{10T_i}{I}\right)^{\alpha}, 0 \leq T_i < 26.5 \\ -415.85 + 32.24T_i - 0.43T_i^{\,2}, T_i \geq 26.5 \end{cases},$$

where T_i is the average monthly temperature in degrees Celsius, N_i is the number of days in the month, L_i is day length at the middle of the month, $\alpha = (6.75 \times 10^{-7})I^3 - (7.71 \times 10^{-5})I^2 + (1.792 \times 10^{-2})I + 0.49$, and the heat index $I = \sum_{i=1}^{12} (\frac{T_i}{5})^{1.514}$.

Each of our three sets of climatic variables (plus the moisture index) thus captures distinct aspects of weather variation; for the averages, variation in the levels of rainfall and temperature; for anomalies, variation that is large relative to typical variation for that country; and for gradual changes, gradual trends in rainfall or temperature over medium-term time scales. The moisture index captures interactions between rainfall and temperature that are likely to matter for agricultural productivity. In all cases, our weather variables are defined and included in our regressions such that we are using the variation in weather in the previous 5-year period (or in the case of the decennial change variables, over the preceding 10-year period) to explain variation in the outcomes of interest. Specifically, our rainfall observation for 1990 is defined as the average over 1985-1989.

Weighting by population and city-specific versions

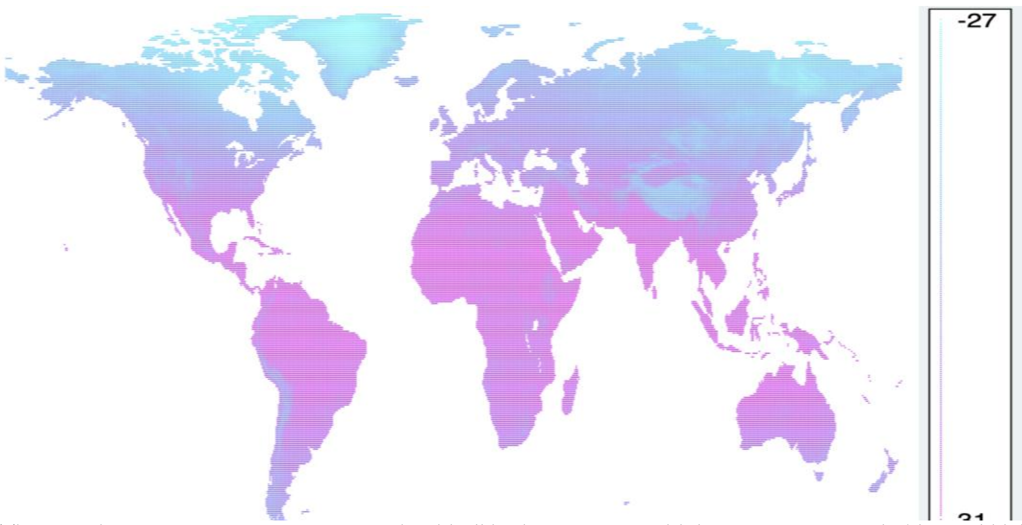
As noted in Section 2.1 of the main text, for robustness we also construct a global gridded weather dataset, merged with gridded population data, and urban area identifiers, from which we derive a number of alternative aggregations of the weather data. The gridded weather data we use for this purpose are from the CRU TS version 4.03 dataset from the University of East Anglia.[47] This is a gridded dataset of historical weather observations for 1901-2018, on a global 0.5-degree grid. These weather data were merged with gridded population data (also for a global 0.5-degree grid) from the Global Population of the World v4 dataset.[48] Urban gridcells in the data were identified using the urban area polygons from the Global Rural Urban Mapping Project (GRUMP) v1 dataset, which is based on urban extents circa 1995.[49] In practice, we identify a gridcell as

[47] The data are available from https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/ (last accessed June 2020).
[48] The data are available from https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-count-adjusted-to-2015-unwpp-country-totals-rev11/data-download (last accessed June 2020). We use the version of the population data adjusted to match UN country totals, and we take population estimates for the earliest available year in the data (2000).
[49] These data are available from https://sedac.ciesin.columbia.edu/data/collection/grump-v1/sets/browse (last accessed June 2020).

"urban" if the centroid of at least one urban area from the GRUMP dataset falls within that grid-cell.

For the city-level analysis reported in Section 3.3, we further construct city-specific versions of our climate variables for robustness, based on weather variation in the proximity of the city, and based on national level weather variation weighted by distance to the city. Specifically, we take coordinates of the centroid of each city in our data (the primary city, or largest urban agglomeration, in each country), from the UN WUP dataset, and calculate: a simple area-weighted aggregation of weather observations for gridcells within 500km of the city (and within national boundaries); population and distance-weighted aggregations of all gridcells in a country; and finally, population and distance-weighted aggregations of the rural (non-urban) gridcells only. Summary statistics for each of these alternative ways of aggregating the climate data, at both the national and city level, for the full sample, and by income group, are included in Table B.1.

Figure B.1: Map showing illustration of global gridded climate data



Note: The map shows average temperature at each gridcell in the year 2015, with lower temperatures in blue and higher temperatures in purple/pink. Each dot on the map represents one 0.5 degree gridcell. As the legend shows, the local average temperature in 2015 for gridcells ranges from -27 to +31 degrees C.

Table B.1: Summary stats for alternative climate variables

	World	Low	Middle	High
Panel A: National level climate variables				
Ave Rain	1.03	1.10	1.08	0.87
(St.Dev.)	(0.74)	(0.66)	(0.82)	(0.65)
Ave Temp	18.18	23.05	18.81	13.67
(St.Dev.)	(8.44)	(5.52)	(7.65)	(9.19)
Ave Rain (pop-weights)	1.09	1.20	1.04	0.85
(St.Dev.)	(0.72)	(0.61)	(0.72)	(0.53)
Ave Temp (pop-weights)	18.34	23.38	18.51	14.03
(St.Dev.)	(7.59)	(4.35)	(7.24)	(7.29)
Ave Rain (pop-weights, rural only)	1.10	1.22	1.04	0.84
(St.Dev.)	(0.71)	(0.61)	(0.71)	(0.53)
Ave Temp (pop-weights, rural only)	18.30	23.35	18.49	14.00
(St.Dev.)	(7.55)	(4.26)	(7.22)	(7.25)
Moisture	0.86	0.79	0.86	0.88
(St.Dev.)	(0.54)	(0.45)	(0.56)	(0.59)
Panel B: City level climate variables				
Ave rain (pop-weights & dist-weights)	1.02	1.23	1.02	0.81
(St.Dev.)	(0.68)	(0.64)	(0.72)	(0.53)
Ave Temp (pop-weights & dist-weights)	18.20	23.28	18.30	14.22
(St.Dev.)	(7.50)	(4.73)	(7.39)	(6.99)
Ave Rain (rural only)	1.02	1.23	1.01	0.81
(St.Dev.)	(0.68)	(0.65)	(0.72)	(0.53)
Ave Temp (rural only)	18.19	23.26	18.31	14.17
(St.Dev.)	(7.52)	(4.74)	(7.41)	(6.98)
Ave Rain (<500km)	1.05	1.15	1.09	0.87
(St.Dev.)	(0.71)	(0.63)	(0.80)	(0.57)
Ave Temp (<500km)	18.11	23.23	18.61	13.54
(St.Dev.)	(7.96)	(5.36)	(7.52)	(7.65)

Note: The first two variables (first four rows) in the table are the (area weighted) country level average rainfall and temperature variables used in our baseline specifications, included here for comparison. The remaining rows are alternative ways of aggregating gridded climate data to the national level, as described in the text. The "rural only" variables are population weighted (and distance weighted in the case of the city-level variables), but only aggregating across gridcells that are non-urban (as per description in the text). Rainfall is measured in meters per year, and temperature in degrees Celsius.

