# Droughts and the growth of cities

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**Abstract**

Some researchers and policymakers posit that climate change should increase city growth and urbanization as rising temperatures make rural livelihoods precarious, while others argue that climate change might trap rural households who cannot afford to migrate because of increasing poverty. Existing empirical evidence on the link between climate and urbanization is inconclusive. This paper exploits novel data mapping city growth for 7,000 cities in 108 low to middle income countries across 23 years to provide new evidence on the relationship between drought and urbanization. Cities experience large and persistent declines in growth rates after major drought events: after 11 years, cities are 0.7 percent smaller compared to a drought-free counterfactual. I show that fully accounting for dynamic effects is essential to correctly understand the relationship between drought and city growth and that a positive correlation between drought and contemporaneous city growth is misleading. Consistent with models that envision a drought-migration poverty trap, the negative effects on urbanization are more pronounced for the poorest, and most agricultural countries.

**Key words:** city; climate; drought; migration; urbanization

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# 1 Introduction

Climate scientists predict that with climate change, the frequency, intensity and severity of droughts will increase (IPCC, 2022). How this will affect the growth of cities is unknown, presenting a major problem for urban planners and policymakers who must make infrastructure and planning decisions with time horizons of several decades. Researchers and policymakers alike claim that more extreme weather events will lead to an increase in migration, projecting the number of internal climate migrants in developing countries to reach 200 million by 2050 (Clement et al., 2021), many of whom are likely to move to cities (Cattaneo & Peri, 2016). But adverse weather events might also decrease migration, especially for the poorest and agricultural households who are liquidity constrained, because it wipes out the funds needed to migrate (Bryan, Chowdhury, & Mobarak, 2014; Kleemans, 2023). Our understanding of this relationship has been constrained by the absence of disaggregated or high-frequency data on city growth, necessary to trace out the effects of specific weather events over time at lower spatial scales.

In this paper, I address these challenges by first assembling data on the annual growth of cities – as measured by city footprint – for 7,000 cities in 108 low to middle-income countries, where the effects of droughts are likely to be most salient. I then combine these data with historical weather data to measure the effect of drought exposure on the growth of cities over the course of 23 years.

I study the reduced-form relationship between droughts and city growth with an event study-distributed lag model framework, using it to trace out the dynamic response of cities following exposure to a drought. Fully accounting for these dynamic effects is critical for several reasons. Omitting the lagged effects of weather events introduces bias in estimated coefficients, because of serial correlation in weather variables (Nath, Ramey, & Klenow, 2023; Newell, Prest, & Sexton, 2021). Moreover, the impact of weather shocks can be the result of temporal displacement, where effects observed in one time period are completely reversed in a later period, as highlighted by e.g. Deschenes and Moretti (2009) and Hsiang (2016). Lastly, estimating the dynamic effects allows me to both recover the cumulative impact of a drought, and determine whether this impact persists in the long run.

I find that droughts have a large, negative and persistent impact on the growth of cities. I trace the effects on city growth up to 11 years after drought exposure to cities and their hinterlands. I find that cities continue to diverge from their counterfactual growth trajectory over the course of seven years following a major drought, equivalent to a 1-in-50 year event. After this time cities remain 1.2 percent smaller compared to a drought-free counterfactual. While the effect fades over time, city growth does not recover completely, and remain 0.7 percent smaller 11 years after a drought. The median city expands by 24 percent over the course of 11 years – hence, a major drought effectively undoes around 3 percent of this total growth. While less intense droughts also have large effects after seven years, they are less persistent.

These results show that major droughts have long term effects on the growth of cities, implying that a model which only accounts for contemporary effects is misleading. Indeed, the contemporaneous correlation between drought and city growth is weakly positive – however these effects are overturned when accounting for the lagged effects. The results are robust to a battery of specification tests and alternative approaches to estimation and inference, including randomization-based inference based on reshuffling observed weather conditions across time, and showing that the impact is not the result of spatial spillovers from other cities.

Studies have highlighted that urbanization has progressed differently across continents[1] and that climate change could have heterogeneous effects on urbanization,[2] suggesting the impact of droughts could vary across geographical regions. I run subsample analyses by continent. I find the largest and most persistent effects in Africa. After 11 years, the estimated effect of a major drought is 2 percent, which is substantially larger than the average effect. For Asia, comprising a large share of the sample[3], the results are similar to the average effects. I find that the impact of droughts is statistically insignificant in North America, South America, and Oceania.

I further examine whether droughts impact cities in poorer countries more than in richer countries – poorer countries have been found to be more vulnerable to disasters and weather shocks (Dell, Jones, & Olken, 2012; Kahn, 2005). Partitioning the

[1]See Henderson and Kriticos (2018) and Henderson and Turner (2020) for a review.
[2]Barrios, Bertinelli, and Strobl (2006) and Henderson, Storeygard, and Deichmann (2017).
[3]About two thirds of the cities in the sample are located in Asia.

sample into low, lower-middle and middle income countries, I find the impact is most pronounced in the two former categories, while I find statistically insignificant impacts for the middle income countries. Lower income countries are agriculturally dependent, and the agricultural sector is particularly vulnerable to weather shocks (Schlenker & Roberts, 2009). I therefore investigate the role of agriculture, as measured by the national share of employment in agriculture, dividing the sample into low, middle and high shares. Cities in countries with the highest share of agricultural employment remain 3.5 percent smaller 11 years after a major drought. I find no impact for the cities in countries with the lowest share.

What do these results imply for the growth trajectory of cities? The median expansion for a city in poorer countries is 23 percent, a major drought undoes 10 percent of that growth, or the equivalent of a whole year. For cities in the most agricultural countries, it undoes the equivalent of almost two years of growth.

My results have two major implications. The first is that rather than inducing growth, droughts inhibit the growth of cities, which is contrary to the working hypothesis of many policymakers and researchers. This pattern holds across large parts of the sample, which together represent billions of people. As the size of a city's footprint is highly correlated with its population,[4] my results also suggest that droughts decrease rather than induce city population growth. Moreover, city population growth is connected to urbanization (the share of urban population) and often driven by rural-to-urban migration (Brueckner & Lall, 2015), suggesting droughts do not drive either urbanization or migration to urban areas.

The larger and more persistent effect of drought exposure on cities in poorer and more agricultural countries is consistent with models which envision environment-migration poverty traps. These models predict that adverse weather shocks could effectively trap already resource poor people in agriculture and further poverty, since shocks worsen their liquidity constraints and reduces their ability to pay for migration costs (Cattaneo & Peri, 2016; Mayda, 2010). This chain of events could contribute to explaining the persistent gaps between rural and urban sectors in developing countries, where the higher overall amenities and income enjoyed by urban dwellers leads

[4]The correlation between city population and footprint are high, ranging between 0.75 and 0.85. The results of these analyses are shown in Figure 9.

Henderson and Turner (2020) to question why urbanization is not happening at an even higher rate.

This paper relates to three strands of the literature. First, I build on a vast and still-growing literature evaluates the socio-economic effects of climate change. Examples include Dell, Jones, and Olken (2012), Hsiang and Jina (2014), and Nath, Ramey, and Klenow (2023) studying the impact on GDP, Deschênes and Greenstone (2007) and Schlenker and Roberts (2009) on agricultural yields, and Kahn (2005) on mortality.

My findings connect specifically to the literature on the links between climate change and urbanization. This literature has studied how longer-run changes in climate have affected the share of urban population in Sub-Saharan African districts (Henderson, Storeygard, & Deichmann, 2017), or using yearly weather variation in cross-country analyses (Barrios, Bertinelli, & Strobl, 2006; Castells-Quintana, Krause, & McDermott, 2021). Contemporaneous work studies the effect on built up area using global grid cells as the level of analysis (Chlouba, Mukim, & Zaveri, 2023). I add to this literature by extending the city-level evidence[5] to five different continents. Using city level data, I study disaggregated weather shocks, which are important since there is considerable variation in weather within larger administrative units, and internal migration is often local. Additionally, in contrast to the previous literature, I trace out the dynamic (and cumulative) effects of weather shocks and show that they are both persistent and different from contemporaneous correlations.

The climate and urbanization literature is closely related to the literature on climate change and migration, especially internal migration, an already vast literature. Recent reviews include Hoffmann, Šedová, and Vinke (2021) and Kaczan and Orgill-Meyer (2020). Research in this literature focusing on internal migration has largely studied single countries (Bohra-Mishra, Oppenheimer, & Hsiang, 2014; Gray & Mueller, 2012; Kleemans & Magruder, 2018) primarily using survey or panel data. I build on this literature by showing that city growth in especially poor and agricultural countries are impacted by droughts, results that are consistent with environment-

[5]Henderson, Storeygard, and Deichmann (2017) uses a city-level analysis to examine the impact of rainfall on city income, and Castells-Quintana, Krause, and McDermott (2021) limit their city sample to the largest city in each country.

migration poverty traps.

This paper is organized as follows. In Section 2, I describe the context of this study. Section 3 describes the data and its sources, followed by Section 4 detailing the empirical framework of the paper. Section 5 presents the results, Section 6 the heterogeneity results, and I end the paper with a discussion and conclusion in Section 7.

# 2 Context

Countries in the developing world are urbanizing rapidly. This is especially the case in Asian and African countries, albeit from relatively low levels compared to the rest of the world (Henderson & Kriticos, 2018). The majority of the population in these countries undergoing urbanization still live in rural areas however. The main economic sector in these rural areas is agriculture, either as subsistence farming or as agricultural workers. Food production in these areas is generally local, and net food imports are as low as 5 percent. Hence, most of the agricultural production is for domestic consumption (Gollin, Parente, & Rogerson, 2007). This implies that rural areas are by extension particularly vulnerable to adverse weather shocks, as opposed to urban areas which usually have a larger variety of economic production.

This is also the setting of this paper. In Figure 10, I compare the countries in my sample to the rest of the countries in the world. I show that the countries in my sample are less likely to live in an urban area in the year 1992. Additionally, people living in my sample countries are also more likely to be employed in agriculture in 1992, which is the beginning of my study period.

In Figure 11, I turn to showing how the distribution of yearly city growth rates in terms of city footprint. I show this in two ways: first by showing the distributions according to country-level income categories (panel a), for countries within my sample. The distribution looks similar across categories - although the low and lower middle income countries have longer right tails, the median is similar in cities for both low and middle income countries.

Figure 4b again shows the distribution of city growth rates, but by the country-level agricultural share of employment. Contrary to what one might expect, the growth rate is somewhat higher in the countries which are less agricultural (the first tercile), whereas the lowest growth rate is among the cities in the countries which are the most agriculturally dependent.

# 3 Data

This section describes the data used in this paper, and the different sources from which I retrieve and combine data in order to create the final panel.

## 3.1 Sources and construction

**Sample** I restrict my sample based on geography and the income categories as determined by the World Bank. I exclude all European countries from my analysis, and countries which have been classified as high income countries for a substantial length of the panel. This includes e.g. Japan, South Korea and the US. I also exclude small island states, because they lack data on drought conditions, and high income jurisdictions, e.g. the Dutch Caribbeans and Overseas France.[6]

**City size** The underlying data I use to calculate the city growth measure is the World Settlement Footprint (WSF) Evolution (Marconcini et al., 2021). It is the result of classifying pixels in remote sensing images, primarily from the Landsat satellites, on a yearly basis. Each pixel in the images goes through a binary classification exercise[7], where it is classified as either built up or not.[8] The value of each pixel represents the year in which it was classified as built up. The resolution of the WSF data is 30 meters. The data is available from 1985 until 2015. However, as a result of the orbits of the satellites which captured the remote sensing imagery, some areas have missing data for some years. Therefore, I exclude the cities which do not have an unbroken sequence of observations starting in 1992, the year in which the data

[6] Includes departments and territories outside of mainland France, including Réunion and Guadeloupe.

[7] This is further detailed in Rentschler et al. (2022).

[8] Built up is a category in land use classification which represents impervious surface area, or man made structures.

becomes more consistent.[9]

Using the WSF data, I record the year in which each pixel was classified as built up, and sum these pixels within the boundaries of each city. To define cities, I use metropolitan area boundaries as defined by Moreno-Monroy, Schiavina, and Veneri (2021), called Functional Urban Areas (FUA). They represent estimated commuting zones of urban areas with a population of at least 50,000 in 2015. By this approach, I avoid limiting the analysis to the political boundaries of a city, as these can both change over time and be endogenously determined. The associated data is provided by Schiavina et al. (2019). Figure 1 showcases an example of the FUA boundary and city growth in Jaipur, India.

An advantage with using these data is that the measures should be unaffected by differences in e.g. institutional quality, or definitions of what a city is, across countries.[10] In addition, the quality of the data should not be affected by the economic and political conditions in a country, which could introduce endogeneity (Hsiang & Jina, 2014).

**Drought conditions** I use the standardized precipitation evapotranspiration index (SPEI) as a measure of drought conditions (Vicente-Serrano, Begueria, & Lopez-Moreno, 2010). SPEI is calculated using a combination of precipitation and temperature to measure the climatic water balance[11] of a location. An advantage of SPEI relative to other drought indices is the inclusion of temperature, which has a documented effect on agricultural yields (Schlenker & Roberts, 2009). The values of the index are standardized by pixel, and are therefore comparable across different geographical regions. This is an important feature considering there are large climatic differences across the cities in my sample.

SPEI data is provided by Vicente-Serrano et al. (2022).[12] An advantage of these

[9]This is also noted in Rentschler et al. (2022), who show that input data quality is worse before 1992.

[10]Observational data can be manipulated, for example because of political incentives, which has been highlighted for certain census data in Nigeria Okafor, Adeleke, and Oparac (2007).

[11]By calculating the difference between precipitation and potential evapotranspiration, which is estimated using the FAO-Penman-Monteith equation.

[12]The authors now recommend this data over their previous versions, the SPEI-Base, which is calculated using weather station data.

data is that the climate data used to calculate SPEI is from the ERA5 Climate reanalysis. Weather station data pose empirical challenges[13], especially in regions with few weather stations, for example Africa. The original temporal resolution of the data is weekly, and the spatial resolution is 0.5 degrees, equivalent to around 55 kilometers. I use data from 1980 to 2020, since that is the time period used to calibrate the index (Vicente-Serrano et al., 2022).

**Additional data** I complement the data set with country level data on the share of agricultural employment and GDP per capita. These data both come from the World Development Indicators of the World Bank (Bank, 2023). I also use data from the United Nations Statistics Division (UNSD) to identify subregions. These are shown in Figure 12a.

## 3.2 Descriptive figures and tables

In Table 1, I report descriptive statistics of the data for the whole sample as well as divided by continents. The variables include city population in 2015 from Schiavina, Freire, and MacManus (2019), city growth which is the outcome used in this paper, GDP per capita, share urbanized and agricultural employment shares from Bank (2023).

The countries in the sample are relatively poor, with an average GDP per capita of 2207 USD across the study period, and are largely agricultural. However, countries in North and South America are richer, less agricultural, and have higher urbanization rates compared to Africa and Asia. The growth in city size is high across the sample, at a median growth rate of 2 percent per year, or 3 percent in for example Asia.

Figures 13, 14, 15, and 16 show the spatial variation in the growing season SPEI average, by each year of data in the sample.

[13]This point is further elaborated in Auffhammer et al. (2013).

# 4 Empirical framework

This section details the empirical framework. I begin by explaining how I define the treatment, drought exposure. I then describe the specification in more detail. I also examine the potential pitfalls in omitting the lagged terms of drought, or weather shocks in general.

## 4.1 Drought exposure

Previous studies have used drought to study its impact on various outcomes, such as conflict (Harari & Ferrara, 2018) or internal migration (Albert, Bustos, & Ponticelli, 2021; Imbert & Ulyssea, 2022), but to my knowledge, there are no established best practice in how droughts should be defined. Imbert and Ulyssea (2022) use crop value weighted indices, Harari and Ferrara (2018) averages the values of drought indices over a dominant crop's growing season, and Albert, Bustos, and Ponticelli (2021) use values above the mean. Seeing as my data on annual city growth is both highly spatially and temporally disaggregated, I have to make explicit choices in how I define drought exposure for cities and their hinterlands (or catchment area).

I define the catchment area of a city as a 100 kilometer buffer around it, within country borders, as migration is to a large extent internal in developing countries (Jónsson, 2010). This captures both the effect of droughts on the city as well as its rural hinterlands, where droughts are likely to be more salient, as rural areas are largely dependent on agriculture. Since i) the broader climate impacts literature has shown that weather shocks have the largest effect on the agricultural sector (Burke, Hsiang, & Miguel, 2015; Zappalà, 2023), and ii) agriculture is the main economic sector in rural areas, I assume that the relevant temporal dimension is the agricultural growing season. Following Ortiz-Bobea et al. (2021), I approximate the main growing season for each pixel in the SPEI data using the month for which the NDVI is the highest. I then aggregate the SPEI values over the two preceding months, the highest value month, and the succeeding two months.

