Droughts, dams, and economic activity

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Abstract: This paper examines the global effects of droughts on economic activity and the influence of local and upstream large dams on this relationship. We use spatially-specific data on drought severity and nighttime lights data as a measure of economic activity. The analysis shows that severe and extreme droughts reduce local economic activity. In preliminary analyses, local dams appear to improve the ability of an area to withstand droughts in least squares equations; however, with instrumental variables to address endogeneity in dam placement, dams appear to worsen the impacts of droughts. Upstream dams also appear to increase the sensitivity of a region's economic activity to local drought.

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1. Introduction

Drought regularly affects more people than any other natural hazard. However, limited research addresses the economic impact of drought and the potential mediating effects of policies and infrastructure. Though climate change may increase precipitation in many parts of the world, climate models predict increased aridity in the 21st century through much of Africa, southern Europe, East and South Asia, and eastern Australia; observed drying trends since 1950 are consistent with these predictions, which also forecast increased frequency of severe drought in the next 30-90 years (Dai, 2013). Thus, developing estimates of the global impact of these natural hazards on economic activity is a critical research goal. Drought impacts may include reductions in agricultural productivity, hydropower generation, and urban and industrial water use, loss of ecosystem services (such as fish habitat or navigation supported by streamflow), and increases in regional out-migration.

Adaptation to climate-related changes in the frequency and severity of water cycle extremes – drought and flood – may be a greater challenge than adaptation to changes in mean temperature and precipitation (Hansen *et al*., 2011). A primary purpose of dams is to smooth the variability of water supply. Thus, dams are an important component of adaptation plans for many countries. Water management infrastructure is among the top three categories of estimated adaptation costs for developing countries (Narain *et al*., 2011). One estimate suggests that global reservoir storage capacity will increase between 2010 and 2050 by 2800-3000 cubic kilometers, at an annual average net cost of about $12 billion (Ward *et al*., 2010). Yet, there is little empirical evidence that dams are welfare improving, and some evidence to the contrary both domestically (Duflo and Pande 2007, Holland and Moore 2003) and internationally (Olmstead and Sigman 2015).

This paper examines the global effects of drought on economic activity and the influence of large dams on this relationship. We use spatially-specific data on drought severity and on economic activity (using the nighttime lights index as a proxy) to identify local effects that have not been previously studied. Examining these local influences allows estimation of the effects of dams in either mitigating or exacerbating the link between drought and economic activity. We separate the effects of water infrastructure near the dam from those in downstream areas and address the potential endogeneity in dam locations. The scope of the analysis is global, allowing us to draw conclusions about the influence of drought on economic activity, and the mitigating or exacerbating influence of dams at different spatial scales and in a variety of geographic and economic environments.

Preliminary results suggest that severe and extreme droughts reduce local economic activity. Local dams appear to improve the ability of an area to withstand droughts in least squares equations; however, with instrumental variables to address endogeneity in dam placement, dams appear to worsen the implications of droughts. Upstream dams also appear to increase the sensitivity of a region's economic activity to local drought.

2. Previous Research

This paper relates to two areas of previous literature in economics. First, many recent papers use econometric models with geographic fixed effects to investigate the empirical linkage between local weather or climate and local economic output. For the most part, these studies have focused on the impacts of temperature increases, although some other short-run weather phenomena, such as cyclones, have also received attention (e.g., Hsiang, 2010). This literature has found negative effects of temperature extremes on agricultural productivity (Schlenker and Lobell, 2010; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007), on labor productivity (Heal and Park, 2014), on conflict (Hsiang *et al*., 2011, Burke *et al*., 2009) and on overall economic output (Dell *et al*., 2013).

We use an econometric approach that is similar to the approach in this literature, but with a more specific focus on drought. Two previous studies use the nighttime lights data to examine the effect of droughts. Henderson *et al*. (2014) examine the link between nighttime lights and rainfall in Africa in modeling the influence of aridity on rural-to-urban migration. Fisker (2014) conducts a global analysis of the effects of droughts, but with some restrictive specification choices. However, most of the econometric literature on the economic effects of drought focuses on specific events or parts of a regional or national economy.[1] For example, Hornbeck (2012)

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[1] Studies prepared by state and federal public agencies have examined the economic impacts of individual droughts, calculating the market value of crop and livestock losses and often including "multiplier effects" on other industries. For example, the U.S. Federal Emergency Management Agency (FEMA) has estimated average annual drought costs in the United States of $6 to 8 billion per year, making it the country's most costly category of natural disaster (FEMA, 1995).