Table B.2 Summary stats for climate data, by world region

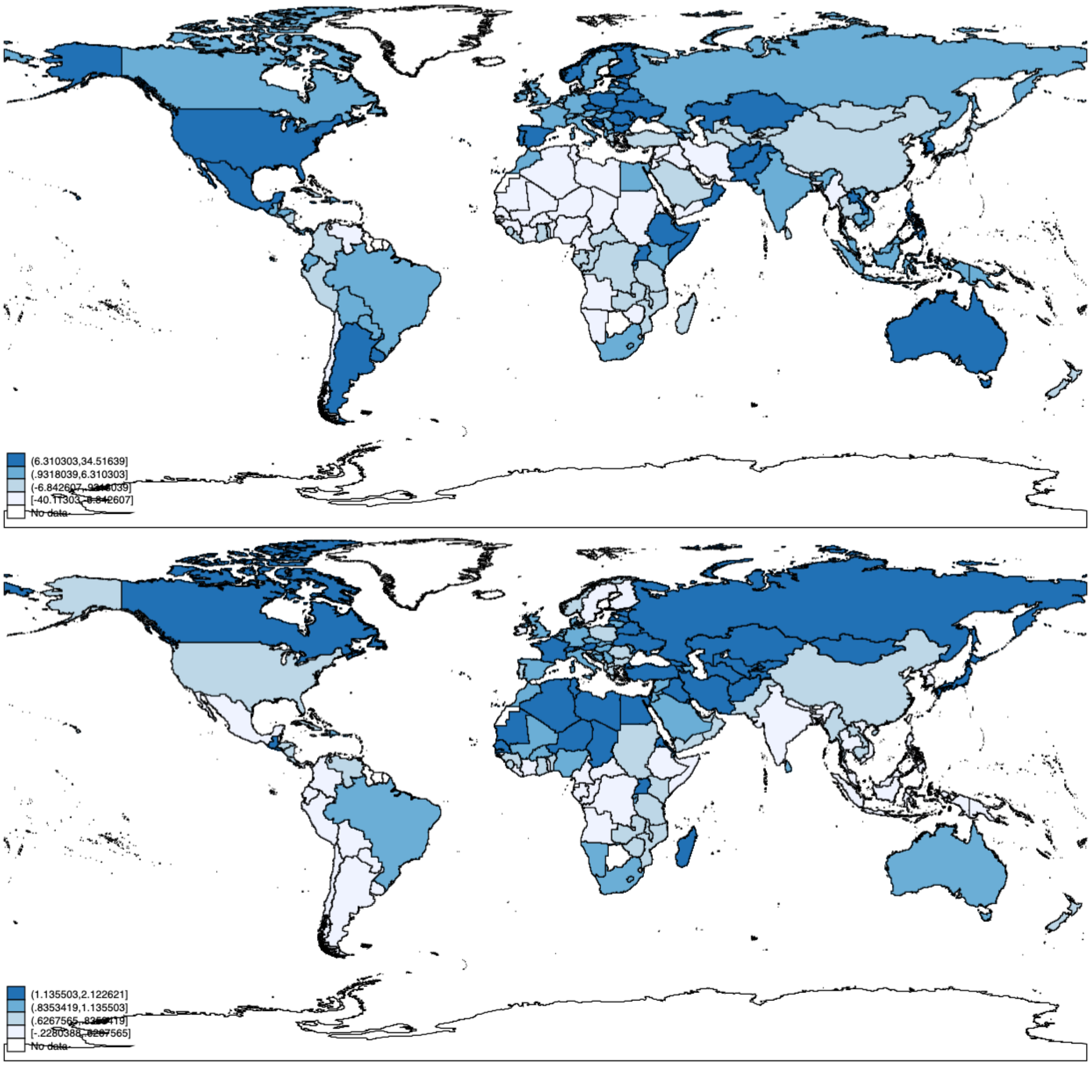
	N Am	LATAM	Europe	Oceania	SSA	MENA	SE Asia	C Asia
Panel A: Long-run averages (1950-2015)								
Ave Rain	0.56	1.74	0.79	1.75	1.04	0.24	1.75	0.40
	(0.10)	(0.68)	(0.24)	(1.07)	(0.58)	(0.23)	(0.71)	(0.22)
Ave Temp	0.27	22.35	8.29	18.85	24.82	22.05	20.74	7.82
	(6.98)	(4.16)	(4.03)	(6.55)	(2.79)	(4.40)	(7.19)	(4.91)
Rain Anom	0.35	0.08	0.08	0.10	0.00	-0.06	0.01	0.12
	(0.61)	(0.52)	(0.46)	(0.47)	(0.65)	(0.54)	(0.54)	(0.48)
Temp Anom	0.27	0.26	0.24	0.33	0.16	0.34	0.27	0.30
	(0.72)	(0.74)	(0.70)	(0.68)	(0.88)	(0.78)	(0.82)	(0.70)
Rain_dec_ch	6.52	0.26	9.11	1.37	-1.16	-4.67	-2.99	2.25
	(22.29)	(233.70)	(90.84)	(171.37)	(104.16)	(51.06)	(197.95)	(55.04)
Temp_dec_ch	0.06	0.09	0.17	0.09	0.09	0.19	0.11	0.19
	(0.48)	(0.42)	(0.67)	(0.30)	(0.39)	(0.50)	(0.29)	(0.53)

Panel B: Long-run changes (1950-2015)

Ave Rain	40.04	34.81	53.80	35.73	-67.81	-23.23	-24.36	5.93
	(23.18)	(174.97)	(61.39)	(43.39)	(118.06)	(32.08)	(234.68)	(17.91)
Ave Temp	0.94	0.60	1.02	0.52	0.80	1.13	0.58	1.54
	(0.35)	(0.38)	(0.37)	(0.43)	(0.39)	(0.31)	(0.29)	(0.36)
Rain Anom	1.34	0.14	0.53	0.30	-0.58	-0.52	-0.03	0.11
	(0.04)	(0.72)	(0.47)	(0.49)	(0.88)	(0.59)	(0.82)	(0.30)
Temp Anom	1.44	1.40	1.32	1.18	1.83	1.77	1.39	1.86
	(0.14)	(0.81)	(0.42)	(0.92)	(0.60)	(0.47)	(0.63)	(0.28)
Rain_dec_ch	10.54	-274.97	112.62	-21.35	44.12	-7.37	-44.23	-18.27
	(22.87)	(431.74)	(151.66)	(76.17)	(130.02)	(59.21)	(358.62)	(81.06)
Temp_dec_ch	0.69	0.41	0.15	0.37	0.15	0.67	-0.06	1.22
	(0.06)	(0.32)	(0.50)	(0.47)	(0.57)	(0.48)	(0.23)	(0.32)

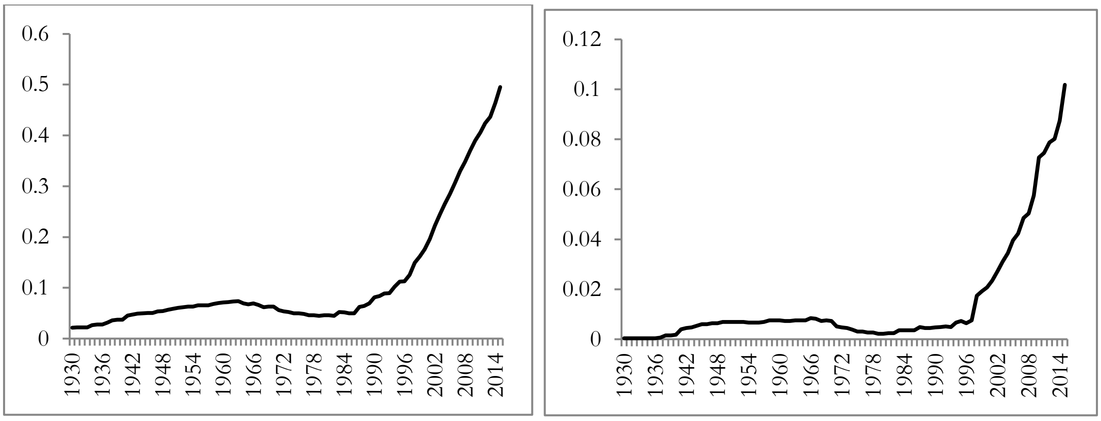
Note: The table shows mean values for each variable by world region (panel A) and long-run changes in these variables by world region (panel B). Standard deviations in parentheses. Variables are as defined in the text and here in Appendix B. For ease of interpretation, average rainfall figures are in m per year and changes in rainfall are in mm. The regions are as defined in the map in Figure A.1 in Appendix A.