I match the annual SPEI value described above, and calculate a city-specific SPEI value by taking the area-weighted average of the values within each buffer of a city. Finally, I dichotomize the drought exposure measure, where the indicator $D_{it}$ takes on the value 1 if the value in a year $t$ in a city $i$ is 1, 1.5 or 2 SD above the average (between 1980 and 2020) of each city. I vary the threshold to both make sure the results are not the result to a specific cut off, and to understand whether intensity of droughts matters for city growth. The following equation describes how the measure of drought exposure is defined:

$$D_{i,t} = \begin{cases} 1, & \text{if } S_{it} \geq \bar{S}_i + \lambda SD(S_i), \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where $\bar{S}_i$ is the city level buffer 40-year average of the SPEI, and $SD(S_i)$ is the standard deviation. $\lambda$ represents the different cutoffs, where $\lambda = \{1, 1.5, 2\}$. Hence, for each year $t$, if the SPEI value for city $i$ is higher than the mean and the standard deviation, I define it as a drought year.

The values of the cutoffs are informed by previous research which characterizes droughts as moderate (1 SD), severe (1.5 SD) or extreme (2 SD) using standard deviation cutoffs (Wang et al., 2014).

Accordingly, droughts happen less frequently as they become more intense. A 1 SD drought is on average a 1-in-6 years event, 1.5 SD drought a 1-in-16 year event and a 2 SD drought is a 1-in-50 year event. However, this does not mean that they are never happen in the data: in Figure 3 I show the share of cities in the sample which experience a 1.5 or 2 SD drought every year. In a given year, between 1 and 5 percent of cities experience a drought in my sample.

## 4.2 Specification

To estimate the causal effects of local droughts on city growth, I adopt an event study-distributed lag model approach,[14] modeling city growth (first difference of the logarithm of city footprint) as a function of drought exposure $D_{i,t}$ out to a maximum lag length $k$. I estimate the following model using ordinary least squares:

[14]The parameters recovered from the an event study specification and distributed lag models are identical under certain assumptions, as discussed in Schmidheiny and Siegloch (2023)

$$\Delta ln(Y_{i,t}) = \sum_{l=-5}^{11} \gamma_l D_{i,t-l} + \alpha_i + \delta_{st} + \varepsilon_{d,t} \tag{2}$$

where cities are indexed by $i$ and year by $t$, and the parameters of interest are the coefficients $\gamma$.

This approach follows the general framework for identifying the effects of weather shocks (Deschênes & Greenstone, 2007; Hsiang, 2016): I include city fixed effects, $\alpha_i$, to account for time-invariant properties of cities, which includes for example institutions or geography, and could lead to differences in average growth rates between cities. Since the outcome is defined in growth terms, it is the first derivative of city footprint. Hence, including city fixed effects is equivalent to controlling for a linear trend in city size.

I include subregion-by-year fixed effects, $\delta_{st}$, to account for common nonlinear trends and shocks at the UNSD subregional level.[15] This non-parametrically adjusts for all factors that are common across cities within a subregion by year, such as crop price levels. However, as highlighted in Deschênes and Greenstone (2007), if there exists local segemented markets, prices will not be held constant using this approach. While this could be accounted for by introducing more spatially fine fixed effects, such as country-by-year fixed effects, the caveat is that introducing ever finer fixed effects absorb a great deal of the variation in weather and climate (Fisher et al., 2012).

I assume that the disturbance term, $\varepsilon_{it}$, may exhibit both spatial correlation, and autocorrelation within a city over time. To account for this possibility, I estimate standard errors that are clustered in two dimensions: within ADM1-by-year and cities. ADM1 denotes the first level of administrative division in each country. This includes for example states in India or provinces in Indonesia. A map delineating the first administrative levels is available in Figure 2b.

Conditional on each city's average climate and trend in climate, which is absorbed by city fixed effects and the time fixed effects, the timing and intensity of drought exposure should be unpredictable and stochastic across years. Hence, the specification allows me to assume that drought exposure $D_{it}$ is plausibly exogenous and

[15]Subregions are large; for example Africa is divided into North Africa and Sub-Saharan Africa. A map of the subregions are found in Figure 12a.

uncorrelated with most other unobserved factors which could influence city growth. As an additional test that these assumptions hold, I include five years of leads in the specification. This is added as a placebo test (Hsiang, 2016), and to make sure there are no anticipatory effects (Schmidheiny & Siegloch, 2023). In order for these assumptions to be plausible, the coefficients of the leads should be close to zero.

**Interpretation of the coefficient** For a drought which takes place in year $t$, I am interested in the longer-run effects on the growth of cities, i.e. effects until the period $t+j$. These are the dynamic treatment effects, or the cumulative (treatment) effects,[16] of drought exposure. The coefficients $\gamma$ capture the incremental, or marginal, changes in the dynamic treatment effects. Therefore, we can construct the dynamic effects by summarizing the marginal effects year-to-year. Let $\beta_l$ be the dynamic treatment effect up to $j$ years after drought exposure:

$$\beta_k = \sum_{l}^{k} \gamma_l \tag{3}$$

For clarity, I only report the dynamic treatment effects, $\beta_k$ throughout the paper, and exclude estimates of $\gamma_l$.[17]

With this empirical approach, I also need to make an explicit choice in how many lags and leads should be included in the model, as this is an assumption on when effects have been fully materialized. To the best of my knowledge, there is no empirical precedent or theoretical model to directly inform this choice with regards to the relationship between city growth and droughts, or adverse weather events generally. Therefore, I choose the number of lags based on the available data, where eleven is roughly half the length of the outcome data (city growth). As for the number of leads, I choose the maximum number available in the drought conditions data that does not change the effective sample for estimation. There are two additional assumptions worth mentioning. The first is that the effects are assumed to be additively separable,

[16]Dynamic treatment effects, cumulative treatment effects, cumulative effects, and intertemporal treatment effects are for all intents and purposes used interchangeably in the economics literature (see e.g. de Chaisemartin and d'Haultfoeuille (2022)).

[17]The marginal effect, $\gamma_l$ can be recovered from the dynamic treatment effects, since $\beta_{k=l} = \beta_{l-1} + \gamma_l$.

i.e. that the effect of drought exposure in each year is independent of the effect in a previous year. The second is that the treatment effects are homogenous across cohorts and years. I explore the second assumption in a robustness test, and show that this is not likely to be a concern in this study.

### 4.3 Shorter run vs. longer run effects

Modeling how city growth could be affected by city growth is not obvious, since the functional form has no precedent. However, there are parallels in the climate impacts literature, where we can learn some important features. The first is that dynamic effects of weather shocks are important in understanding the overall effects. As highlighted in Hsiang (2016), weather shocks can result in temporal displacement effects, where a shock in period $t$ brings an event that would otherwise occur in a future time period, e.g. $t + j$, forward in time. Deschênes and Greenstone (2007) illustrate this phenomenon by showing that a substantial number of deaths related to heat would have taken place in the near future, even if a heat wave had not occurred. If that were the case in this paper, the dynamic treatment effect as expressed in Equation 3 would be equal to zero.

Secondly, there is good reason to believe that the effects of weather shocks on city growth could be delayed. While it is plausible to assume that construction can take place faster in developing countries, which often lack zoning requirements (or the institutional capacity to enforce them) it is still reasonable a priori to assume that droughts could have delayed effects. For this reason, the lagged effects are of interest.

Lastly, a large literature emphasizes that measures of weather often exhibit considerable serial correlation (Nath, Ramey, & Klenow, 2023; Newell, Prest, & Sexton, 2021). Because of the serial correlation, it is important to include a sufficient number of lags of the weather events to recover unbiased causal estimates of their effect.

## 5 Results

In this section, I first examine the effects of drought exposure on city growth for the entire sample, and establish that the effect is indeed substantial, statistically significant and persistent. I then continue by exploring whether there is a significant impact in geographical sub-samples, more specifically by continent.

## 5.1 Main result

Figure 4 and Table 2 presents the main analysis of this paper, the longer-run effects of drought exposure on city size relative to a drought-free city counterfactual. Each subgraph in the figures show the dynamic treatment effects, $\beta_l$, from five years before (year $-5$) up until 11 years after drought exposure. The estimates are the result of using the three different intensities of drought exposure in separate analyses, where the threshold used in creating the drought is varied. 1 SD represents the least intense drought measure, and 2 SD the most intense drought.

Following exposure to a drought, city size declines for up to 11 years after exposure. However, the result varies highly across drought intensity. The results from estimating Equation 2 using the least intense measure of drought, 1 SD, do not show either statistically or economically significant results over 11 years. Turning to the 1.5 SD or 2 SD events, the results are statistically significant and also larger in magnitude than those of 1 SD events.

Focusing on the 1.5 and 2 SD measures, there are also interesting patterns in persistence. While the 1.5 SD events are estimated to decrease city size by 0.5 percent 7 years after the exposure, this effect dissipates substantially over the course of the effect window, and seems to revert back to trend after 11 years. The pattern is similar for 2 SD events, but the estimated effects are almost twice as large in terms of magnitude. After 7 years, the effect is 1.2 percent - this effect decreases somewhat 11 years after, but does not entirely dissipate, although confidence intervals become wider.

The fact that results differ considerably across drought intensity also suggests that there is some degree of non-linearity in the effects of droughts on city growth. This can also be understood when considering the in-sample probability of each event. Droughts which occur as often as every 5-6 years could be easier to cope with, while shocks that happen once every 15-50 years likely represent events which are more both more damaging to agricultural production and unprecedented.

## 5.2 Robustness of the main result

In order to ensure the robustness of the results described above, I perform a number of robustness tests. These include a randomization test, changing the main specification, using alternative standard error estimation, and using alternative estimators. I go through them in the paragraphs below.

**Randomization inference test** I use randomization inference tests to understand how likely it is that my estimated effects are observed by chance, in the spirit of Fisher (1935). I randomize drought conditions by shuffling years while keeping the cross-section constant, keeping the spatial correlation across the sample intact (Heß, 2017). I then compare the point estimate $\beta_7$ I recover from the true data to the distribution of point estimates recovered from the randomized placebo assignments. The results of this exercise are shown in Figure 8. While the results are weaker for the 1.5 SD droughts, with a p-value slightly above 0.1, the 2 SD is highly unlikely to be observed by chance, with a p-value safely below 0.05. Hence, the results are unlikely to be spurious.

**Alternative non-parametric time controls** I replace the subregion-by-year fixed effects with a less aggregated level of regions, intermediate regions-by-year, to verify that the results are not driven by the choice of fixed effects. In Figure 21, I show that the results are not sensitive to changing the specification to include these finer scaled fixed effects, as they remain almost identical to the results using my preferred subregion-by-year fixed effects.

**Alternative standard errors** In my preferred specification, I control for spatial correlation by clustering by ADM1-by-year. I also control for spatial correlation in the residuals by estimating the standard errors using Conley (1999) standard errors. I vary the cut off between 250 and 500 kilometers. In these specifications, I also allow for serial correlation up to 20 years using Newey and West (1986) standard errors. The resulting confidence intervals are similar to my main specification, as shown in Figure 18.

**Varying SPEI measure** The SPEI can be calculated using different time lengths. In my main specification, I use SPEI-3, i.e. the SPEI is calculated using the water balance from the three previous months. I instead use the SPEI-6, which uses the six previous months, and construct the drought exposure measures in the same way. This is the preferred specification in e.g. Harari and Ferrara (2018) who argue that it captures the effect on agriculture. I present the results in Figure 20. The estimates are not substantially different from using SPEI-3, suggesting that the exact time length does not substantially affect the results.

As noted in Section 3, I construct the drought variable following Ortiz-Bobea et al. (2021) to approximate the agricultural growing season. In Figure 20, I instead construct the drought measure using the entire calendar year. This has a slightly different implication, since it relies on the assumption that each month is equally important. The results do not change drastically - the one important difference is that the effects of a 2 SD are somwhat smaller after 11 years, at 0.5 percent (compared to 0.7 percent in the main analysis).

**Spatial spillovers** I assess whether spatial spillovers across cities affect or drive the results. I account for potential spatial spillovers by estimating a spatial lag model, taking into account drought events which have occurred within pre-defined annuli from each city, following the procedure outlined by Hsiang and Jina (2014). Hence, city $i$'s growth is modelled as a function of drought exposure within a 100 kilometers, and all temporal lags in the exposure of neighbors $j$ whose centroids fall within concentric annuli (around $i$) with 100 kilometer widths. This regression model is detailed in Section B, and the results are found in Figure 24. The results show very little evidence of spatial spillovers, as the growth in city $i$ is not affected by droughts in neighboring cities $j$ - the point estimates are close to zero and are statistically insignificant.

**Lag structure** I examine whether the lag length $k$ I select changes my results by estimating the model as specified in Equation 2 using $k = \{3, ..., 10\}$ lags. I include the five leads in each regression. The results of this exercise are found in Figure 23, where I omit the confidence intervals and only include point estimates. The pattern of the result is remarkably stable across the number of included lags. The point estimate at e.g. lag 7 is almost identical regardless of whether 7 or 11 lags are included in the regression. Hence, I draw the conclusion that the choice of the number of included lags do not meaningfully change the estimates and results.

**Auto-regressive lag model** The main specification does explicitly control for the potential of serial correlation in the outcome variable. If there is a strong serial correlation in the dependent variable, the estimates may be biased, as argued by (Nath, Ramey, & Klenow, 2023). I amend the main specification in Equation 2 to include one or two lagged terms of the dependent variable, as detailed in Section B in the appendix. The results are shown in Figure 19. The main difference compared to the regressions without any autoregressive controls is that the point estimates are somewhat larger, and the results, especially for the 1.5 SD measure, dissipates less towards lag 11. The conclusions remain unchanged.

**Local projections** Local projections, originated by Jordà (2005), have been used frequently in macroeconomic research to estimate impulse response functions in time series. Local projections is increasingly used in applied micro-economic work, where it is used to identify causal dynamic treatment effects (Miller, 2023), for example in Tran and Wilson (2020) to study the local effects of disasters. Colmer, Evans, and Shimshack (2023) argues that "under plausible conditions, the local projections estimator is the most consistent for identifying the dynamic effects of repeat transitory shocks". I amend Equation 2 to a local projections framework, specified in Equation 6 in the appendix. The results of estimating the LP equation is found in Figure 22, panel a). The estimated effects are somewhat larger than those in the main analysis, and confidence intervals are smaller.

**Heterogenous treatment effects** The recent literature on heterogeneous treatment effects has shown that many of the estimators used in the broader event study-difference in differences empirical framework can be problematic if treatment effects are heterogenous across e.g. cohorts. To make sure my results are robust to these concerns, I use the newly developed estimator from de Chaisemartin and d'Haultfoeuille

(2022)[18] and show that the results are in line with those recovered in my main analysis. These results can be found in Figure 22. The main difference is that estimates are somewhat smaller until lag 8 – after 11 years, the point estimate is 0.7 percent, which is the same as the main analysis. This suggests that heterogeneous effects are not a main concern for identification using my main specification.

## 5.3 Results by continent

Having established that droughts have a substantial and persistent impact on cities over the course of several years, I examine whether this pattern is driven by certain regions in the sample. Urbanization patterns vary across countries in the sample – there are stark differences between for example South America, where the population is largely urban at the beginning of the sample period, and Africa. While the countries included are also relatively low income compared to the world average, there is significant heterogeneity between them.

I turn to examining whether the impact of drought is the same across the different continents in my sample, or whether specific continents drive the average effects. I run sub-sample analyses for each continent at a time, still using the specification in Equation 2. Since Africa and Asia have subregions within the continent, subregion-by-year fixed effects will be included, whereas for North America, and South America, the subregion is larger than these continents. Hence, the analysis for these countries include a year fixed effect. I omit results from Ocenia since the sample is very small.[19]

I find that the results vary substantially across continents. The results for the separate analysis of Asia can be found in Figure 5. The pattern of the results is strikingly similar to those using the entire sample, which is plausibly explained by the fact that cities in Asia represent around two thirds of the cities in the entire sample. The largest difference is that the estimates are less persistent - there is marked reversion to zero 11 years after a drought. Additionally, the confidence intervals are also wider. This suggests that the effects of droughts are less persistent in Asia as a whole. Needless to say, the Asian continent also spans a large geographical area.

[18]Using the *did_multiplegt_dyn* Stata package.

[19]There are a total of 6 cities in Oceania. This largely because SPEI data is not available at a fine enough resolution for many of the island states in Oceania.