finds that the severe and persistent drought that contributed to the U.S. Dust Bowl in the 1930s had permanent negative impacts on agricultural productivity and population in affected counties. Recent droughts in Brazil caused rural wage losses lasting several years (Mueller and Osgood, 2009) as well as job losses and pay cuts in local manufacturing and service sectors (Bastos *et al*., 2013). Estimates of drought's economic costs are sparse and far from comprehensive. The evidence from this literature does suggest, however, that regional impacts may be strong and long-lasting. Our approach extends the assessment of drought impacts to the global level, allowing attention to differential impacts by region, and using comprehensive measures of aridity, rather than estimating the effects of discrete drought events.[2]

A second area of related literature concerns the economic impacts of dams. A number of papers consider the benefits and costs of dams with increasing specificity in attention to upstream and downstream effects. Hansen *et al*. (2011) demonstrate significant increases in welfare among local downstream beneficiaries of federal irrigation dams in the United States. Duflo and Pande (2007) quantify the local and upstream impacts of irrigation dams in India; they find that these welfare costs appear to outweigh downstream benefits, suggesting that dams may reduce welfare at the national level. By contrast, Strobl and Strobl (2011) find large downstream benefits of African dams, but no beneficial local effects. In a departure from the typical focus on irrigation dams, Lipscomb *et al.* (2013) consider the economy-wide benefits from hydroelectric dams in Brazil, identifying large positive impacts on development.

The literature often focuses on the effects of dams in typical years, but a few recent studies have examined whether dams mitigate the economic effect of drought. Hansen *et al*. (2011) estimate the impacts of drought and excessive precipitation on agricultural productivity in five north-central U.S. states between 1900 and 2002, testing for a mitigating impact of federal irrigation dams, and accounting for potential endogeneity in dam placement. They find that in the arid portions of these five states, irrigation dams increased agricultural productivity for some crops during both drought years and flood years. A study that assumes exogenous dam

[2] Our approach does have important limitations. First, the fixed effects analysis we conduct will not capture longer run effects of drought; human health effects, for example, tend to occur *in utero* or in infancy or young childhood, with potential long-run educational and income impacts (Almond and Currie 2011, Maccini and Yang 2009, Dinkelman 2013, Shah and Steinberg 2013, Alderman *et al.,* 2006). Second, the focus on economic activity does not fully capture households' welfare losses, including those from reduced direct consumption of water (Mansur and Olmstead, 2012).

placement finds positive impacts of dams on agricultural productivity in Idaho, which appear to increase during droughts (Hansen *et al*., 2014).

We allow a more expansive role for dams by considering broader economic implications, beyond agricultural productivity, and also many types of dams (the previous literature on drought and dams considers irrigation dams only). We use global data, allowing us to study not just the United States but also low- and middle-income countries, where vulnerability to droughts may be more severe.[3] We use hydrologic information to identify effects for downstream regions that might counterbalance local effects. The question of whether dams may redistribute drought vulnerability (and its economic impacts) over geographic space, rather than reducing it altogether, has not yet been addressed in the literature.

In principle, the local impact of water development projects on drought impacts at any point in time could be positive or negative: in the short run, such projects might reduce vulnerability to climate shocks, but in the long run, as irrigators plant more water-intensive crops, and industry and households install more water-intensive technologies, vulnerability may increase. This non-monotonic effect has been demonstrated for access to groundwater which, like a reservoir created by a dam, may be a substitute for available river water. In the U.S. Great Plains, the historical accessibility of water from the Ogallala Aquifer initially decreased agricultural drought sensitivity but resulted in no long-run impact because farmers switched to more water-intensive crops (Hornbeck and Keskin, 2014). Our research will allow us to examine the net effect of the dams given such behavioral responses.

3. Basic Econometric Model

A basic model for the effect of drought on nighttime lights has the form:

$$L_{it} = f(D_{it}) + \alpha_i + \nu_t + \varepsilon_{it} \tag{1}$$

[3] Kahn (2005) demonstrates that developing countries experience more severe death tolls from natural disasters (though drought is not included in the analysis) and concludes that "economic development provides implicit insurance against nature's shocks," via income and higher-quality institutions to mitigate impacts.

where L_{it} is the average of the nighttime lights index for area i in year t, D_{it} is a drought severity index, and α_i and v_t are area and year fixed effects. The error term, ε_{it}, may be clustered over time and/or within river sub-basins. The relationship between lights and droughts, *f(.),* could take many forms. One flexible approach classifies observations into bins defined by the value of a drought severity index (Eq. 2). In Section 5, we estimate several such models, using different sets of thresholds for the bins, with the estimated coefficients γ_k demonstrating how drought responses may change across the distribution of drought severity.

$$L_{it} = \sum_{k=1}^{K} \gamma_k bin_{it} + \alpha_i + \nu_t + \varepsilon_{it} \tag{2}$$

In Section 6, we consider models that allow heterogeneity in the response to droughts, γ_k, by characteristics of the subbasin, especially the presence of dams. Those models use a two-stage approach that is described below.