Figure B.2: Maps of changes in average rainfall and temperatures, 1950-2015



Note: Top panel shows percentage changes in average annual rainfall and bottom panel shows changes in temperature (in degrees Celsius), by country, 1950-2015.

Figure B.3: Frequency of temperature anomalies



Note: Rolling 30-year average of frequency of temperature anomalies >+1 (left panel) and >+2 (right panel) for the countries in our sample. Each observation in the figures represents the average over the preceding 30-year period, such that the first observation in the chart (at 1930) represents the average over 1901-1930.

Gradual warming has a pronounced effect on the frequency of extremes

Focusing on temperature anomalies, we can observe the changing frequency of anomalies >+1, >+2, <-1, and <-2 in our data. Given how the anomaly variables are defined, a temperature anomaly >+1 represents a temperature observation (annual average temperature) more than 1 standard deviation above the mean for that country, and similarly for >+2, <-1, <-2. Warming on average might be expected to increase the frequency of higher than average temperatures, while decreasing the frequency of below average temperatures. Comparing the decade from 1901-1910, with the decade from 2006-2015, the frequency of annual temperature anomalies >+1 showed a 34-fold increase, while the frequency of annual temperature anomalies >+2 showed a 256-fold increase. These increasing frequencies are illustrated in Figure B.2. Turning to below average temperatures, the frequency of temperature anomalies <-1 declined from 28% to 0.7% over the same period, a 38-fold decline in frequency, while the frequency of temperature anomalies <-2 declined from 1.5% to 0.15%, a 10-fold decline in frequency. These figures underline how gradual warming can have dramatic effects on the frequency of more extreme observations, with a more pronounced increase in the frequency of relatively hot years.

Appendix C: Urban data [Corresponding to Section 2.2 in the main text]

Table C.1: Summary statistics of urban variables by region

	NA	LATAM	Europe	Oceania	SSA	MENA	SE Asia	C Asia
Panel A1: Country-level variables, latest available year (2010/15)								
Urb Rate	80.85	71.54	69.46	62.64	38.73	71.55	52.00	46.23
	(0.12)	(14.50)	(12.76)	(42.99)	(17.00)	(19.48)	(28.69)	(14.85)
Urb > 1m	44.47	29.76	12.77	29.79	10.34	24.55	24.34	15.56
	(0.04)	(15.51)	(10.48)	(30.11)	(10.66)	(19.62)	(29.91)	(15.28)
Urb < 1m	36.38	41.77	56.79	32.84	28.79	45.76	27.65	30.66
	(0.15)	(11.40)	(12.29)	(22.30)	(17.55)	(22.67)	(21.90)	(10.46)
Urb Largest	11.05	25.14	15.99	17.22	15.57	20.98	23.83	19.36
	(7.24)	(14.01)	(7.26)	(12.33)	(11.23)	(15.32)	(33.56)	(11.89)
Urb Non-Largest	69.80	46.39	53.48	45.42	23.13	49.65	28.16	26.86
	(7.12)	(14.67)	(14.26)	(32.74)	(10.33)	(15.89)	(19.51)	(9.46)
Primacy	13.67	35.36	23.70	30.38	38.82	30.13	35.57	40.68
	(8.93)	(15.17)	(11.59)	(6.99)	(14.39)	(14.22)	(29.86)	(15.39)
Ave. City Size	1385.51	1421.38	912.69	929.66	1249.04	1170.11	2023.18	1006.27
	(55.71)	(532.91)	(436.69)	(732.23)	(640.83)	(603.99)	(1773.57)	(374.97)
Panel A2: Variables at the primary city level, latest available year (2010/15)								
Pop	12292.98	5156.71	2454.76	1964.29	2643.47	4004.15	10195.36	1678.50
	(8909.89)	(6289.51)	(2995.25)	(2002.46)	(2938.37)	(4640.83)	(9876.78)	(1183.89)
Density	1553.51	2926.83	1712.27	2400.06	3245.51	3690.94	4816.76	3043.00
	(498.15)	(767.08)	(375.42)	(1503.95)	(1193.65)	(1695.00)	(5428.30)	(1262.67)
High dens share	86.90	90.01	77.53	87.98	92.32	86.96	80.03	87.29
	(6.79)	(9.36)	(16.91)	(8.67)	(13.20)	(11.57)	(21.98)	(13.04)
Light per capita	123.06	28.09	79.21	37.32	11.16	120.55	35.26	39.27
	(5.34)	(14.17)	(60.43)	(22.62)	(10.81)	(193.91)	(34.65)	(40.07)
Gini	37.94	29.53	29.18	19.84	25.11	38.26	37.77	32.66
	(11.37)	(5.64)	(8.34)	(6.24)	(6.99)	(9.26)	(9.36)	(9.00)
Moran's I	91.79	84.44	82.74	74.61	76.39	83.27	88.69	83.70
	(4.13)	(5.46)	(8.54)	(20.51)	(9.36)	(10.08)	(6.65)	(5.06)
Panel B1: Country-level variables, long-run changes								
Urb Rate	11.33	27.53	18.80	8.89	24.68	28.49	20.18	7.94
	(0.78)	(9.09)	(9.22)	(1.52)	(11.79)	(15.21)	(13.81)	(10.81)
Urb > 1m	10.06	10.73	2.58	5.54	6.70	5.62	7.74	4.30
	(6.07)	(10.18)	(4.86)	(5.32)	(7.10)	(10.53)	(7.36)	(7.95)
Urb < 1m	1.27	16.80	16.62	3.35	18.21	22.59	12.44	3.64
	(5.29	(6.96)	(7.62)	(5.22)	(13.25)	(14.69)	(10.02)	(4.23)
Urb Largest	2.27	7.74	3.64	4.54	9.95	2.31	5.27	4.73
	(5.89)	(9.76)	(4.25)	(5.50)	(7.31)	(12.25)	(4.94)	(7.87)
Urb Non-Largest	9.06	19.79	15.16	4.35	14.76	26.16	14.91	3.21
	(5.11)	(7.78)	(7.15)	(4.19)	(7.76)	(12.83)	(11.99)	(4.37)
Primacy	-0.15	-4.39	-1.79	0.50	0.22	-8.99	-3.17	2.92
	(5.24)	(10.06)	(4.93)	(7.78)	(17.56)	(16.30)	(8.18)	(7.88)
Ave. City Size	972.91	1181.13	397.57	691.04	1191.08	1066.96	1668.06	778.59
	(61.08)	(540.30)	(256.24)	(497.40)	(605.42)	(550.14)	(1370.84)	(401.79)
Panel B2: Variables at the primary city level, long-run changes								
Pop	5589.59	4259.25	1121.82	1408.68	2517.29	3613.72	8655.70	1314.08
	(940.67)	(5333.74)	(1475.17)	(1313.68)	(2797.07)	(4148.20)	(8043.01)	(1167.23)
Density	332.71	-457.36	-779.74	447.47	-278.98	-910.32	-829.60	305.23
	(288.98)	(1857.97)	(1973.44)	(56.32)	(1247.49)	(4691.02)	(5620.49)	(1223.69)
High dense share	13.27	-0.26	0.76	7.42	6.49	6.26	-3.24	1.42
	(7.82)	(10.15)	(11.21)	(3.63)	(14.95)	(19.73)	(22.85)	(20.68)
Light p.c.	-38.88	4.22	21.14	0.63	-0.76	-23.83	10.72	23.56
	(66.54)	(10.07)	(37.25)	(5.83)	(7.45)	(74.99)	(19.73)	(36.53)
Gini	-0.28	-5.37	-1.15	-4.69	-19.93	-2.58	-11.00	7.47
	(5.40)	(6.57)	(10.43)	(3.66)	(10.69)	(11.59)	(11.03)	(13.49)
Moran's I	-0.04	1.54	0.73	0.60	-3.71	-1.65	-0.97	6.60
	(0.44)	(4.94)	(6.06)	(5.64)	(5.62)	(3.48)	(3.51)	(7.72)

Notes: See Table 2 in the main text. The regional classifications are North America, Latin America and the Caribbean, Europe, Oceania, Sub-Saharan Africa, Middle East and Northern Africa, South East Asia, Central Asia.