The differences are more pronounced when considering the sub-sample results for Africa. Here, the results are both very persistent and larger in magnitude, compared to both the other continents and the entire sample. The impact of a major (2 SD) drought increases with every lag, and only shows signs of dissipating somewhat after 8 years. In contrast, the 1.5 SD drought estimates do not dissipate at all after 11 years, and remain at an effect of 2 percent 11 years after a drought. Interestingly, the impact of a 1.5 or 2 SD drought is approximately the same in Africa. The results can be found in Figure 5.

The results for the analysis in South and North America are found in the appendix Figure 17. The results for South America are highly statistically significant with very small point estimates throughout all lags. This suggests that drought do not have an impact on city growth in these countries. The estimates for the analysis of North American cities is somewhat more complicated. While all the point estimates are statistically insignificant, the point estimates until lag 4 are negative, whereas the negative is overturned after lag 6 and become positive. Because of the irregular pattern and the large confidence intervals, the estimates do not suggest that droughts impact cities in North American cities.

## 5.4 Relation to results in previous literature

The results in this paper differ from most of the previous evidence found in the literature studying the effect of climate change or weather shocks on urbanization or built up area, although they differ in important aspects, such as their aggregation of data or unit of analysis. While Barrios, Bertinelli, and Strobl (2006) find that less rainfall leads to higher urbanization rates at a country-level, Henderson, Storeygard, and Deichmann (2017) find no general impact of drier conditions on district-level urbanization for a subset of Sub-Saharan African countries. On the other hand, find strong and large negative effects on city growth, particularly for Africa. These differences might arise because of a number of reasons. The first is that the level of aggregation is different between this study and the aforementioned. Barrios, Bertinelli, and Strobl (2006) use data which is aggregated to the national level, and as Henderson, Storeygard, and Deichmann (2017) points out, such data relies heavily on interpolation between years. This also ignores within-country variation, which is often considerable. Additionally, I consider the dynamic effects of droughts, whereas the temporally sparse data in the previous studies consider longer-term shifts in the average climate.

Henderson, Storeygard, and Deichmann (2017) uses actual census data, but these are often collected at highly infrequent intervals, and makes it possible to only study a subset of countries in Sub-Saharan Africa. The quality of these data are also likely a function of a country's institutional quality, and can be subject to error due to political incentives, which is why e.g. Nigeria is omitted.

# 6 Heterogeneity and channels

This section discusses the results based on further heterogeneity analysis, as well as a discussion regarding potential channels of the results.

## 6.1 Agriculture and income

The large and persistent impact of drought in Africa, and a smaller but also negative impact in Asia, whereas the suggest further investigation into the relationship between drought and city growth. As outlined in Dell, Jones, and Olken (2012), macroeconomic models of climatic effects have often underlined the importance of agriculture and income. This has been corroborated by more recent empirical studies on the relationship between e.g. temperature and GDP, for example Burke, Hsiang, and Miguel (2015), Nath, Ramey, and Klenow (2023), and Zappalà (2023), where the impact is larger on agricultural GDP or the agricultural sector.

Therefore, I investigate whether agriculture and income are plausible potential channels which could explain the differences in the impact between countries. I partition the sample by income categories as defined the by World Bank, as well as by the share of employment in agriculture, and run sub-sample analyses.

**By country income** I estimate Equation 2 separately for each income category of countries, as defined by the World Bank; low income, lower-middle income and middle income countries. The results of these analyses are presented in Figure 6.

The results for the low income countries are presented in panel a) in Figure 6. The magnitude of the effect is larger than the effects in the entire sample, but only for the 2 SD measure, i.e. the most intense drought. For the 1.5 SD measure, I find close to no effect. Additionally, the effect is highly persistent, remaining around 1.5 percent 11 years after drought exposure.

The results for the lower-middle income countries are presented in panel b). These effects are highly significant, and large in magnitude. The effect of drought exposure results in a steady decline in city size across both the 1.5 SD and 2 SD measures, although they show some sign of levelling off towards the end of 11 years. The magnitudes are large: at around 2 percent for the 1.5 SD measure, and around 2.5 percent for the 2 SD measure.

Finally, panel c) shows the results for the middle income countries. These results show a result close to zero for the 1.5 SD measure across the whole time period, while the 2 SD measure shows, if anything a positive effect on city size, but this result is only substantially different from zero after around 5-6 years. In addition, the results are both statistically insignificant across all lags, while leads are statistically significant, indicating that these results are not necessarily as robust.

All together, the results suggest that the cities which are most impacted by local droughts are cities in lower and lower-middle income countries. Somewhat surprisingly, the effect is not the largest in the poorest category of countries, the low income countries. However, this could be explained by the fact that certain natural resource rich countries, e.g. Angola have higher levels of GDP while the general population is poor.

**By share of agricultural employment** In order to better understand the driving forces of pattern of results, I continue by studying whether cities in countries which are more agricultural are more impacted than less cities in countries with a smaller agricultural sector. How to measure the share of a country's agricultural sector is not clear cut. I do this by using the agricultural share of employment in 1992, the beginning of the study period.

I divide the cities into three groups based on the distribution of agricultural employment share at a national level, which creates three terciles of the distribution. I present the results from estimating Equation 2 for each of these sub-samples in Figure 7.

The results for the cities which belong to countries which have the lowest employment in agriculture, the first tercile, are statistically insignificant and small, although they increase from lag 5 and onwards.

The cities in the second most agricultural countries are heavily impacted by drought. While the results are larger than those of the global sample, we see that the effect for the 1.5 SD droughts are less persistent - while the effect is almost 1 percent after 6-7 years, cities do recover after 11 years. However, the 2 SD droughts do not show any sign of recovery, and instead remain at 2 percent after 7 to 11 years.

The largest effect is found in the third tercile, the cities with the highest share of employment in agriculture. In fact, the effect of the most intense drought events, 2 SD, is almost 4 percent after 7 years, and do not show much sign of dissipating after 11 years, suggesting that the effect is both large and highly persistent. Likewise, the 1.5 SD shows a steady decline in city size, resulting in a 2.2 percent decrease after 11 years.

It should be noted that the number of cities (observations) is unevenly distributed across sub-samples. However, despite the fact that the third tercile only has 784 cities, it still represents a population from 27 countries totaling hundreds of millions, which is still sizeable.

The results suggest that both country-level income and the agricultural share of the economic sector are important channels in understanding the magnitude of the impact of drought on city growth. This is plausible, considering that agriculture is heavily impacted by adverse weather events and climate.

## 6.2 Potential mechanisms

What potential mechanisms could explain the results of this paper? While the reduced-form nature of my analysis calls for a certain degree of caution, seeing as I am unable to pinpoint specific mechanisms, I will discuss two potential mechanisms.

An important driver of urbanization, and city growth, in developing countries is rural to urban migration (Brueckner & Lall, 2015). Although I cannot observe migration directly, there is evidence to suggest that this channel is a plausible explanation behind the results.

As I observe city growth (as measured in my data by built up area), as opposed to population, I cannot directly measure whether a drought in cities' hinterlands lead to exodus of populations living there. However, I show that my data is highly correlated with measures of population. I show this using the data collected by Jedwab and Storeygard (2022) for cities in Sub-Saharan Africa. In Figure 9, I plot the logarithm of urban area (my data) against the logarithm of city population (Jedwab and Storeygard (2022) data). I also estimate the correlation, which is 0.76. As such, it is plausible that the negative effects on city size that I recover, are also indicative of negative effects on population in cities. This would in turn suggest that migration toward cities is decreasing.

A potential alternative explanation is that the data mainly captures built up area in the form of non-residential buildings. I argue that this explanation is unlikely for two reasons. The first is that built up area is often used in estimating population size when there is sparse other data, such as census data. Built up area is used in e.g. the GHSL data suite in estimating population across space.

# 7 Discussion

This paper studies the effects of drought on the growth of cities. I find that drought exposure leads to a large, negative and persistent effect on the growth of cities. Following a major drought, cities remain smaller up to 11 years, which is the longest time period I study. This effect is larger in Africa and Asia, which hosts several countries and regions undergoing rapid urbanization. I find that the most important predictor of where drought exposure will have a large effect is agricultural dependency, as measured by the national share of employment in agriculture.

Together, these results suggest that adverse weather shocks can have an impact on the spatial allocation of people. The size of the effect varies across sub-samples, but the cities in countries with a large agricultural sector remain 4 to 5 percent smaller after exposure to a local drought, compared to the counterfactual of no drought. This

By utilizing a novel data set, and using it to construct measures of annual growth of cities at the city level, I am able to overcome some of the constraints of the previous literature, including Barrios, Bertinelli, and Strobl (2006), Castells-Quintana, Krause, and McDermott (2021), and Henderson, Storeygard, and Deichmann (2017), which find positive or null effects. I show that the contemporaneous effects can often be misleading, as they are either close to null effects or positive, suggesting that delayed effects are important when studying the effects of weather shocks on cities and potentially also migration.

The results in this paper have important policy implications. As climate change is expected to increase the number and intensity of droughts, more could be done in order to help the rural and agricultural sector to cope with droughts. This includes technologies such as irrigation, or cultivating other crops, which are the two largest margins of adaptation. My results also suggest that if anything, it is not adverse weather shocks to the agricultural sector which will increase internal climate migration.

In the broader discussion of the effects of climate change, there are those who are concerned that climate change will lead to inevitable urbanization, straining already at capacity cities and urban areas. While this could still hold true, especially for already large and congested cities which are at risk of becoming too large for agglomeration benefits, my results suggest that this is less of a worry concerning a large share of cities, which are hindered rather than induced to grow. However, I note that these results do not speak directly to other climate hazards which face many people in developing countries, including cyclones and floods. These events could have a different effect compared to that of droughts.

A large literature has been dedicated towards understanding urbanization in developing countries. Researchers have highlighted the fact that urbanization takes place at much lower levels of GDP in Africa and Asia compared to that of the Western hemisphere - 'urbanization without growth' (Jedwab & Vollrath, 2015). Why do cities grow without overall economic growth? Climate change has been hypothesized to be a potential explanation, as it could be a push factor towards cities, hence explaining why structural transformation or economic growth is not needed, if people are essentially fleeing ever worsening conditions (Castells-Quintana, Krause, & McDermott, 2021; Henderson, Storeygard, & Deichmann, 2017). However, this does not explain the fact that large differentials still exist across the urban and rural sectors, where urban residents enjoy better amenities, wages and consumption levels, prompting Henderson and Turner (2020) to suggest we could actually see too little urbanization.

This paper could serve as a potential alternative to both of these hypotheses. Climate change increases droughts, which in turn impacts largely agricultural and low income countries. Since the growth of cities is usually associated with a higher level of urbanization, this could suggest that delayed urbanization is partly a result of climate hazards.

Finally, I conclude by mentioning and discussing some of the limitations to this paper. The data used in this paper measures city footprints (built up area), which is not necessarily correlated with city population, especially if the footprint is capturing the e.g. industrial areas. However, I show that there is solid correlation between urban area and urban population, suggesting that I do capture effects on population as well. Secondly, while I provide suggestive evidence, I cannot definitively conclude that the effect is driven by reduced rural-to-urban migration, or that agriculture is the definitive channel. This would require a more structurally oriented analysis, which could be an avenue for future work.

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# Figures

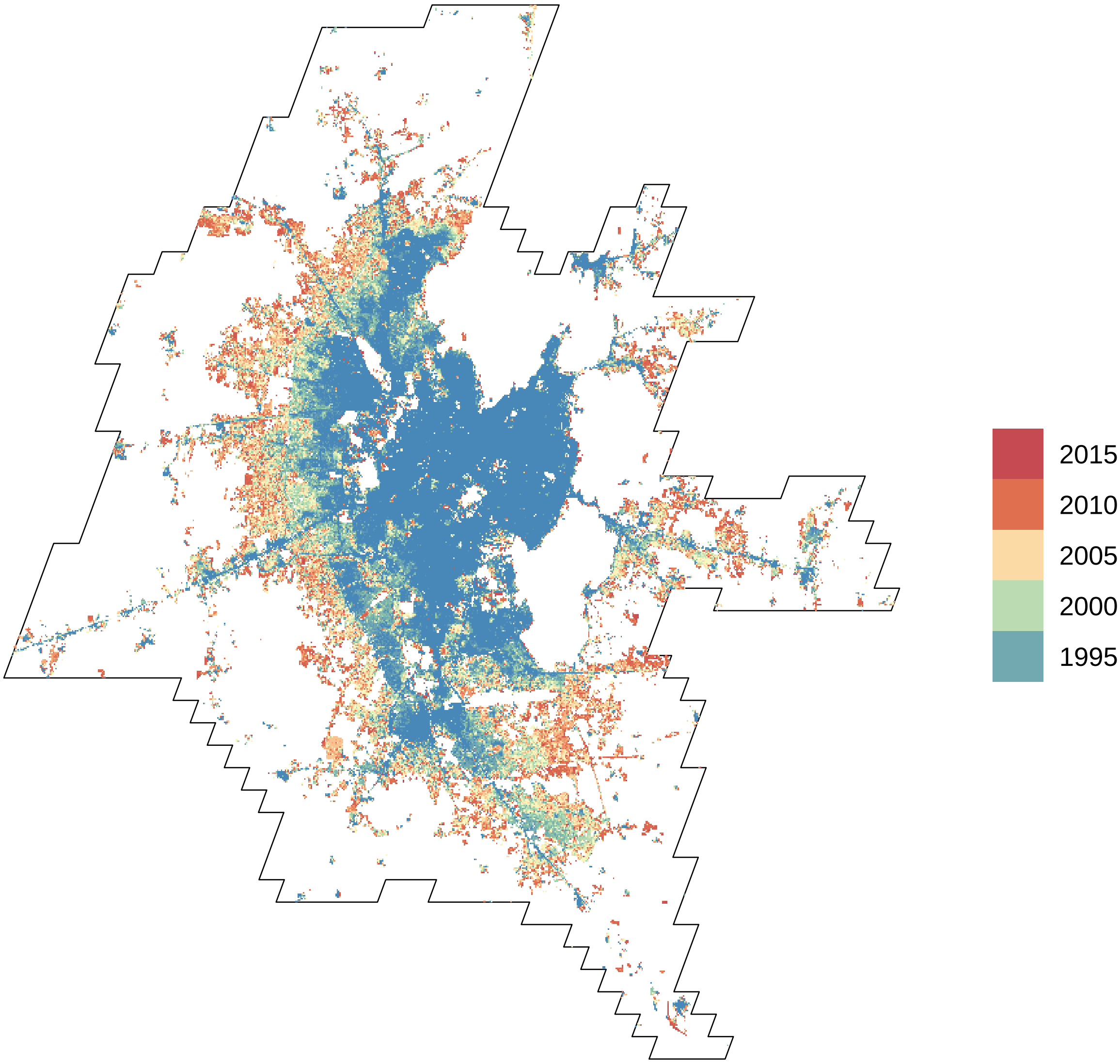
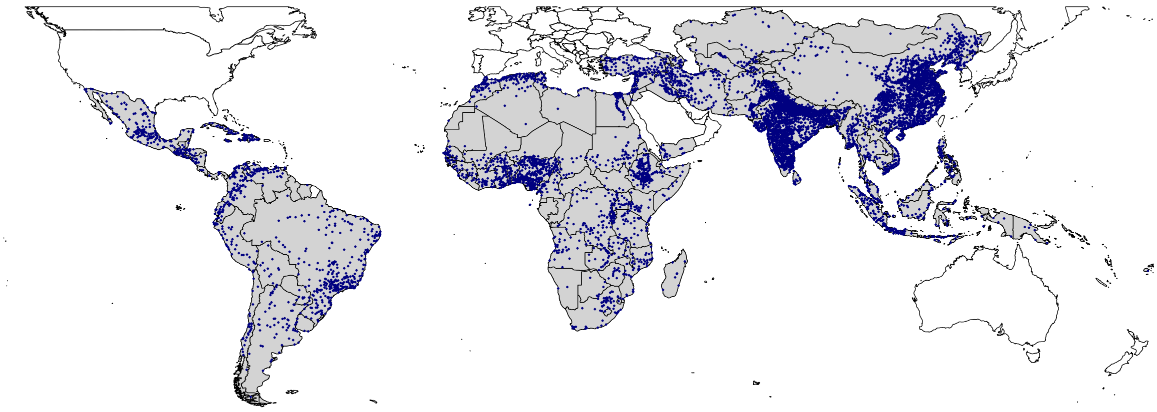
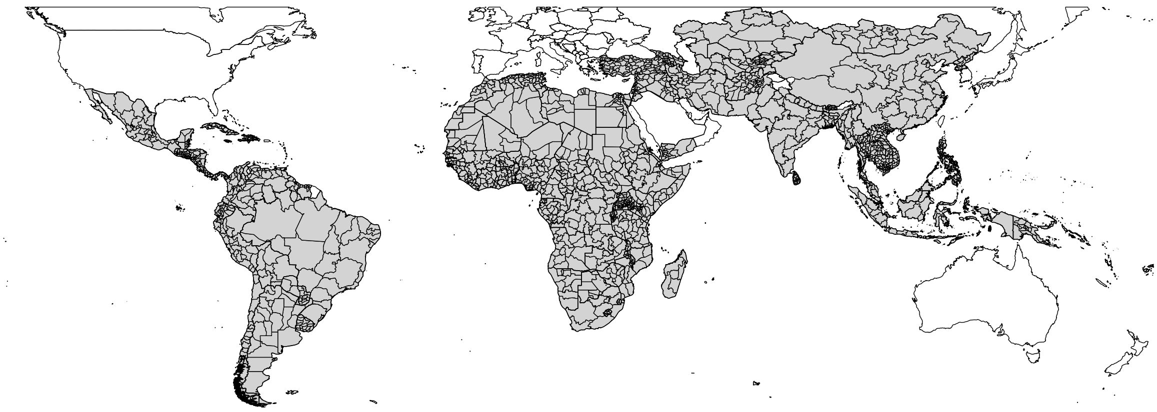



**Figure 1:** This figure depicts the growth of Jaipur, India. The colors depict the year in which each pixel was classified as built up, aggregated to 5-year increments, using the World Settlement Footprint (Marconcini et al., 2021). The solid black line delineate the functional urban area (FUA) (Schiavina et al., 2019).