Additional information on satellite data and measures for the spatial structure of cities

***Top Coding Corrected Satellite Data*:**

While satellite data of night-time lights have become established as a proxy for local economic activity in development economics in recent years (see Henderson et al., 2012, Donaldson and Storeygard, 2016), their use in urban economics has been limited. One drawback of the DMSP-OLS data, the most-often used time series data of night-time lights, is that they suffer from top-coding due to sensor saturation. This poses a problem for big cities in particular, because many pixels reach the end of the scale in terms of light intensity and appear equally bright. Inner-city differences as well as evolutions of luminosity over time cannot be measured appropriately. Bluhm and Krause (2018) propose a solution to the top-coding problem based on the observation that the world's brightest lights follow a Pareto distribution. With a geo-referenced replacement algorithm, in which top-coded pixels get assigned value from the Pareto distribution, they provide a corrected worldwide night-time lights dataset. The corrected data have been applied to the analysis of city growth and inner-city differences by, inter alia, Bluhm and Krause (2018) as well as Düben and Krause (2019).

Moran's I as Measure of Spatial Autocorrelation:

Following Moran (2015), a measure of spatial autocorrelation indicates to what extent a unit is located close of others of similar or dissimilar value. In our city application it captures whether similar light intensities cluster together and thus indicates how the city is structured. We compute Moran's I using the formula:

$$I = \frac{N}{S_0} \frac{\sum_i \sum_j w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

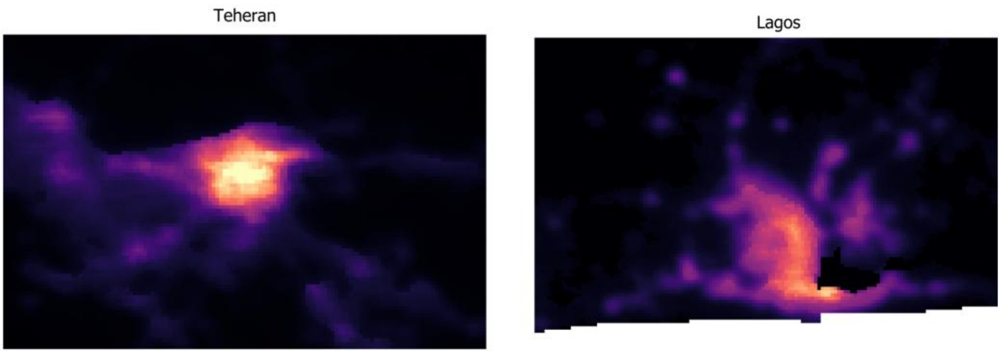
where in our case N is the number of pixels in the city, $w_{i,j}$ are elements of the spatial weights matrix (for which we use the Euclidean inverse distance matrix), S_0 is the sum of all the elements in the spatial weights matrix, x_i and x_j denote light intensities of pixels i and j, and $\bar{x}$ is the mean light intensity in the city.

Positive values of Moran's I indicate that pixels are surrounded by others of similar luminosity (positive autocorrelation), while negative values reflect a checkerboard pattern (negative autocorrelation). While light intensities within cities are known to be positively spatially correlated, there are clear differences in Moran's I across cities.

Following Tsai (2015), this can be interpreted in terms of urban structure as follows: the higher Moran's I, the more strongly monocentric the city is, while lower values are associated with polycentric structure, and ultimately fragmentation.

The two pictures below illustrate our use of the night-lights-based measure to capture the spatial structure of cities. Brighter values indicate higher light intensities (with respect to the city's maximum luminosity) and represent satellite data from 2013: Teheran, with a Moran's I of 0.9399, has a more monocentric city structure than Lagos (Moran's I of 0.8349). In Teheran, the bright city centre can easily be discerned and luminosity decreases rather gradually towards the outskirts. This happens to a much lower degree in Lagos, suggesting more fragmentation.

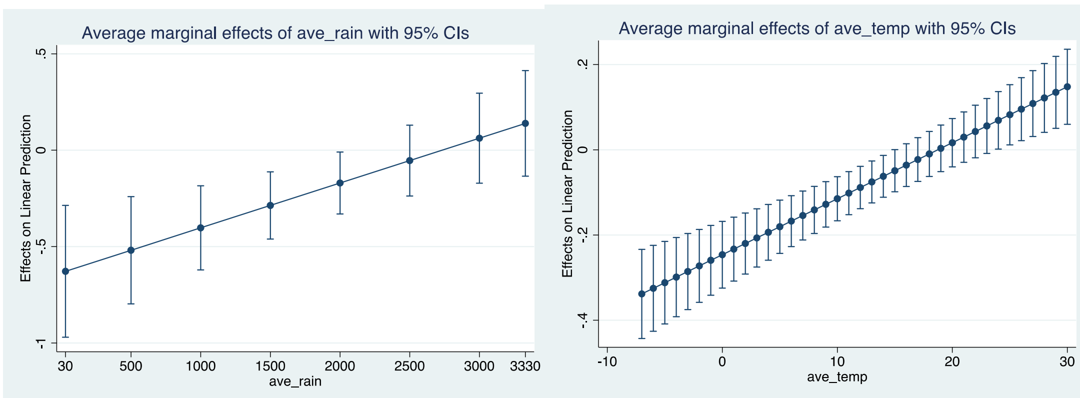
Figure C.1: Examples illustrating contrasting city structure



Note: The colours represent the light intensity with respect to the city's maximum luminosity, ranging from black (dark) over purple and red (medium-bright) to yellow (very bright). The extents of the maps are chosen for illustrative purposes, with the cut at the bottom of Lagos representing the sea.