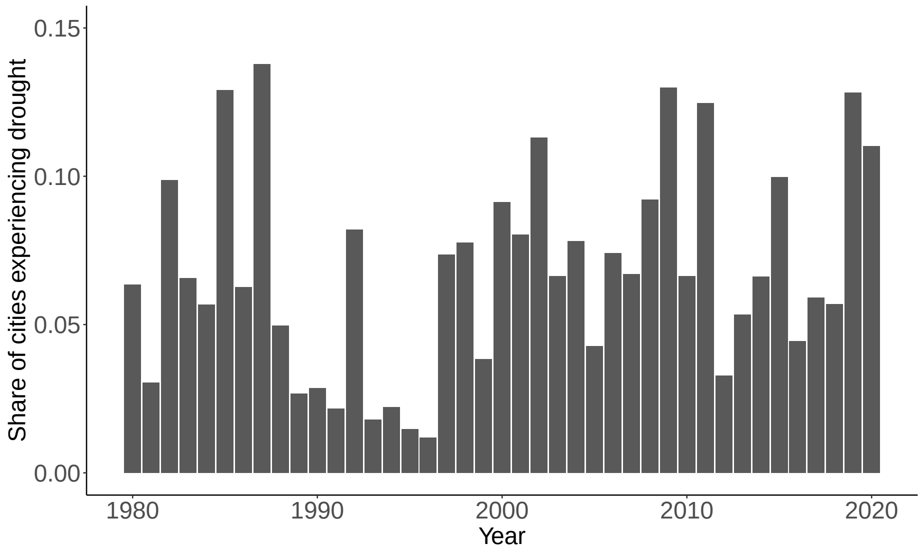


**(a)**

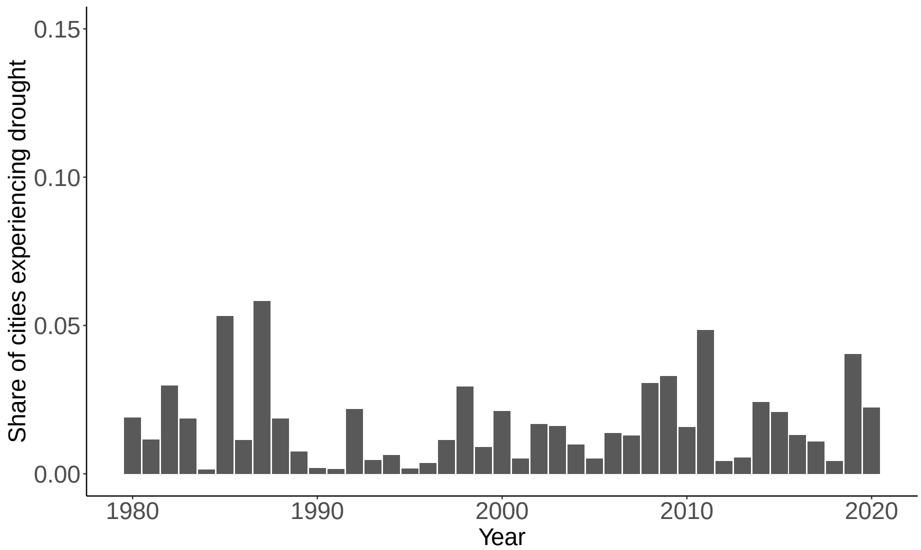


**(b)**

**Figure 2:** Panel a) shows the countries which are included in the sample, colored in gray, and the points show each city. Panel b) shows the ADM1 regions of the countries included in the sample, again colored gray.

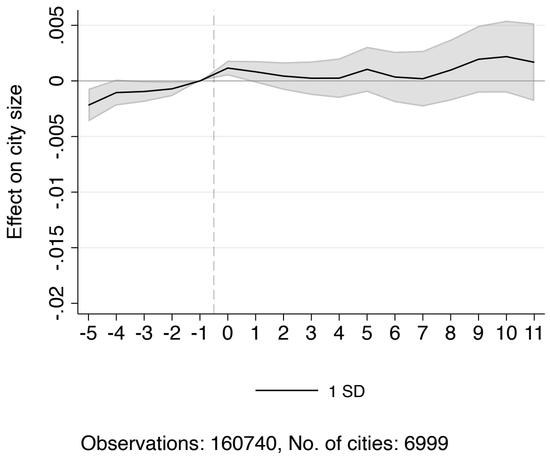



**(a)**

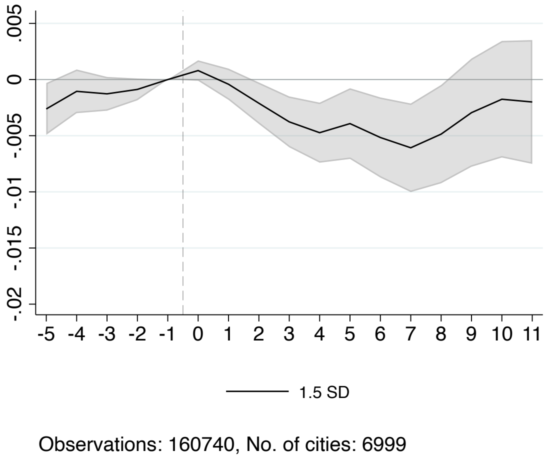



**(b)**

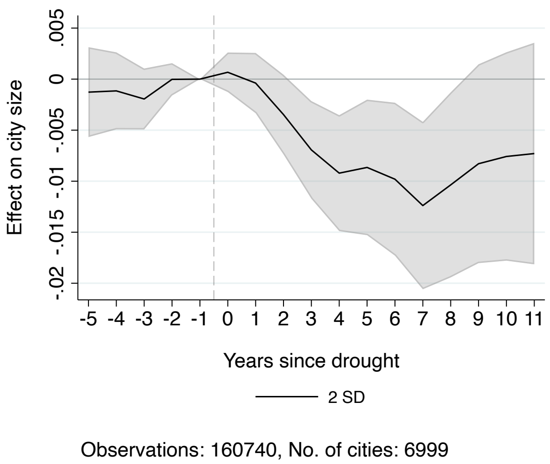
**Figure 3:** Panel a) shows the share of cities which experience a 1.5 SD drought at a given year. Panel b) shows the share of 2 SD drought.



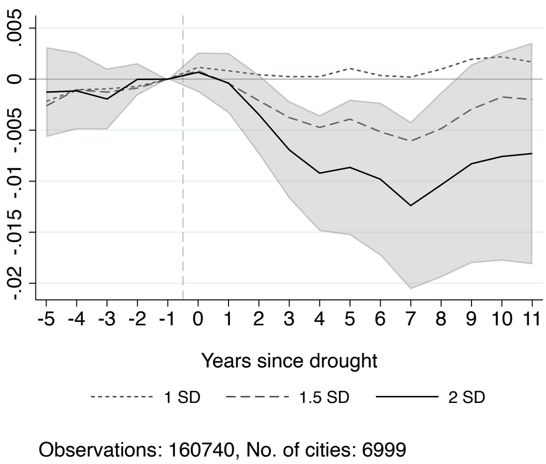

**(a)**




**(b)**

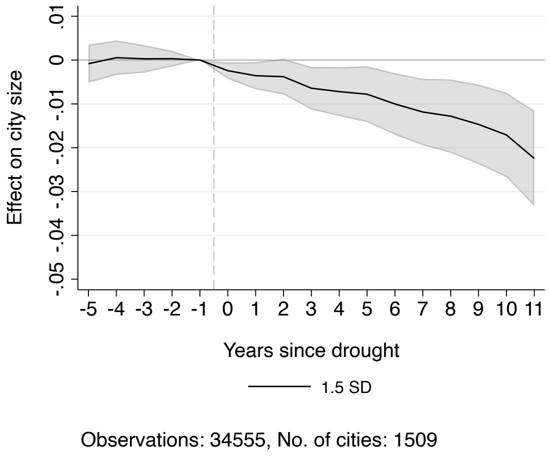



**(c)**

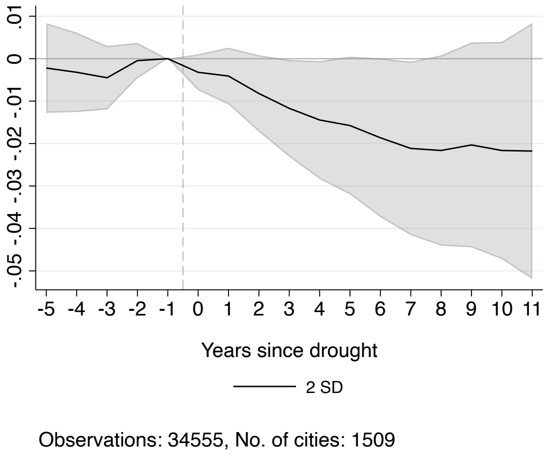



**(d)**

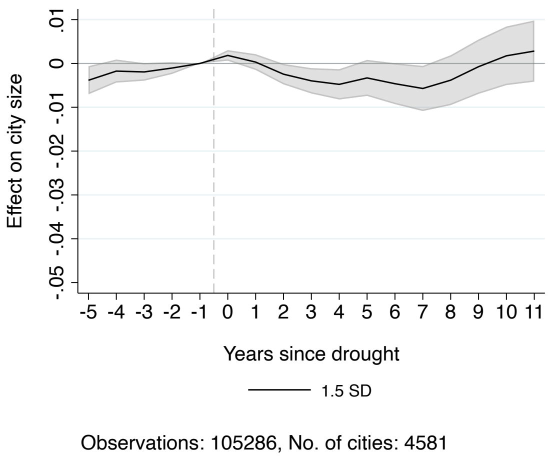
**Figure 4:** Estimates based on model in Equation 2. Estimates show the dynamic treatment effects of a drought on city size. Panels a)-c) show the effects of each drought intensity, which have been estimated separately. Panel d) shows the analyses of a)-c) in the same plot. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before drought ($\beta_{t=-1} = 0$).



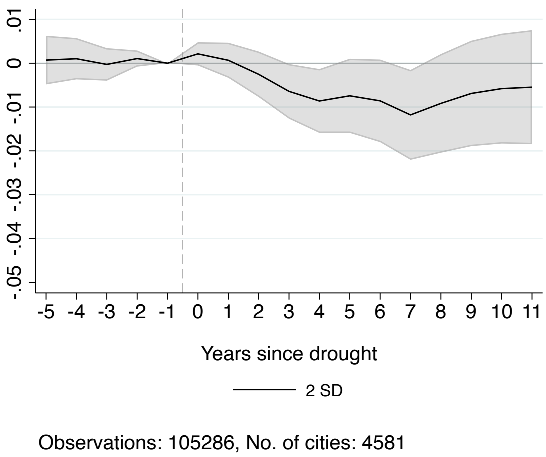

**(a)** Africa.




**(b)** Africa.

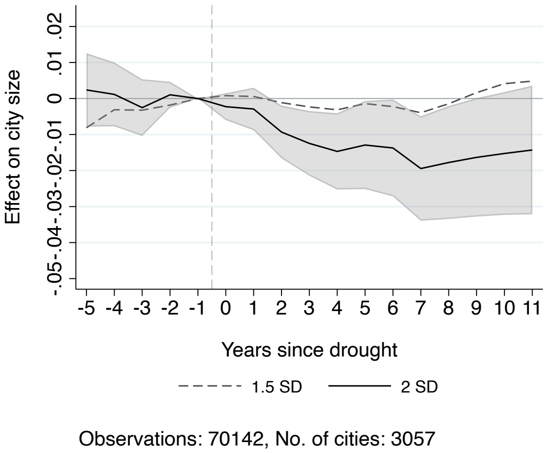



**(c)** Asia.

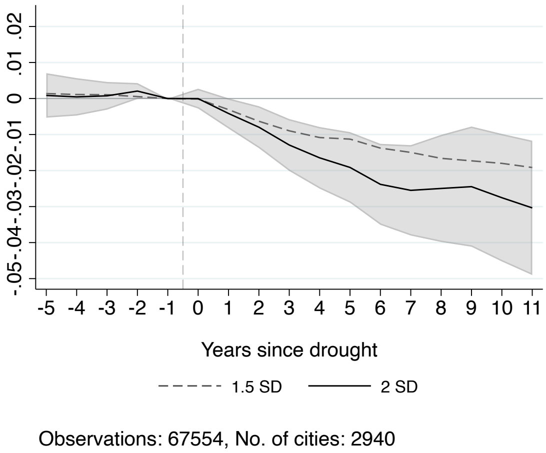



**(d)** Asia.

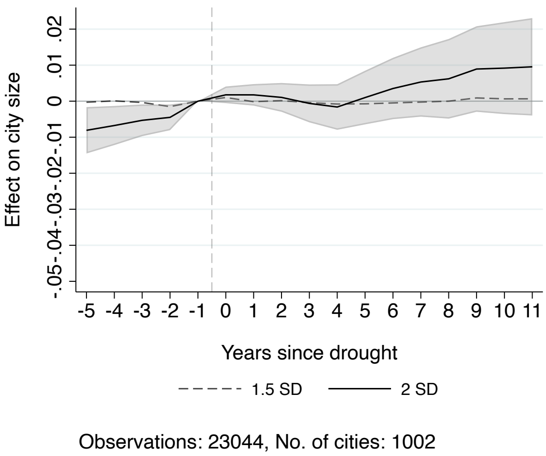
**Figure 5:** Estimates based on model in Equation 2. Estimates show the dynamic treatment effects of a drought on city size. Panel a)-b) show the effect of a 1.5 and 2 SD drought in Africa, respectively. Panel c)-d) show the effect of a 1.5 and 2 SD drought in Asia, respectively. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before drought ($\beta_{t=-1} = 0$).




**(a)** Low income countries.

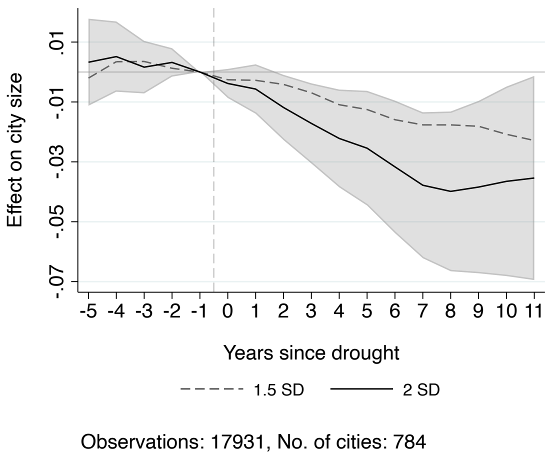



**(b)** Lower-middle income countries.

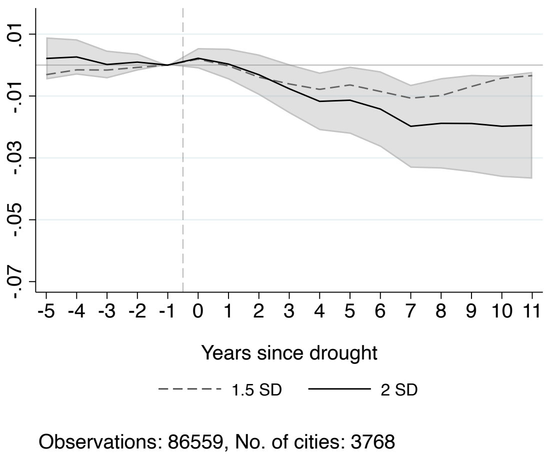



**(c)** Middle income countries.

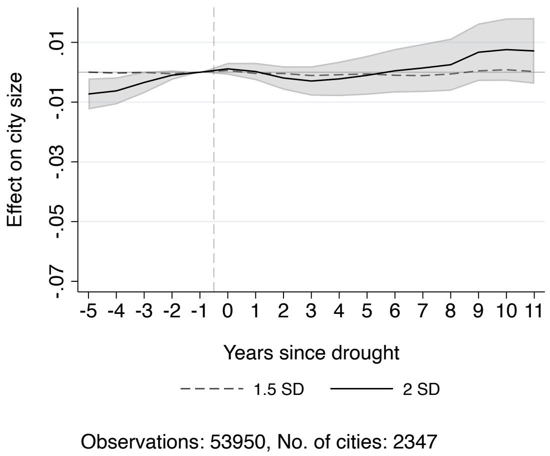
**Figure 6:** Estimates based on model in Equation 2. Estimates show the dynamic treatment effects of a drought on city size. Panel a) shows the effects on the sub-sample of cities in low income countries, by level of drought intensity. Panel b) shows the effects on lower-middle income countries. Panel c) shows the effects on middle income countries. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before drought ($\beta_{t=-1} = 0$).




**(a)** Highest share, third tercile.

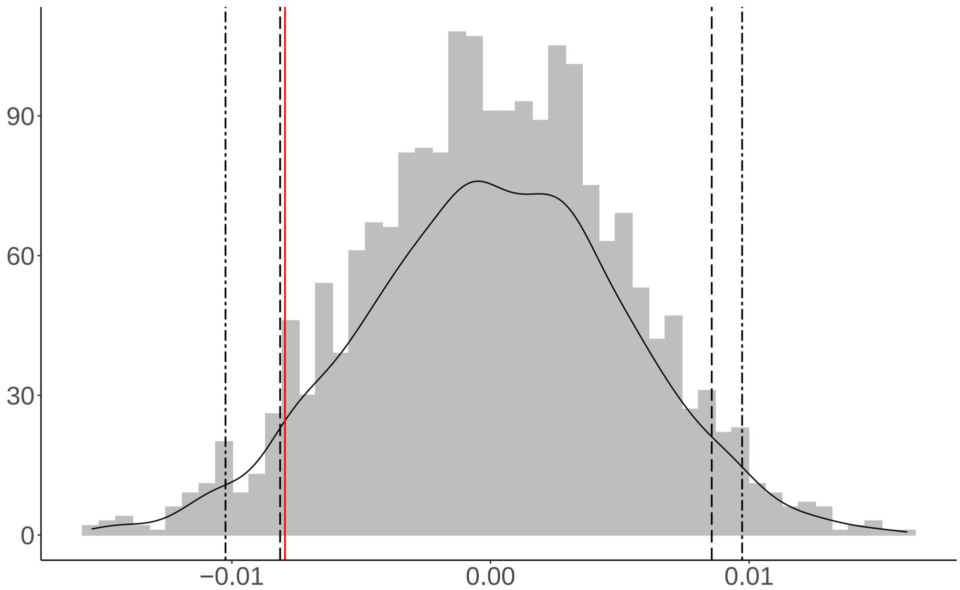



**(b)** Middle share, second tercile.

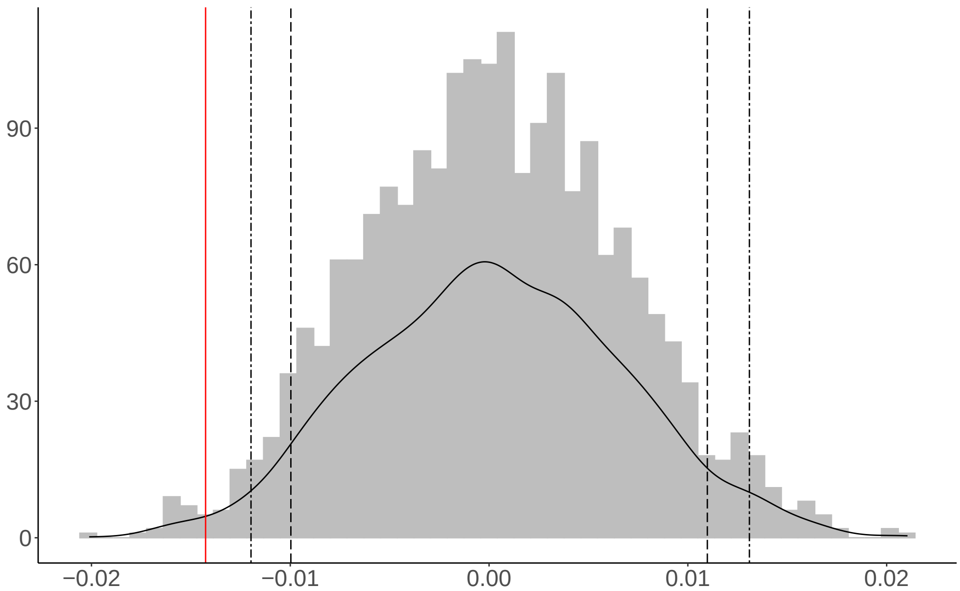



**(c)** Lowest share, first tercile.

**Figure 7:** Estimates based on model in Equation 2. Estimates show the dynamic treatment effects of a drought on city size. Panel a) shows the effects on the sub-sample of cities in countries with the highest share of agricultural employment, the third tercile, by level of drought intensity. Panel b) shows the effects on the second tercile. Panel c) shows the effects on the first tercile, the lowest share. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before drought ($\beta_{t=-1} = 0$).

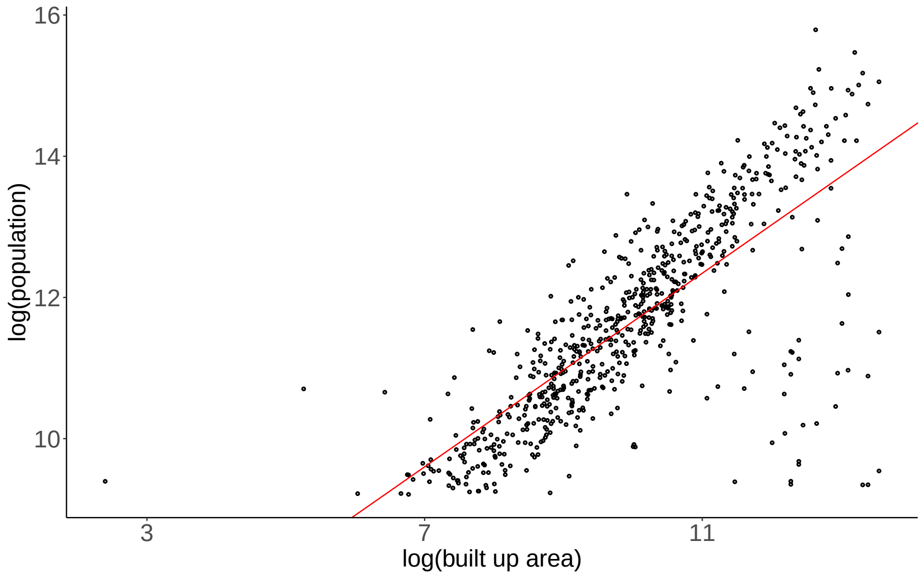



**(a)** 1.5 SD.

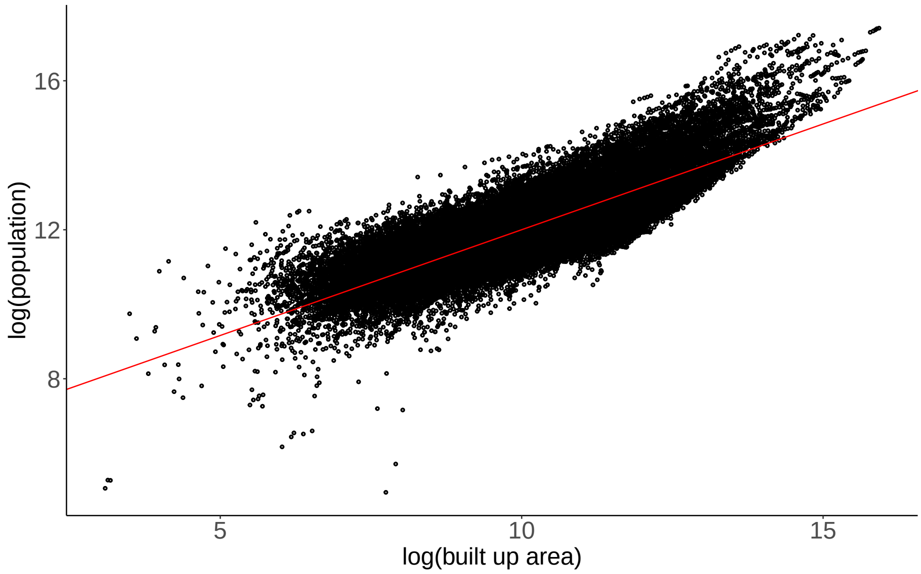



**(b)** 2 SD.

**Figure 8:** Histogram shows the dynamic treatment effect of a drought on city growth after 7 years ($\beta_7$) from the results of 2,000 regressions using Equation 2 where drought conditions are randomly assigned across years. Panel a) shows the results for 1.5 SD droughts, panel b) for 2 SD droughts. The solid red lines show the estimates from the real data, found in Figure 4 or Table 2. The dot-dashed, and dashed lines reflect the critical values for a two-sided hypothesis test that the effect of a drought is zero at a 10 %, and 5 % level of significance, respectively.




**(a)**




**(b)**

**Figure 9:** This figure shows the correlation between city population measures and the data on city footprint used to construct annual city growth, WSF (Marconcini et al., 2021). I plot the logarithm of the measures of city footprint (x-axis) against the logarithm two different sources of city population (y-axis). The solid red line show the estimates of a regression of the aforementioned measures. Panel a) shows the results from comparing data from Jedwab and Storeygard (2022), for the years 1990, 2000, and 2010 with WSF data from the same years. Panel b) shows the results from GHS Population (Schiavina, Freire, & MacManus, 2019), for the years 1990, 2000, and 2015.

# Tables

**Table 1:** Descriptive statistics

| | Mean | Median | SD |
|---|---|---|---|
| **Entire sample** | | | |
| City pop. 2015 | 394,127 | 138,913 | 1,294,501 |
| GDP per capita | 2207 | 1097 | 2665 |
| Percent urbanized | 42.6 | 35.9 | 18.26 |
| Agricultural employment share | 52.8 | 58.5 | 17.0 |
| City growth (percent) | 0.03 | 0.02 | 0.05 |
| **Africa** | | | |
| City pop. 2015 | 293,870 | 117,559 | 878,728 |
| GDP per capita | 1259 | 627 | 1535 |
| Percent urbanized | 36.6 | 36.5 | 14.9 |
| Agricultural employment share | 58.3 | 55.2 | 18.6 |
| City growth (percent) | 0.03 | 0.02 | 0.07 |
| **Asia** | | | |
| City pop. 2015 | 425,490 | 150,028 | 1,403,754 |
| GDP per capita | 1863 | 1023 | 2200 |
| Percent urbanized | 38.4 | 32.8 | 12.8 |
| Agricultural employment share | 56.6 | 58.5 | 10.4 |
| City growth (percent) | 0.04 | 0.03 | 0.04 |
| **North America** | | | |
| City pop. 2015 | 451,203 | 143,241 | 1,421,678 |
| GDP per capita | 5258 | 5276 | 3308 |
| Percent urbanized | 65.8 | 73.7 | 13.7 |
| Agricultural employment share | 29.5 | 25.9 | 7.9 |
| City growth (percent) | 0.03 | 0.02 | 0.04 |
| **South America** | | | |
| City pop. 2015 | 418,154 | 125,225 | 135,0774 |
| GDP per capita | 5969 | 4981 | 3647 |
| Percent urbanized | 80.1 | 82.2 | 8.4 |
| Agricultural employment share | 20.1 | 19.2 | 7.2 |
| City growth (percent) | 0.03 | 0.02 | 0.03 |
| **Oceania** | | | |
| City pop. 2015 | 132,205 | 98,267 | 71,281 |
| GDP per capita | 1501 | 1236 | 897 |
| Percent urbanized | 17.0 | 13.2 | 10.4 |
| Agricultural employment share | 37.0 | 37.8 | 7.0 |
| City growth (percent) | 0.01 | 0.01 | 0.01 |

# Appendices

# A Data appendix

## A.1 List of countries in sample

Afghanistan, Algeria, Angola, Argentina, Armenia, Azerbaijan, Bangladesh, Belize, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Cuba, Democratic Republic of the Congo, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Georgia, Ghana, Guatemala, Guinea, Guinea Bissau, Guyana, Haiti, Honduras, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyzstan, Laos, Lebanon, Lesotho, Liberia, Libya, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Korea, Pakistan, Palestine, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Republic of Congo, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sri Lanka, Sudan, Suriname, Swaziland, Syria, Tajikistan, Tanzania, Thailand, Timor Leste, Togo, Tunisia, Turkey, Turkmenistan, Uganda, Uruguay, Uzbekistan, Venezuela, Vietnam, Western Sahara, Yemen, Zambia, Zimbabwe.

# B Robustness specifications

**Autoregressive distributed lag model** In order to estimate the autoregressive lag model, I amend the main estimating equation to include a lag of the outcome variable, which results in the following equation:

$$\Delta ln(Y_{i,t}) = \Delta ln(Y_{i,t-1}) + \sum_{l=-5}^{11} \gamma_l D_{i,t-l} + \alpha_i + \delta_{st} + \varepsilon_{d,t} \tag{4}$$

which is the AR(1) model. I augment the model further by including two lags:

$$\Delta ln(Y_{i,t}) = \Delta ln(Y_{i,t-1}) + \Delta ln(Y_{i,t-2}) + \sum_{l=-5}^{11} \gamma_l D_{i,t-l} + \alpha_i + \delta_{st} + \varepsilon_{d,t} \tag{5}$$

which results in an AR(2) model.

**Local projections** I amend Equation 2 and estimate it for each time horizon $h$, following e.g. Colmer, Evans, and Shimshack (2023) and Tran and Wilson (2020):

$$\Delta ln(Y_{i,t+h}) = \beta^h D_{i,t} + \alpha_i + \delta_{st} + \varepsilon_{d,t} \tag{6}$$

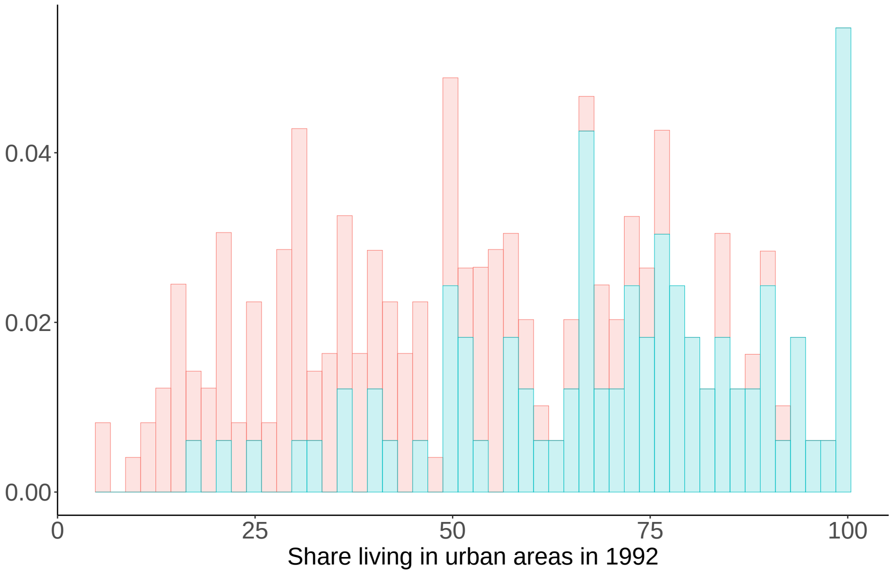
where $\Delta ln(Y_{i,t+h})$ is the change in city growth in the year $t+h$, relative to the year prior. The contemporaneous effect is captured by $\beta^h = 0$ and the effect after 11 years is captured by $\beta^h = 11$. These parameters all represent the dynamic treatment effects.