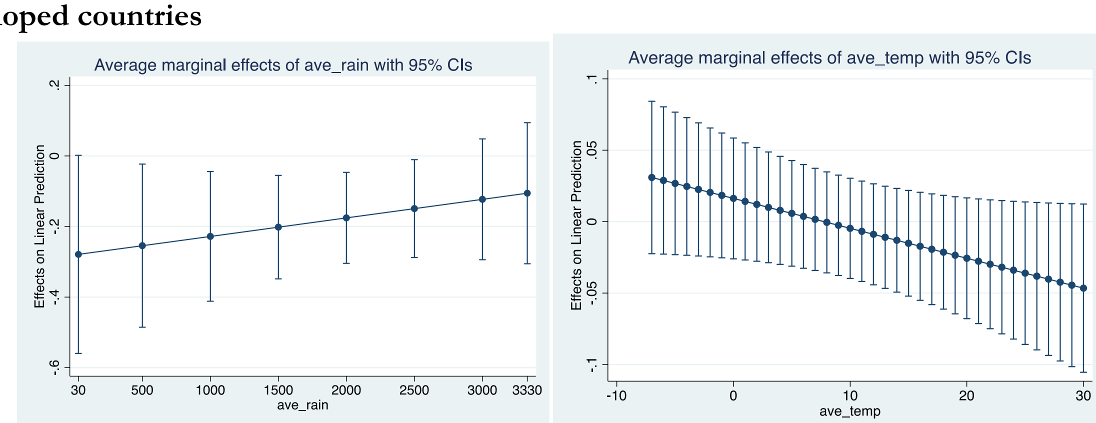
Appendix D: Climate and Urbanisation – Margins plots, additional results using alternative measures of climate, robustness checks and heterogeneity analysis [Corresponding to Section 3.1]

Figures D1: Margins plots for effects of rainfall and temperature on the urban rate, full sample



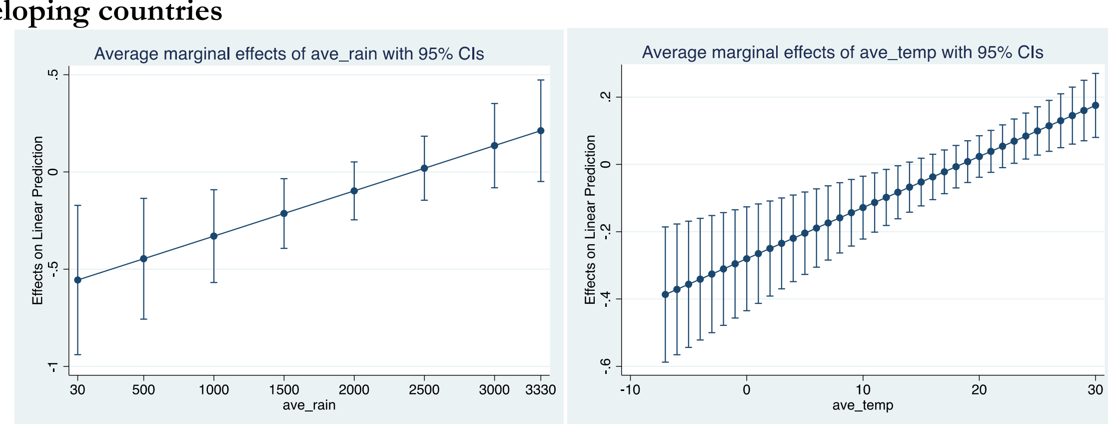
Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 1 of Table 3 in the main text, using the full panel of countries and time periods.

Figures D2: Margins plots for effects of rainfall and temperature on the urban rate, developed countries



Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 2 of Table 3 in the main text, for developed countries only.

Figures D3: Margins plots for effects of rainfall and temperature on the urban rate, developing countries



Note: The figures show the marginal effect of variation in rainfall (in mm per year, left panel) and temperature (in degrees Celsius, right panel) on the log of the urban rate, for different levels of rainfall and temperature. The marginal effects in these figures correspond to the results reported in Column 3 of Table 3 in the main text, for developing countries only.

Table D.1: Replicating Table 3 (Main Results, Urban Rate) weighting by population

	(1) full sample	(2) developed	(3) developing	(4) full sample	(5) developed	(6) developing
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
ave_rain	-0.5836***	-0.3865	-0.6875***	-0.5380***	-0.3553	-0.6372***
	(0.1809)	(0.2562)	(0.1968)	(0.1794)	(0.2556)	(0.1949)
ave_rain2	1.02e-04**	1.57e-04	1.31e-04**	9.03e-05*	1.37e-04	1.19e-04**
	(5.06e-05)	(1.48e-04)	(5.31e-05)	(5.15e-05)	(1.49e-04)	(5.39e-05)
ave_temp	-0.3357***	0.0305	-0.3520***	-0.3436***	0.0311***	-0.3640***
	(0.0526)	(0.0248)	(0.0899)	(0.0528)	(0.0251)	(0.0906)
ave_temp^2	0.0096***	-0.0011	0.0093***	0.0098***	-0.0010	0.0096***
	(0.0016)	(0.0007)	(0.0022)	(0.0016)	(0.0007)	(0.0022)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1573	385	1188	1573	385	1188
No.Countries	143	35	108	143	35	108
R-sq. (within)	0.94	0.91	0.94	0.93	0.91	0.93

Note: Climatic variables are weighted by population. In Columns 1 to 3 rainfall and temperature observations are aggregated across all gridcells in a given country, weighted by population in each gridcell, while in columns 4 to 6 aggregation is across rural gridcells only. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.2: Replicating Table 3 (Main Results, Urban Rate) using decennial changes and anomalies in temperature and rainfall

	(1) full sample	(2) developed	(3) developing	(4) full sample	(5) developed	(6) developing
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_dec_ch	0.0000	-0.0001	0.0000			
	(0.0000)	(0.0000)	(0.0000)			
temp_dec_ch	0.0050	0.0150***	0.0363**			
	(0.0098)	(0.0051)	(0.0160)			
rain_anom				-0.0605***	-0.0178*	-0.0380***
				(0.0126)	(0.0098)	(0.0128)
temp_anom				0.0366**	-0.0158	0.0512***
				(0.0169)	(0.0141)	(0.0181)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1606	396	1210	1606	396	1210
No. Countries	146	36	110	146	36	110
R-sq. (within)	0.60	0.64	0.67	0.61	0.65	0.68

Note: Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.3: Robustness to different clustering of residuals, degree of openness and additional controls

	(1) full sample	(2) high openness	(3) low openness	(4) full sample
Dependent variable:	log(urb)	log(urb)	log(urb)	log(urb)
ave_rain	-0.6352*	-0.6294***	-0.7667**	-0.5396***
	-0.2863	-0.2106	-0.3173	(0.1590)
ave_rain²	1.16e-04*	9.10e-05*	1.81e-04**	1.05e-04***
	-6.00e-05	-4.78e-05	-7.65e-05	(3.83e-05)
ave_temp	-0.2462***	-0.2218***	-0.2183*	-0.1888***
	-0.0466	-0.0452	-0.1118	(0.0409)
ave_temp²	0.0065***	0.0044***	0.0069***	0.0052***
	-0.0012	-0.0014	-0.0025	(0.0011)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Additional controls	NO	NO	NO	YES
Observations	1606	949	657	1213
No. of countries	146	126	103	143
R-Square (within)	0.918	0.623	0.651	0.64

Note: Robust standard errors (clustered by country in columns 2 to 4, and by country and time in column 1) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Additional controls include the lag of GDP pc (in logs) and total population in the country.

Table D.4: Robustness to interdependencies in temperatures and rainfall, and regional and country-specific linear trends

	(1)	(2)	(3)	(4)	(5)
	log(urb)	log(urb)	log(urb)	log(urb)	log(urb)
rain*temp	-0.0426***				
	(0.0104)				
$rain^2*temp^2$	3.38e-7***				
	(9.35e-8)				
moisture		-0.0670***			
		(0.0208)			
$moisture^2$		0.0015***			
		(0.0006)			
principal_comp			-0.7145***	-0.3336**	-0.3436***
			(0.1715)	(0.0774)	(0.0606)
$principal\_comp^2$			0.1913***	0.0721***	0.0648***
			(0.0469)	(0.0259)	(0.0186)
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	NO	NO
Region-specific trends	NO	NO	NO	YES	NO
Country-specific trends	NO	NO	NO	NO	YES
Observations	1606	1581	1606	1606	1606
No. of Countries	146	142	146	146	146
R-squared	0.93	0.60	0.94	0.95	0.98

Note: principal_comp is the principal component of rain and temp, which captures 66% of the joint variance, with an eigenvalues of 1.3. Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table D.5: Heterogeneity of effects on urban rate, by differences in cities per unit area in 1960

	(1) full sample	(2) developed	(3) developing	(4) low income	(5) middle income	(6) high income
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_anom	-0.0675***	-0.0176	-0.0521***	-0.0620**	-0.0329	-0.0240
	(0.0164)	(0.0142)	(0.0175)	(0.0296)	(0.0199)	(0.0153)
rain_anom*cities/area	0.2584	0.0002	0.3909	0.7482	-0.0308	0.0771
	(0.1718)	(0.0981)	(0.2645)	(0.5319)	(0.3822)	(0.0969)
temp_anom	0.0592***	-0.0065	0.0453**	-0.0222	0.0212	-0.0080
	(0.0184)	(0.0139)	(0.0189)	(0.0300)	(0.0210)	(0.0207)
temp_anom*cities/area	-0.4596**	-0.0127	0.0555	2.6150**	-0.0195	-0.1371

	(0.1834)	(0.1264)	(0.3086)	(1.1259)	(0.3414)	(0.1342)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1,573	385	1,188	327	755	458
No. of Countries	143	35	108	44	103	60
R-squared (within)	0.62	0.66	0.69	0.81	0.70	0.52

Note: Robust standard errors (clustered by country) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table D.6: Heterogeneity of effects on urban rate by baseline climate, agri-share, and world region

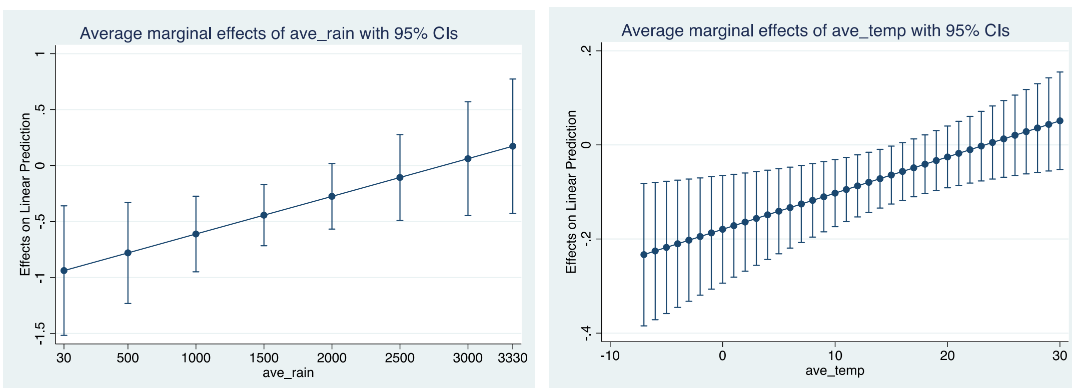
	(1) relative to baseline temperatures	(2) relative to baseline rainfall	(3) by mean agri-share	(4) by regions
	log(urbrate)	log(urbrate)	log(urbrate)	log(urbrate)
rain_anom	-0.0082	-0.0814***	0.0011	-0.0411***
	(0.0225)	(0.0212)	(0.0206)	(0.0103)
temp_anom	-0.1521***	-0.0168	-0.1963***	-0.0803***
	(0.0367)	(0.0262)	(0.0281)	(0.0225)
rain_anom*temp1950	-0.0021			
	(0.0013)			
temp_anom*temp1950	0.0092***			
	(0.0016)			
rain_anom*rain1950		0.0163		
		(0.0159)		
temp_anom*rain1950		0.0380**		
		(0.0152)		
rain_anom*logagrishare_avg			-0.0160*	
			(0.0093)	
temp_anom*logagrishare_avg			0.0866***	
			(0.0102)	
rain_anom*SSA				-0.0755***
				(0.0257)
rain_anom*South_East_Asia				0.0745**
				(0.0295)
rain_anom*LATAM				0.0353**
				(0.0149)
temp_anom*SSA				0.2106***
				(0.0307)
temp_anom*South_East_Asia				0.1519***
				(0.0468)
temp_anom*LATAM				0.0657**
				(0.0254)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1606	1606	1540	1606
No. of Countries	146	146	140	146
R-squared (within)	0.65	0.62	0.68	0.68

Note: The excluded category in Column (4) is the combination of regions not displayed in the table (NA, Europe, MENA, Central Asia and Oceania). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix E: Results for urban structure [Corresponding to Section 3.2 in the main paper]

Figure E.1: Margins plots for effects of annual rainfall and temperature on urbanisation in large cities (top two panels) and small to medium sized cities (bottom two panels)

Marginal plots urb>1m:



Marginal plots urb<1m:

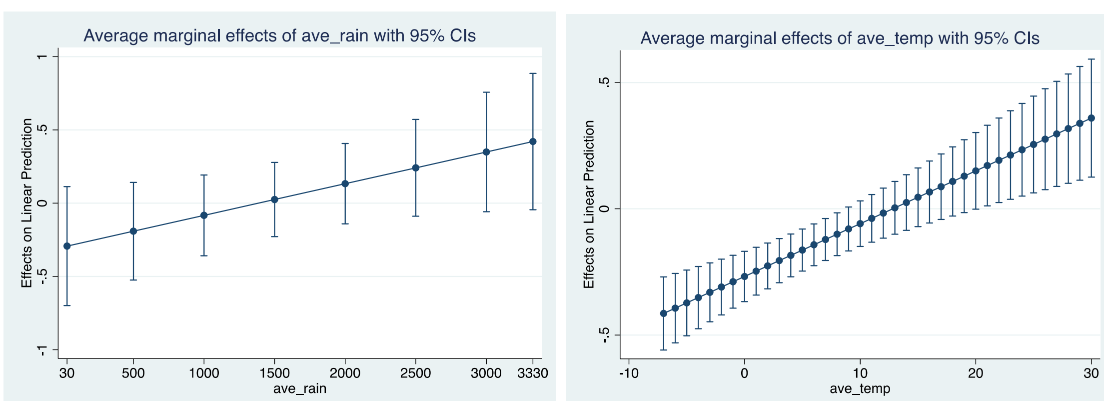


Figure E.2: Marginal plots primacy:

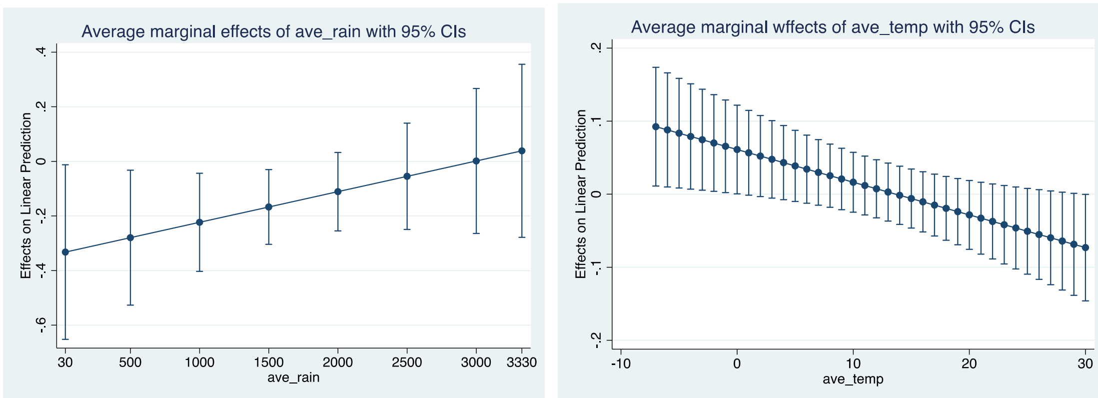


Table E.1: Heterogeneity of effects on urban structure

	(1)	(2)	(3)	(4)
Dependent variable:	Logurb>1m	Logurb<1m	logurb_largest	logurb_nolargest
rain_anom	-0.0370	-0.0380	-0.0355	-0.0369
	(0.0154)**	(0.0167)**	(0.0151)**	(0.0137)***
temp_anom	-0.0871	-0.0402	-0.0730	-0.0576
	(0.0334)**	(0.0300)	(0.0340)**	(0.0273)**
rain_anom*SSA	-0.1349	-0.0110	-0.1786	-0.0243
	(0.0423)***	(0.0306)	(0.0480)***	(0.0290)
rain_anom*SEA	0.0266	0.1356	0.0410	0.1536
	(0.0379)	(0.0536)**	(0.0410)	(0.0477)***
rain_anom*LATAM	0.0322	0.0433	0.0130	0.0446
	(0.0232)	(0.0221)*	(0.0258)	(0.0193)**
temp_anom*SSA	0.2131	0.2062	0.1814	0.2626
	(0.0479)***	(0.0492)***	(0.0412)***	(0.0475)***
temp_anom*SEA	0.1723	0.2924	0.1289	0.2679
	(0.0615)***	(0.1001)***	(0.0609)**	(0.0925)***
temp_anom*LATAM	0.0573	0.0623	0.0087	0.0767
	(0.0416)	(0.0294)**	(0.0442)	(0.0284)***
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Observations	1221	1218	1633	1595
No. of Countries	111	111	149	146
R-squared (within)	0.548	0.527	0.483	0.525