**Spatial lag model** I amend 2 to include both spatial and temporal lags Hsiang (2016) and Hsiang and Jina (2014):

$$\Delta ln(Y_{i,t}) = \sum_{l=0}^{11} \sum_{\pi=0}^{11} \{D_{[j|dist(i,j)=\pi],t-1} \gamma_{l\pi}\} + \alpha_i + \delta_{st} + \varepsilon_{d,t} \tag{7}$$

where $D_{[j|dist(i,j)=\pi],t-1}\gamma_{l\pi}$ is the average drought exposure of all locations $j$ that are at a distance $\pi$ from location $i$ at time $t-l$, where $i$ is the location where the outcome is observed. $dist(i,j)$ is the distance from $i$ to $j$.

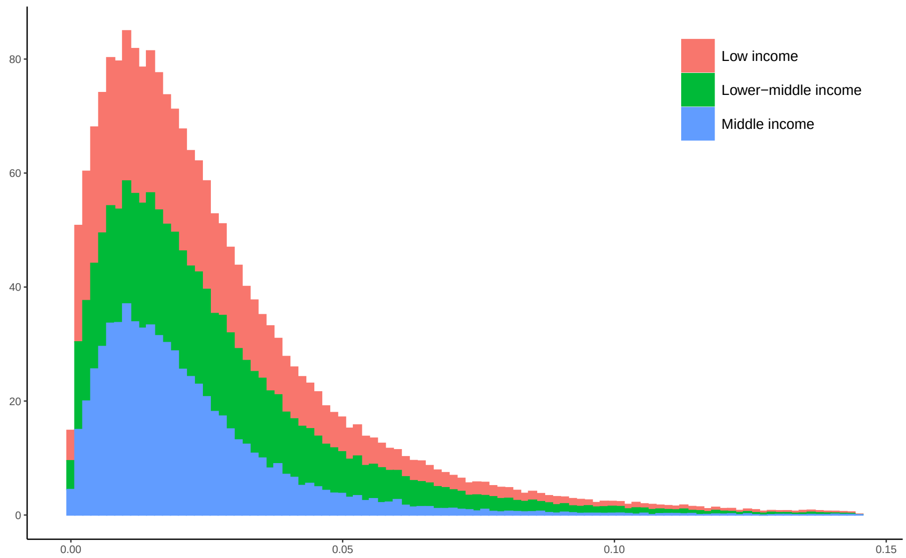
## C Appendix figures



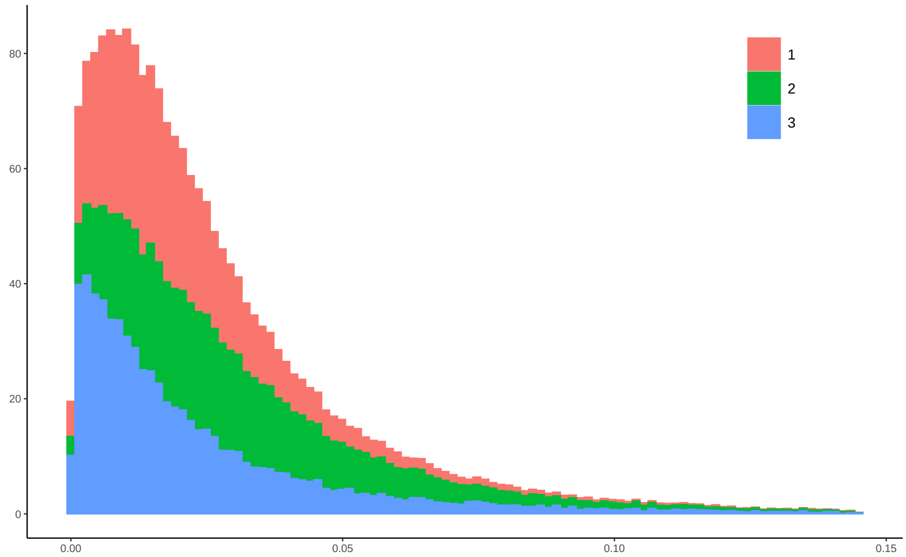

**(a)**


**(b)**

**Figure 10:** The figures show the distribution of urbanization rates and employment in agriculture, respectively. The red distribution are the countries included in my sample, and the blue are the ones not in the sample.

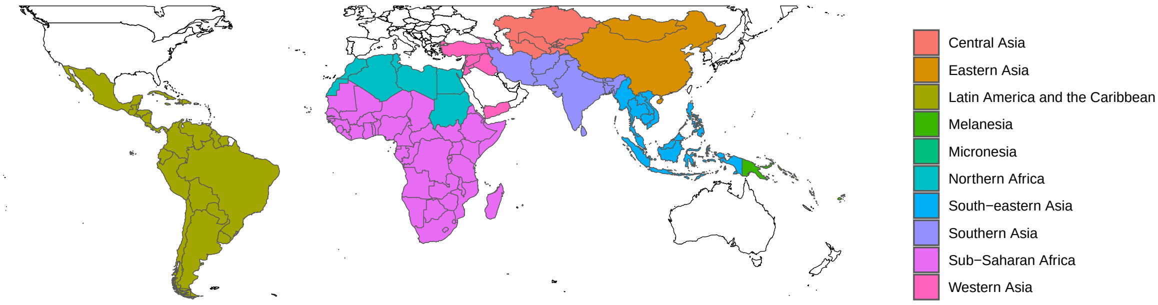



**(a)** The distribution of growth rates by World Bank income categories.

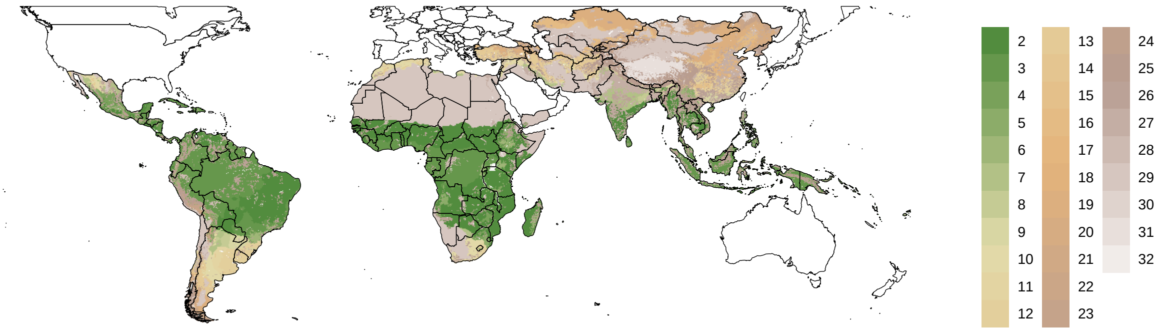



**(b)** The distribution of growth rates by agricultural employment terciles, where 1 represents the lowest shares of the distribution.

**Figure 11:** The figures show the distribution of urbanization rates and employment in agriculture, respectively. The red distribution are the countries included in my sample, and the blue are the ones not in the sample.




**(a)**




**(b)**

**Figure 12:** Panel a) shows the delineation of the UNSD subregions for the countries in the sample. Panel b) shows the Köppen-Geiger climate zones, using data from Fischer et al. (2021). Each value represents a climate zone.

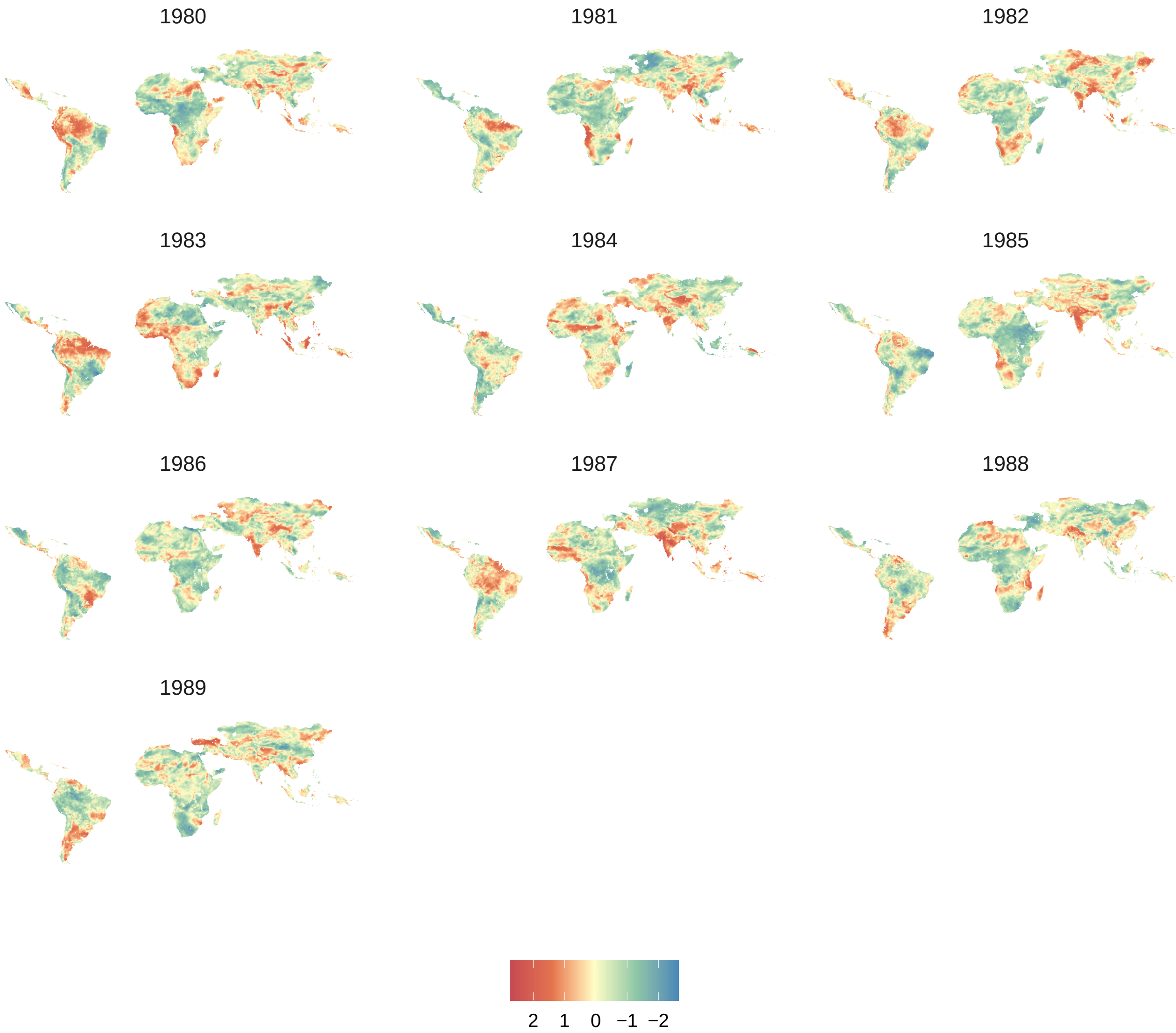



**Figure 13:** Each sub-figure shows the distribution of the yearly average pixel-level SPEI values across the sample, calculated using data from (Vicente-Serrano et al., 2022), over the main growing season Ortiz-Bobea et al. (2021), between 1980 and 1989. Only countries in the sample are displayed. Higher values indicate drier conditions relative to a long term average, and lower values indicate wetter conditions.

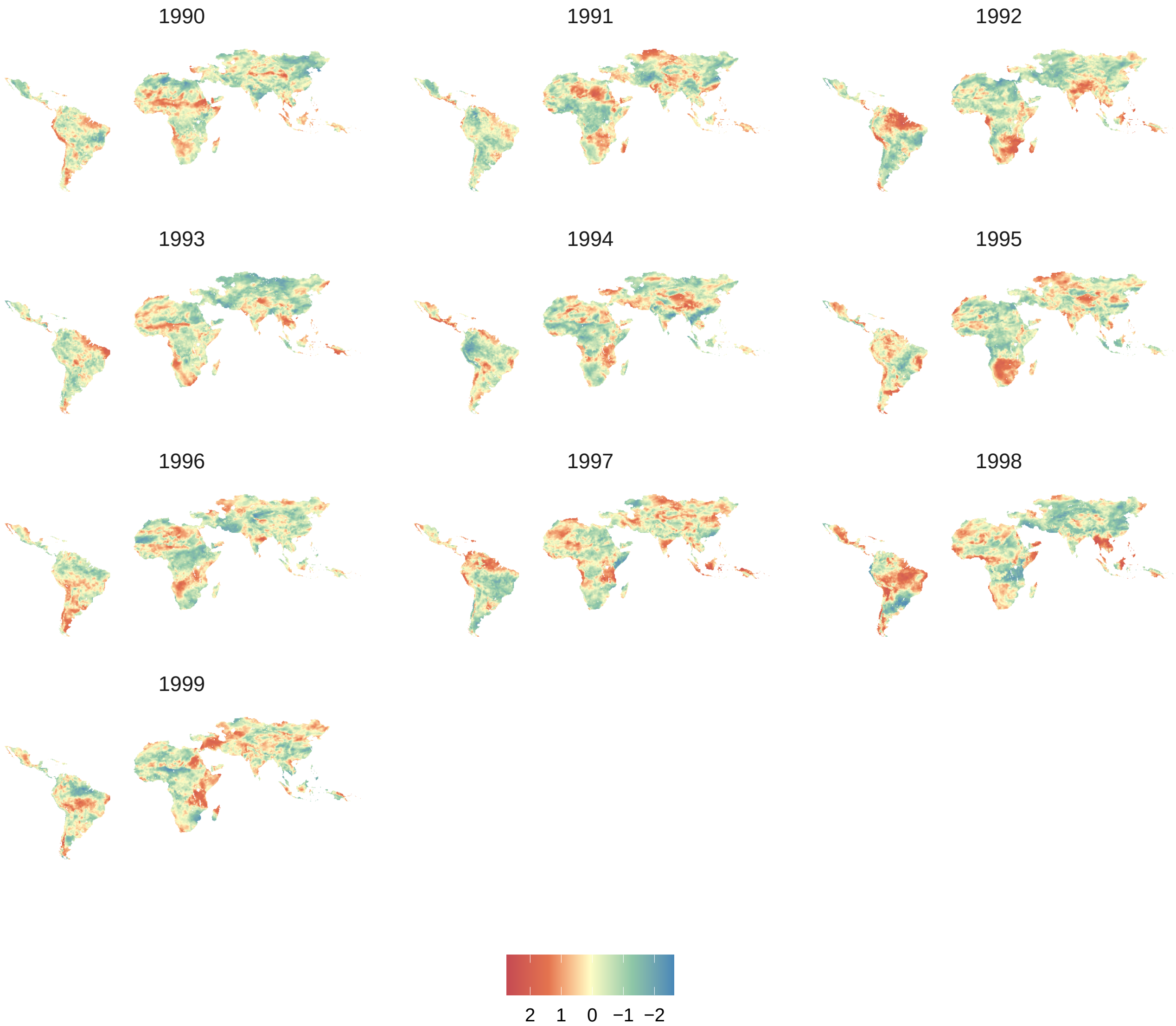



**Figure 14:** Each sub-figure shows the distribution of the yearly average pixel-level SPEI values across the sample, calculated using data from (Vicente-Serrano et al., 2022), over the main growing season Ortiz-Bobea et al. (2021), between 1990 and 1999. Only countries in the sample are displayed. Higher values indicate drier conditions relative to a long term average, and lower values indicate wetter conditions.