Note: The excluded category in each case is the combination of regions not displayed in the table (NA, Europe, MENA, Central Asia and Oceania). Robust standard errors (clustered by country) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix F: Results for city size, density and structure [Corresponding to Section 3.3 in the main paper]

Figure F.1: Marginal plots, city size:

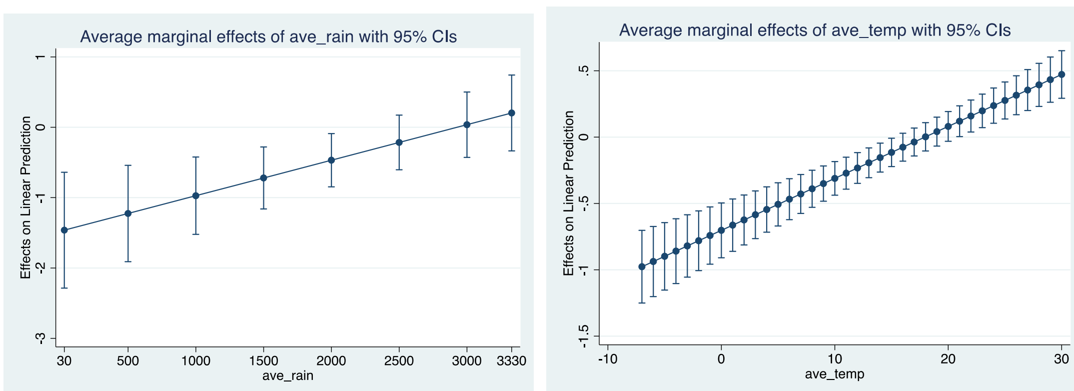


Table F.1: Robustness checks (1) to results in Table 5.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(pop)	log(pop)	log(pop)	log(density)	log(density)	log(density)
ave_rain	-0.8546	-0.2298	-0.4809	-0.0851	0.4465	0.1296
	(1.2515)	(1.1902)	(1.0697)	(1.2652)	(1.2096)	(1.0653)
ave_rain^2	5.35e-05	-1.45e-04	-9.48e-05	-7.56e-05	-2.39e-04	-1.73e-04
	(2.65e-04)	(2.91e-04)	(2.70e-04)	(2.40e-04)	(2.62e-04)	(2.34e-04)
ave_temp	-0.7750***	-0.8426***	-0.8464***	-0.5712***	-0.6024***	-0.6043***
	(0.1625)	(0.1708)	(0.1700)	(0.1514)	(0.1533)	(0.1534)
ave_temp^2	0.0196***	0.0220***	0.0224***	0.0104**	0.0123**	0.0126***
	(0.0049)	(0.0050)	(0.0050)	(0.0048)	(0.0048)	(0.0047)
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Observations	568	568	568	568	568	568
No. of cities	142	142	142	142	142	142

Note: Columns 1 and 4 restrict weather variation to 500 km radius around the city. Columns 2 and 5 also restrict weather variation to 500 km radius around the city but weighting by distance and population. Columns 3 and 6 do the same but excluding urban grid-cells.

Table F.2: Robustness checks (2) to results in Table 5.

	(1)	(2)	(3)	(4)
Dependent variable:	log(pop)	log(pop)	log(pop)	log(pop)
ave_rain	-2.1601**	-2.1601**	0.1770	0.1770
	(0.8948)	(0.9730)	(0.7995)	(0.7388)
ave_rain^2	3.62e-04*	3.62e-04*	-3.91e-05	-3.91e-05
	(2.01e-04)	(1.83e-04)	(1.53e-04)	(1.37e-04)
ave_temp	-0.5541***	-0.5541***	-0.2222	-0.2222
	(0.1348)	(0.1538)	(0.1461)	(0.1479)
ave_temp^2	0.0136***	0.0136***	0.0075**	0.0075**
	(0.0032)	(0.0031)	(0.0038)	(0.0033)
Year FE	YES	YES	NO	NO
City FE	YES	YES	YES	YES
City linear trends	NO	NO	YES	YES
Observations	584	584	584	584
No. of cities	146	146	146	146

Note: log(pop) using GHSL data. Robust standard errors (clustered by city in columns 1 and 3 and by city and time in columns 2 and 4) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F.3: First-step results from Table 6.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$CitySize$	$CitySize$	$CitySize$	$CitySize$	$CitySize$
ave_rain	-0.4206**	-1.5326**	-0.4206**	-1.5326**	-1.2924***
	(0.1925)	(0.6365)	(0.1925)	(0.6365)	(0.4957)
ave_rain^2	8.16e-05*	2.24e-04	8.16e-05*	2.24e-04	1.97e-04*
	(4.66e-05	(1.53e-04)	(4.66e-05)	(1.53e-04)	(1.12e-04)
ave_temp	-0.3705***	-0.4949***	-0.3705***	-0.4949***	-0.4063***
	(0.0311)	(0.0826)	(0.0311)	(0.0826)	(0.0576)
ave_temp^2	0.0104***	0.0113***	0.0104***	0.0113***	0.0137***
	(0.0008)	(0.0023)	(0.0008)	(0.0023)	(0.0015)
Year FE	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES

Observations	886	436	886	436	529
No. of countries	148	146	148	146	143
R-Square	0.67	0.56	0.67	0.56	0.71

Note: *CitySize* all in logs. Columns 1 and 3 use WUP data for population. Columns 2, 4 and 5 use GHSL data. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table F.4: Robustness checks to results in Table 6.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Moran's I	Moran's I	Moran's I	Gini	Gini	Gini
$\widehat{CitySize}$	-0.0700***	-0.0692***	-0.0690***	-0.6333***	-0.6597***	-0.6645***
	(0.0235)	(0.0240)	(0.0239)	(0.1291)	(0.1342)	(0.1341)
Year FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Observations	425	425	425	425	425	425
No. of countries	142	142	142	142	142	142
R-Square	0.44	0.44	0.44	0.11	0.11	0.11
F test on exc inst	45.91***	46.29***	46.32***	45.01***	46.29***	46.32***

Note: Moran´s I, Gini and *CitySize* all in logs. In columns 1 and 4, *CitySize* is estimated using weather variation in a 500km-radius around the city. I columns 2 and 4, *CitySize* is estimated using weather variation in a 500km-radius around the city but weighting by distance and population. Columns 3 and 6, *CitySize* is estimated using weather variation in a 500km-radius around the city but weighting by distance and population and excluding urban grid-cells. Robust standard errors (clustered by city) in parentheses. *** p<0.01, ** p<0.05, * p<0.1

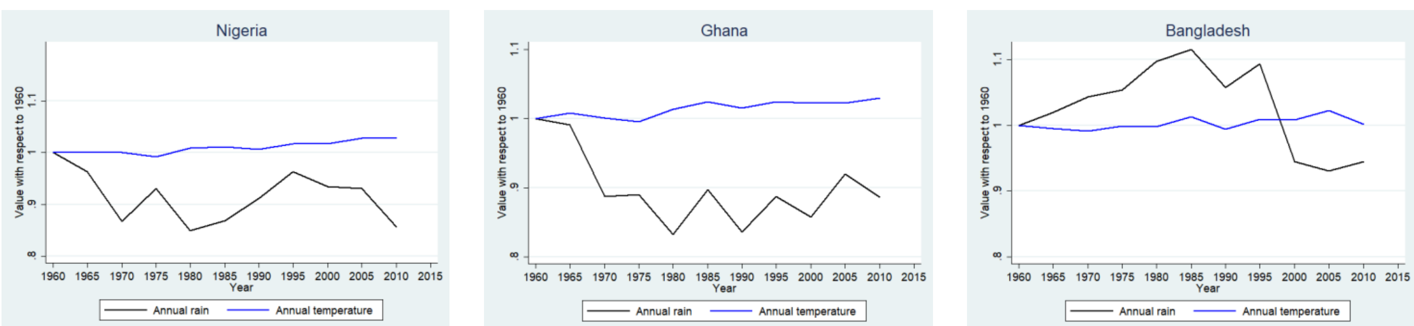
Appendix G: Case Study:

Climate Change and Urban Structure in two African and one Asian Country

Here we present a comparative case study of two Sub-Saharan African countries – Nigeria and Ghana – and one South Asian country – Bangladesh, to highlight commonalities as well as differences in the relation between climate change and urban structure.

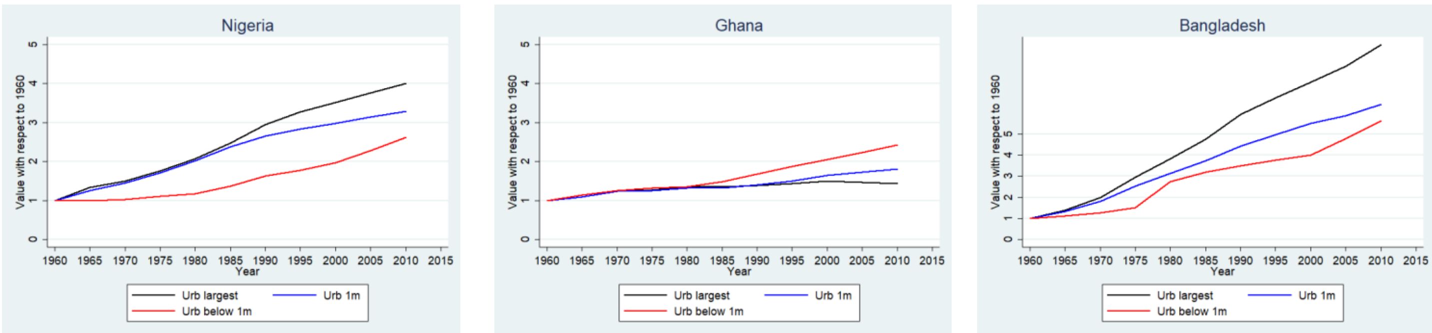
Figure G.1 shows the evolution of annual temperature and rainfall with respect to values in 1960. While the average annual temperature and its increase over time are very similar in the three countries, Bangladesh has a much wetter climate than the two African countries: the annual rainfall in 1960 was 2253mm, nearly twice as high as in Nigeria (1243mm) and Ghana (1311mm). Moreover, in Bangladesh, rainfall has substantially exceeded the initial values in some years and been below these levels in other years. In the two African countries, the trend clearly indicates less rainfall, in line with findings comparing SSA and SEA. Hence, farmers might be driven into cities by a lack of rain in SSA (i.e., Nigeria and Ghana), while both excess rain and a dearth of rain might be affecting individuals in SEA (i.e., Bangladesh).

Figure G.1: Evolution of annual rain and temperature with respect to 1960 values



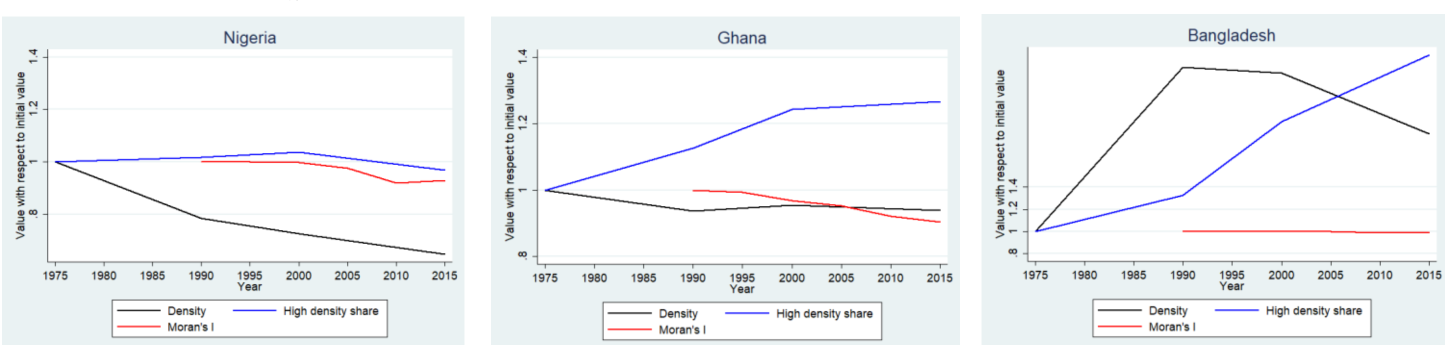
Apart from the climate conditions, these three countries show some variation in their urban structure in 1960, which might shed light on their subsequent changes in urbanization. In 1960, Bangladesh was hardly urbanized at all – its urbanization rate was 5.13% - while Nigeria had an urbanization rate of 15.41% and Ghana one of 23.25%. Despite its low urbanization rate, Bangladesh's urban population was already relatively concentrated in Dhaka, with a primacy rate of 20.52%. Ghana had a high primacy rate of 25.38%, while in Nigeria the urban population was still more dispersed (primacy rate of 10.94%).

Figure G.2: Evolution of urbanization rates in cities of various size (largest city, cities above 1m inhabitants, cities below 1m inhabitants) with respect to 1960 values



The increases in urbanization rates in cities of different size in Figure G.2 reveal that countries with low initial urbanization rates – Nigeria and in particular Bangladesh – experienced larger increases of urbanization rates across the urban structure. Whether smaller or larger cities grew more depended on the initial urban structure. In Ghana, with its comparatively mature urban structure and high primacy rate, urbanization in smaller cities has outgrown urbanization in cities above 1m and in the largest city. In Nigeria and Bangladesh, we observe the opposite: a concentration in primary cities over the last decades. The rise of Dhaka is particularly noteworthy: it has grown from a population of 508,000 in 1960 to 17.6m in 2015, fueled to some extent by its garment industry, which has attracted many migrants. But living conditions are often bad, with 60% of residents living in makeshift structures (The Economist 2019).

Figure G.3: Evolution of primary city variables (density, high density share, Moran's I) with respect to initial values (1975 or 1990)



A closer look into the structure of the primary cities (Figure G.3) reveals heterogeneous developments: Lagos's growth in population has been matched by an expansion in the built-up area, so that population density shows a decrease. Its share of high density areas remains stable. Accra's population growth in Ghana might have been more moderate, but its high-density share increased markedly and Moran's I decreased, indicating a more fragmented city structure. The higher population growth rates in smaller Ghanaian cities might help to ease the pressure on the primary city. The unique pull factor of Dhaka in Bangladesh is mirrored in the escalating density measures. Congestion, pollution and sewage are increasingly considered as severe problems. While the Dhaka city authority is now working on a plan for orderly city expansion, local authorities try to foster decentralization and migration to the country's other cities.

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