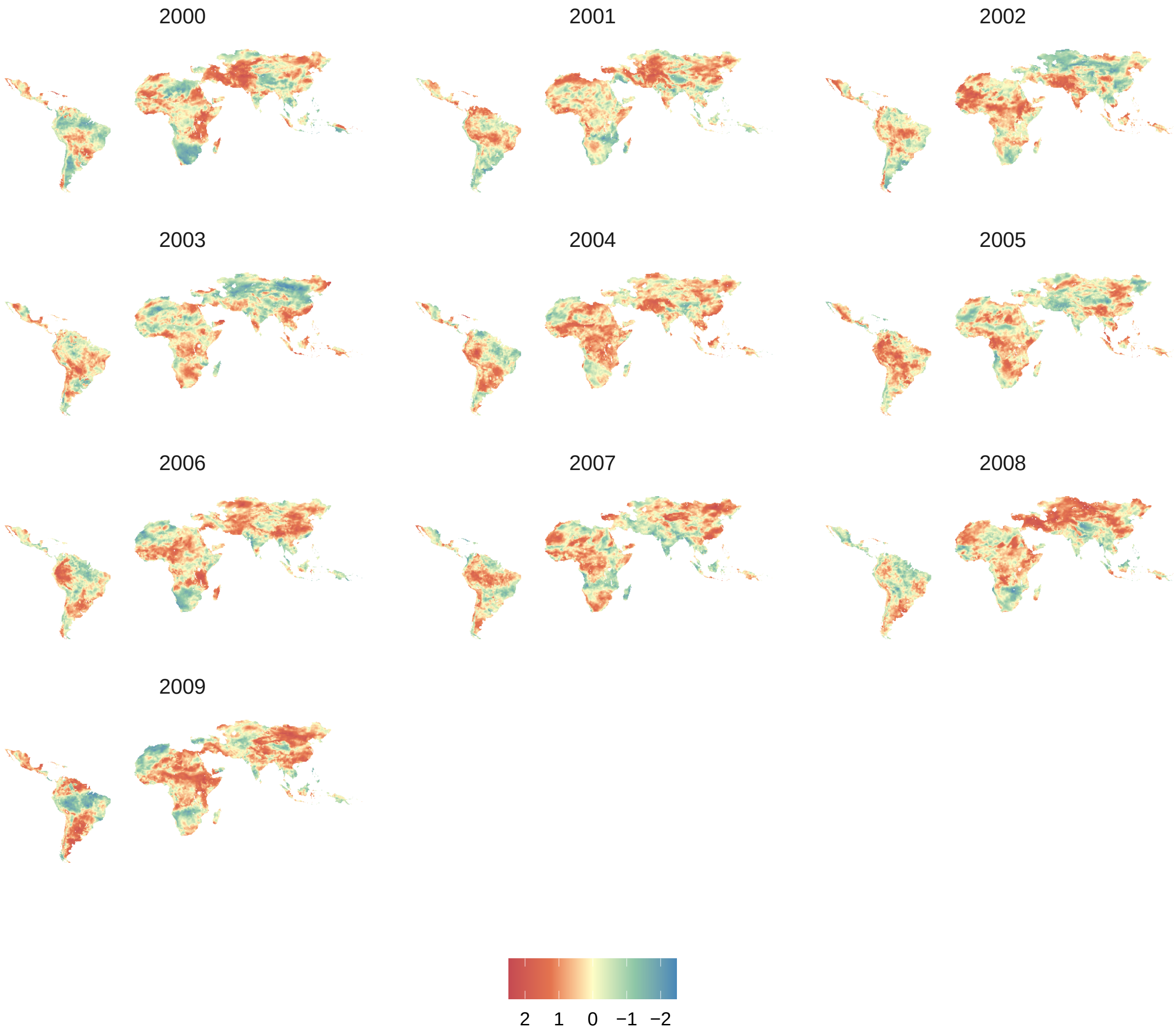



**Figure 15:** Each sub-figure shows the distribution of the yearly average pixel-level SPEI values across the sample, calculated using data from (Vicente-Serrano et al., 2022), over the main growing season Ortiz-Bobea et al. (2021), between 2000 and 2009. Only countries in the sample are displayed. Higher values indicate drier conditions relative to a long term average, and lower values indicate wetter conditions.

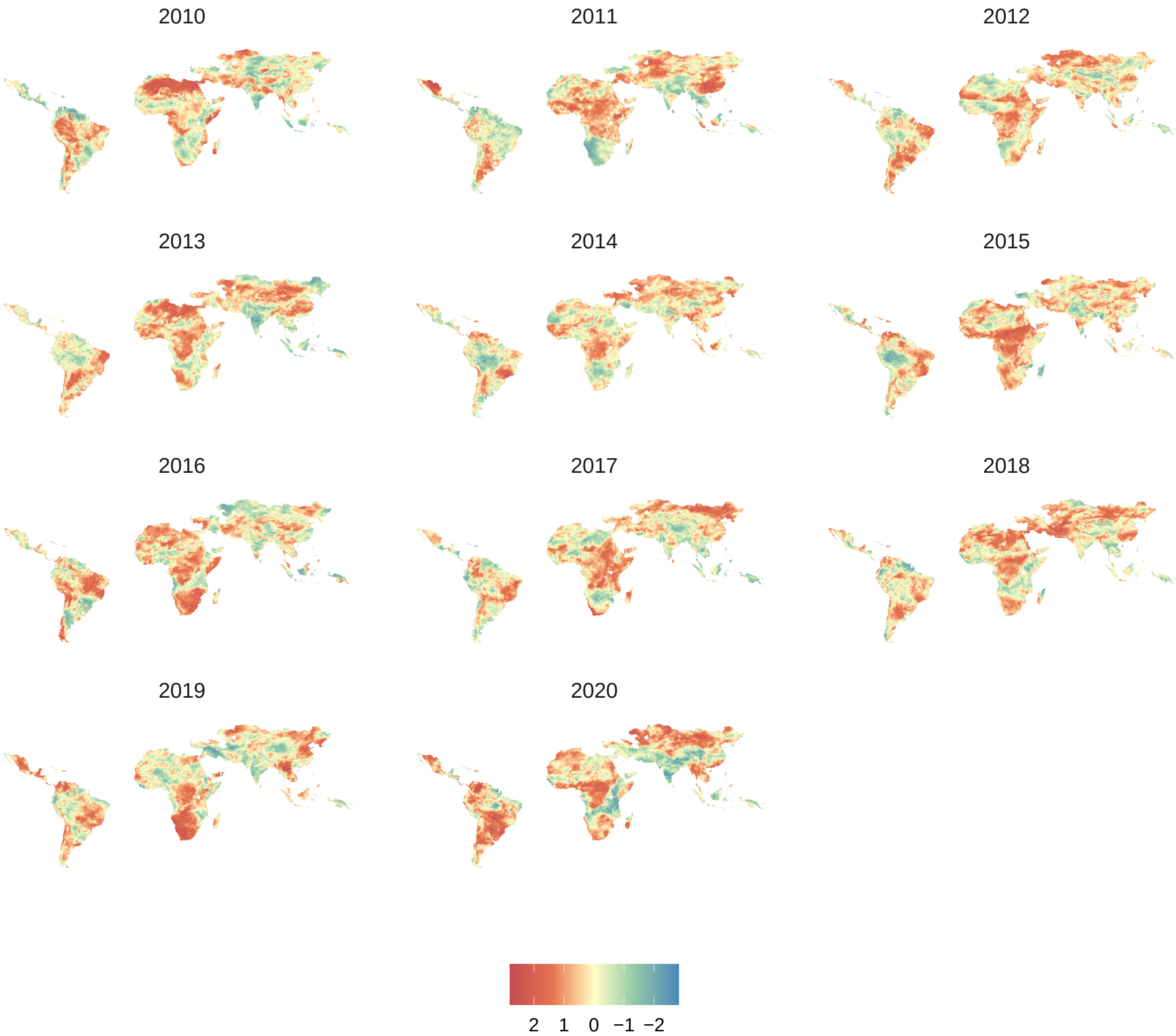
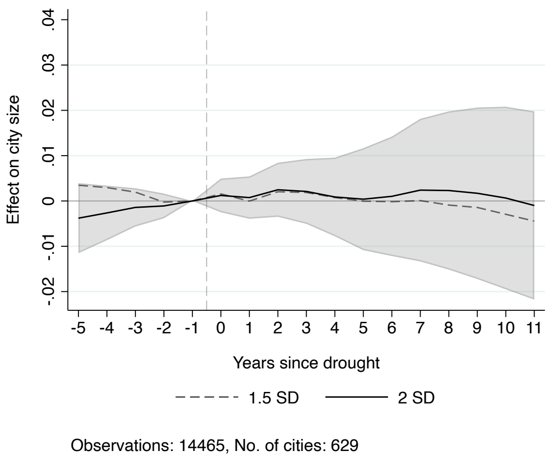
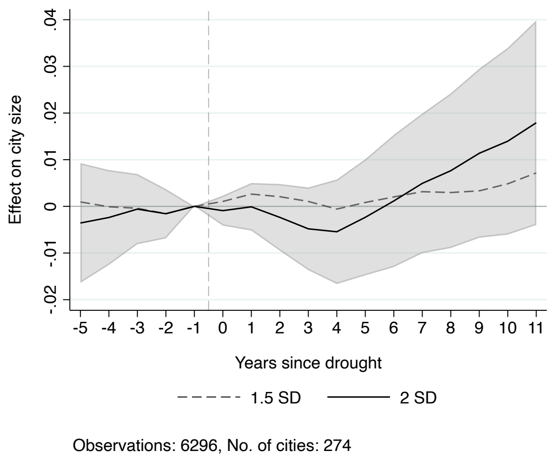



**Figure 16:** Each sub-figure shows the distribution of the yearly average pixel-level SPEI values across the sample, calculated using data from (Vicente-Serrano et al., 2022), over the main growing season Ortiz-Bobea et al. (2021), between 2010 and 2020. Only countries in the sample are displayed. Higher values indicate drier conditions relative to a long term average, and lower values indicate wetter conditions.

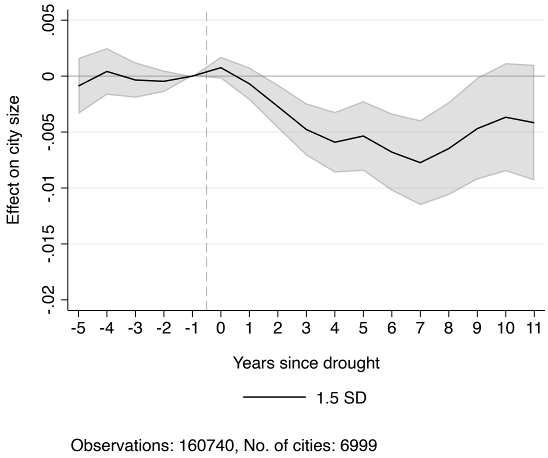



**(a)** South America.

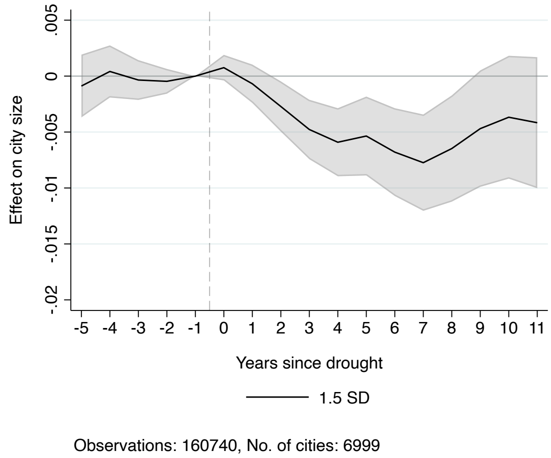



**(b)** North America.

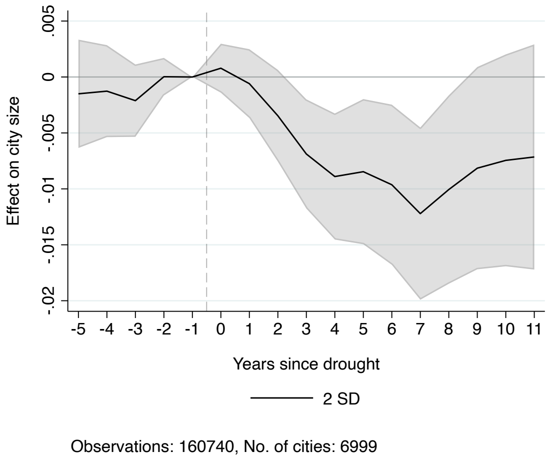
**Figure 17:** Estimates based on model in Equation 2. Estimates are the dynamic treatment effects of a drought on city size. Panel a) shows the effects of a 1.5 SD and 2 SD drought, with analyses run separately, for the cities in South America. Panel b) shows the effects for cities in North America. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals for a 2 SD drought. Normalized to the year before drought ($\beta_{t=-1} = 0$).



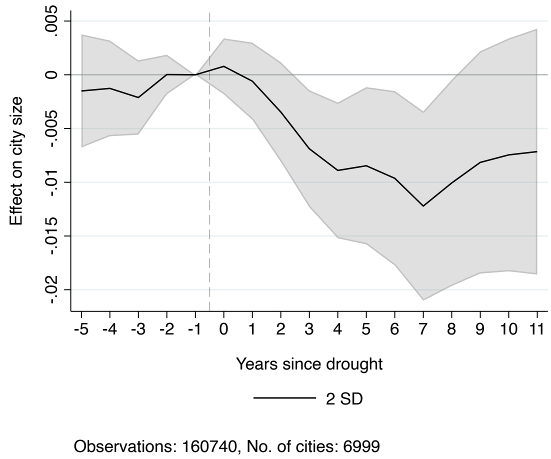

**(a)** 250 kilometer cutoff.




**(b)** 500 kilometer cutoff.

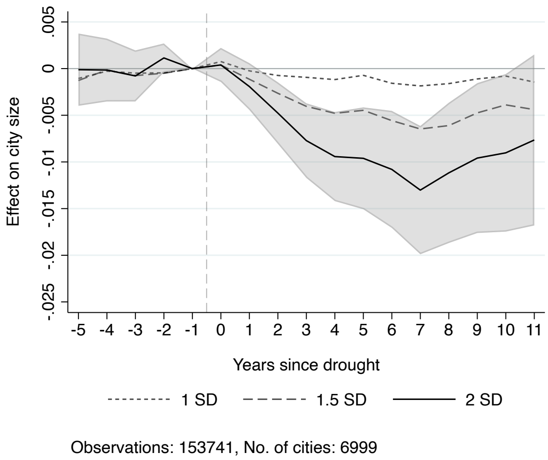



**(c)** 250 kilometer cutoff.

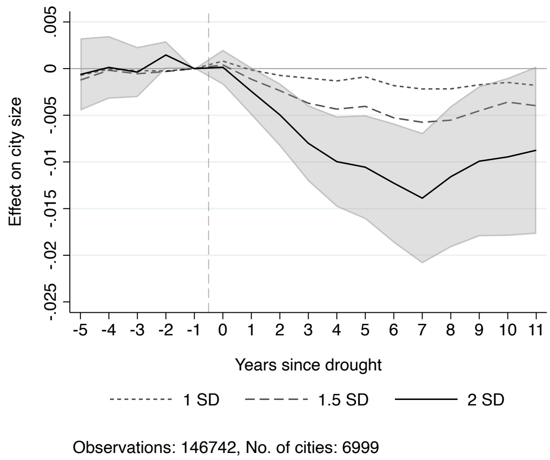



**(d)** 500 kilometer cutoff.

**Figure 18:** Estimates based on model in Equation 2. Estimates are the dynamic treatment effects of a drought on city size. Standard errors are estimated using Conley (1999) and Newey and West (1986). Distance cut off varies, and the lag cut off is 20. Panels a) and b) show the results for a 1.5 SD drought, using a 250 and 500 kilometer cut off respectively. Panels c) and d) show the results for a 2 SD drought, using a 250 and 500 kilometer cut off respectively. City and subregion-by-year fixed effects are included in all estimations. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before drought ($\beta_{t=-1} = 0$).

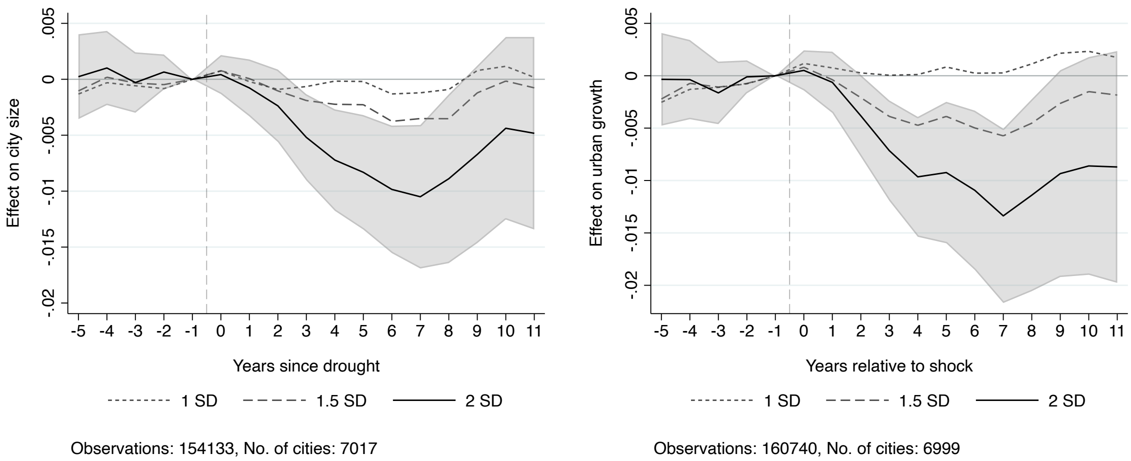



**(a)** AR(1)




**(b)** AR(2)

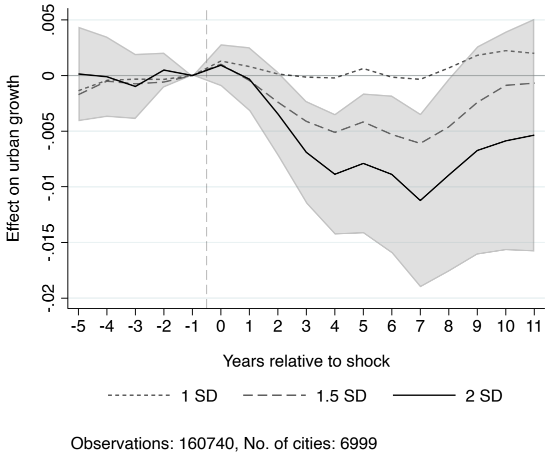
**Figure 19:** Estimates based on models in Equation 4 and 5. Estimates are the dynamic treatment effects of a drought on city size. Panel a) shows the result for an AR(1) model, using the full sample and different levels of drought intensity. Panel b) shows the result for an AR(2) model. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals for a 2 SD drought. Normalized to the year before drought ($\beta_{t=-1} = 0$).



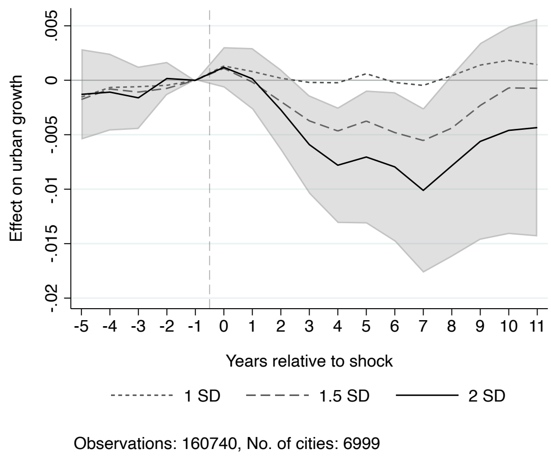

**(a)** Calendar year.

**(b)** SPEI 6.

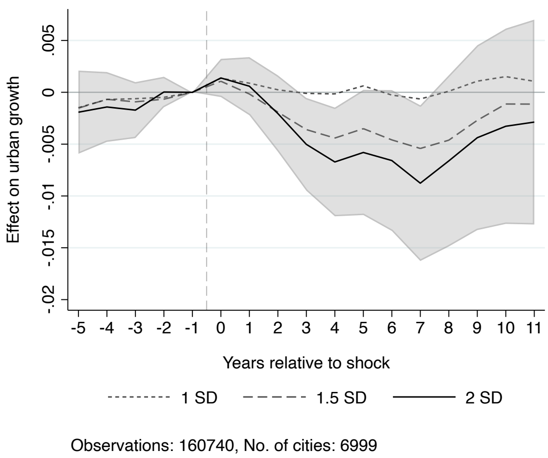
**Figure 20:** Estimates based on models in Equation 2. Estimates are the dynamic treatment effects of a drought on city size. Panel a) shows the results of using the entire calendar year to construct the droughts, using the full sample and different levels of drought intensity. Panel b) shows the results of using SPEI-6 instead of SPEI-3. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals for a 2 SD drought. Normalized to the year before drought ($\beta_{t=-1} = 0$).



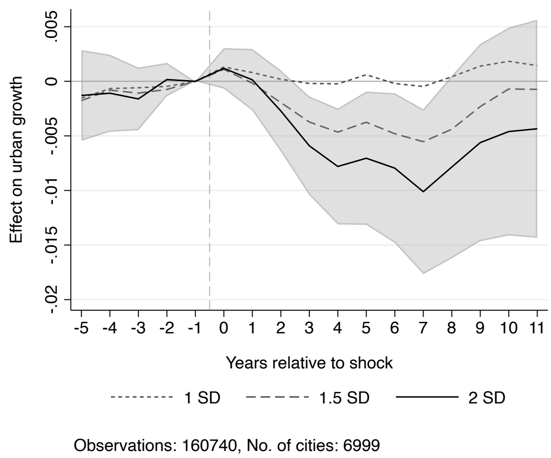

**(a)** Intermediate regions-by-year fixed effects.




**(b)** Winsorizing at 99th percentile.

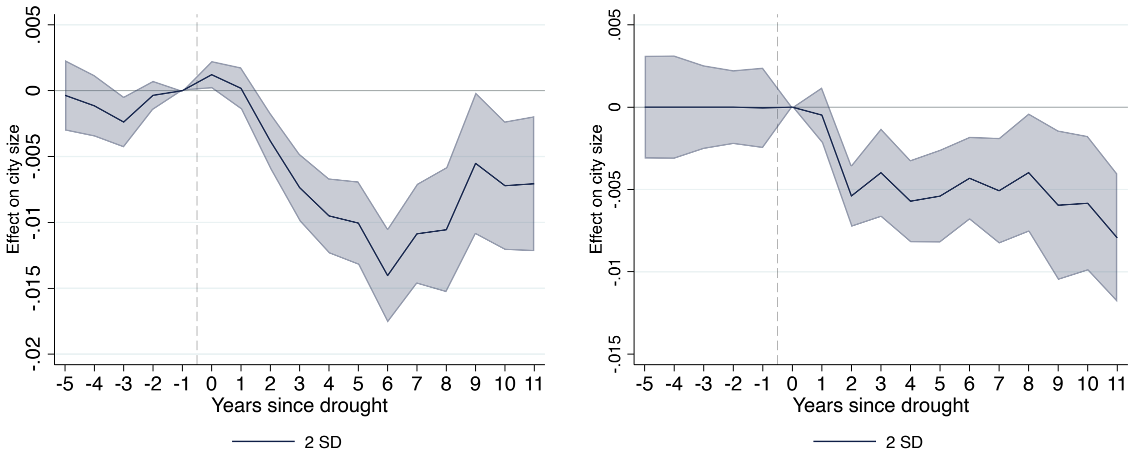



**(c)** Winsorizing at 98th percentile.




**(d)** Winsorizing at 90th percentile.

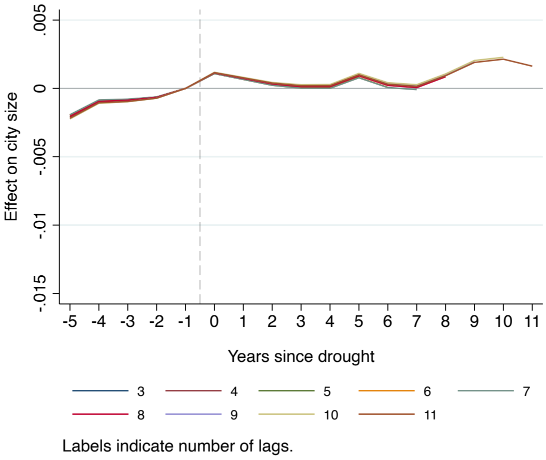
**Figure 21:** Estimates based on models in Equation 2. Estimates are the dynamic treatment effects of a drought on city size. Panel a) shows the results using intermediate regions-by-year instead of subregion-by-year, and city fixed effects. Panel b)-d) shows the results of winsorizing the sample at various cutoffs, with subregion-by-year and city fixed effects. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals for a 2 SD drought. Normalized to the year before drought ($\beta_{t=-1} = 0$).



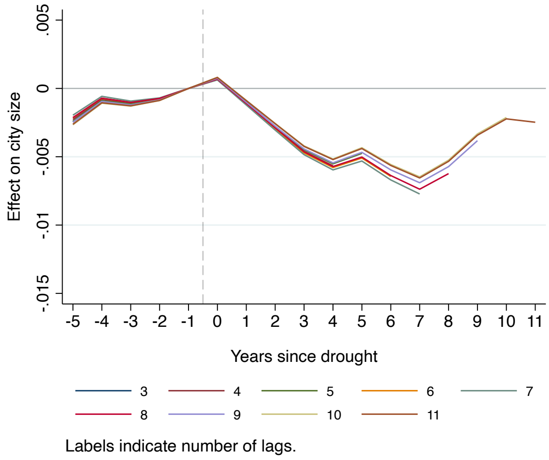

**(a)** Local projections.

**(b)** DCDH estimator.

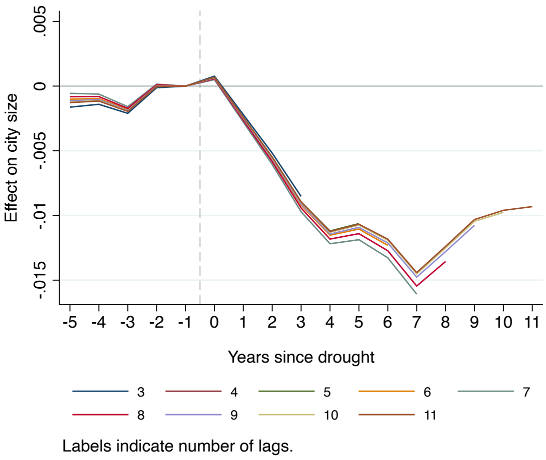
**Figure 22:** Event study estimates based on using alternative estimators to Equation 2. Estimates shown are the dynamic treatment effects of a 2 SD drought on city growth. Panel a) shows the results using a local projections estimator as specified in Equation 6. Standard errors are clustered by ADM1-by-year and city. Solid lines show point estimates at each lag (or lead) and the shaded region show 95% confidence intervals. Normalized to the year before a drought ($\beta_{t=-1} = 0$). Panel b) shows the results using the de Chaisemartin and d'Haultfoeuille (2022) estimator. Standard errors are clustered at ADM1. The dots show point estimates at each lag (or lead), and 95% confidence intervals. Normalized to the year before treatment changes ($\beta_{t=0} = 0$).




**(a)**

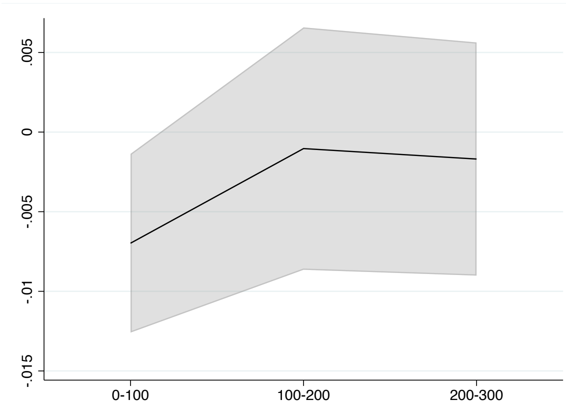



**(b)**

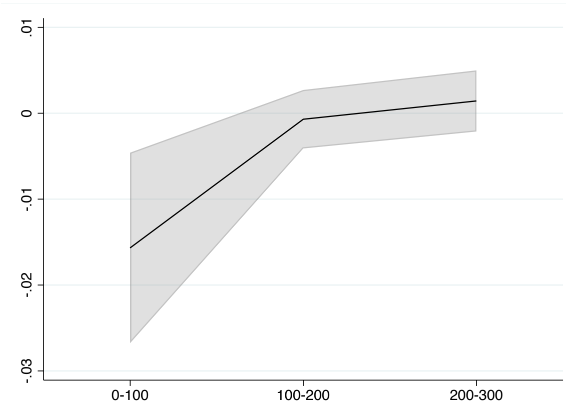



**(c)**

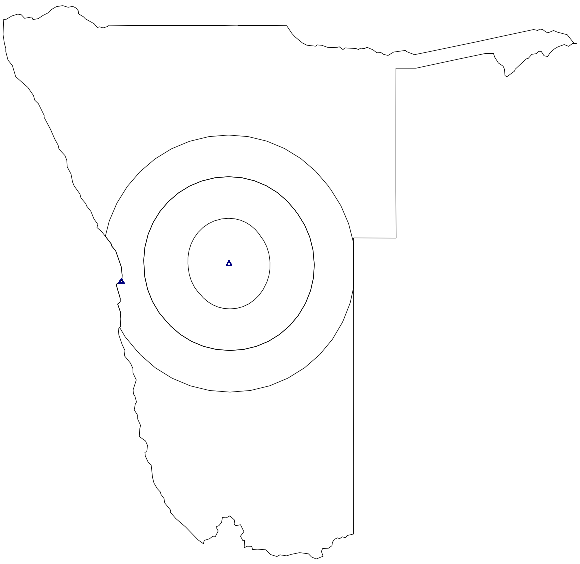
**Figure 23:** Event study estimates based on model in Equation 2. Each line shows the point estimates when varying the number of included lags, from 3 to 11. I include the full set of leads (5) in each estimation. Panel a) shows the results for a 1 SD drought, b) 1.5 SD drought, and c) a 2 SD drought. City and subregion-by-year fixed effects are included in all estimations. Confidence intervals have been omitted. Solid lines show point estimates at each lag (or lead). Normalized to the year before drought ($\beta_{t=-1} = 0$).




**(a)** 1.5 SD




**(b)** 2 SD



**(c)** Annuli.

**Figure 24:** Panels a) and b) show the results of estimating a spatial lag model as specified in Equation 7, illustrating the potential spatial spillover effects of drought exposure. Panels a) and b) show the effects of a drought on city $i$'s size. 0-100 kilometers is the drought exposure measures used in the main results, e.g. 4. 100-200 is the effect on city $i$'s size from droughts in cities within a 100-200 kilometer annuli, and 200-300 within a 200-300 kilometer annuli. Panel a) shows the results for 1.5 SD droughts, and panel b) for 2 SD droughts. Panel c) shows an example of the annuli used to construct the spatial lags, around the city of Windhoek, Namibia, where the outer annuli represents the 200-300 kilometer distance. The shaded area is 95 % confidence intervals.

# D Appendix tables

**Table 2:** Regression table

| | 1 SD | 1.5 SD | 2 SD |
|---|---|---|---|
| | City growth (%) | City growth (%) | City growth (%) |
| Years -5 | -0.00218** | -0.00262* | -0.00127 |
| | (-2.88) | (-2.22) | (-0.57) |
| Years -4 | -0.00105 | -0.00105 | -0.00115 |
| | (-1.76) | (-1.06) | (-0.60) |
| Years -3 | -0.000953* | -0.00127 | -0.00195 |
| | (-1.99) | (-1.66) | (-1.28) |
| Years -2 | -0.000712* | -0.000877 | -0.0000230 |
| | (-2.11) | (-1.77) | (-0.03) |
| Year -1 | 0 | 0 | 0 |
| | (.) | (.) | (.) |
| Year 0 | 0.00116*** | 0.000801 | 0.000672 |
| | (3.40) | (1.72) | (0.68) |
| Year 1 | 0.000818 | -0.000416 | -0.000389 |
| | (1.64) | (-0.59) | (-0.26) |
| Years 2 | 0.000435 | -0.00211* | -0.00347 |
| | (0.68) | (-2.24) | (-1.74) |
| Years 3 | 0.000243 | -0.00377** | -0.00694** |
| | (0.31) | (-3.26) | (-2.84) |
| Years 4 | 0.000249 | -0.00473*** | -0.00921** |
| | (0.27) | (-3.47) | (-3.18) |
| Years 5 | 0.00104 | -0.00392* | -0.00865* |
| | (1.00) | (-2.44) | (-2.55) |
| Years 6 | 0.000352 | -0.00516** | -0.00981* |
| | (0.30) | (-2.84) | (-2.56) |
| Years 7 | 0.000198 | -0.00607** | -0.0124** |
| | (0.15) | (-3.02) | (-2.96) |
| Years 8 | 0.000975 | -0.00486* | -0.0104* |
| | (0.70) | (-2.17) | (-2.24) |
| Years 9 | 0.00195 | -0.00295 | -0.00829 |
| | (1.27) | (-1.20) | (-1.67) |
| Years 10 | 0.00218 | -0.00175 | -0.00758 |
| | (1.32) | (-0.66) | (-1.45) |
| Years 11 | 0.00168 | -0.00200 | -0.00729 |
| | (0.94) | (-0.71) | (-1.32) |
| Observations | 160,740 | 160,740 | 160,740 |
| Cities | 6,999 | 6,999 | 6,999 |
| Adjusted R-squared | 0.3460 | 0.3464 | 0.3459 |

$t$ statistics in parentheses. $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$
Event study estimates based on model in Equation 2. Estimates shown are the dynamic treatment effects of local drought exposure, by levels of intensity, on city growth. City and subregion-by-year fixed effects are included in all estimations. Standard errors are clustered by ADM1-by-year and city.
Normalized to the year before drought shocks, $\beta_{-1} = 0$.