4. Data

We combine several global datasets on economic activity, drought, and the location of dams to estimate our econometric models. The main measure of economic activity, our dependent variable, is a satellite-based measure of the brightness of nighttime lights, which the recent literature suggests is a helpful proxy for economic activity (Chen and Nordhaus 2011, Henderson et al. 2012). We use the Defense Meteorological Satellite Program-Operational Linescan System (DMSP-OLS) Nighttime Lights Time Series, which is available annually from 1992-2013 at a very fine spatial scale (NOAA 2014).[4] The spatial precision of these data is much finer than any measure of economic activity available through traditional national accounts or other survey-based data. However, these data are only a proxy and can deviate from underlying

[4] An alternative gridded measure of economic activity is the Yale G-Econ (Nordhaus *et al*., 2006). G-Econ uses subnational regional gross product or employment data along with gridded population data to estimate 1 degree by 1 degree output at five-year intervals. The data are less suitable for our analysis because it would be difficult to associate annual drought data with five-year changes in output and because there are only two years that overlap with our preferred drought data. Chen and Nordhaus (2011) provide a direct comparison with the nighttime lights data that may help bound or qualify our results.

economic activity in systematic ways. Given that the models we estimate contain grid-cell fixed effects (α_i), we identify effects of drought only from time-series variation in a given area.

To measure the relative water stress in a location over time – our primary independent variable of interest – we use the MODIS Global Terrestrial Drought Severity Index (DSI), based on satellite observations of evapotranspiration and vegetation greenness (Mu *et al*., 2013). Annual averages for the index are provided in a half-decimal degree grid from 2000 through 2011.[5] We merge the nighttime lights and the drought data together at the level of resolution in the drought data (0.5 decimal degree grid cells), dropping all missing cells (oceans, for example), for the full period over which the drought data are available (2000-2011), creating a dataset with about 55 million observations. For tractability, and to keep only the set of grid cells that are relevant to the analysis, we drop observations in subbasins that have no lights, leaving 3,335,140 grid cells over 12 years, creating a panel with 40,021,680 observations.

Table 1 provides summary statistics for the lights index, which ranges from 0 to 63, with a full sample mean value of 2.16. In Table 1, we also summarize the lights index values for sub-samples defined by DSI ranges. The DSI theoretically ranges from unlimited negative to unlimited positive values, but most of the distribution lies between -3 and +3. The DSI bins in Table 1 are defined in Mu et al. (2013), and they correspond to specific definitions of wet and dry conditions of varying severity. The "near normal" category, for example, contains all observations with DSI values between -0.3 (the upper boundary for the "incipient drought" category) and 0.3 (the lower boundary for "incipient wet spell"); there are about 9.3 million observations in this category. Looking at the raw means, lights index values appear to be highest for DIS values near normal, and for somewhat wet conditions, with the exception of the "extreme drought" category, which has the highest mean value.

Many of the models in Sections 5 and 6 condense the DSI bins, forming six bins (or fewer) from the eleven in Table 1. Since our primary interest is drought rather than excess precipitation, we frequently condense all of the positive DSI categories into a single "wet" bin, containing all observations with DSI values above 0.3, leaving the normal bin and four drought bins to contain the remaining observations. Table 2 provides summary statistics for the six

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[5] The MODIS Global Terrestrial Drought Severity Index is provided by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana at http://www.ntsg.umt.edu/project/dsi.

remaining DSI bins. Using this grouping, about 23 percent of observations are in the normal bin, and another 39 percent have positive values above 0.3. The remaining observations are divided between the "dry" DSI bins, with about 11 percent of grid cell-years experiencing average conditions of severe or extreme drought.

We expect the impacts of droughts and the influence of dams on these impacts to depend on local hydrology. Hydrologically-defined river subbasins capture this factor and play two roles in our analysis. First, the estimates cluster standard errors at the subbasin level to allow correlation within subbasins in the impacts of drought on lights. Second, the subbasin defines the area for local and upstream dams. In our analysis, river subbasins are defined by the HYDRO1k dataset from the US Geological Survey (USGS), which uses global elevation data to divide land area into river basins and subbasins (USGS, 2012).[6] The HYDRO1k subbasins are coded using the Pfafstetter system (Verdin and Verdin, 1999), which provides a hierarchical coding of river basins and their subdivisions into several possible levels of subbasins. The finest subbasin classification has 6 digits. We rely on the 4-digit subbasin level, both for clustering standard errors, and to create the dam variables and other subbasin characteristics used in the analysis. Globally, there are about 13,100 4-digit Pfafstetter subbasins; 7,832 remain in our dataset once subbasins that were completely dark in at least one year are dropped.

For data on the location of large dams, we use the Global Reservoir and Dams (GRanD) data set (Lehner *et al*., 2011). GRanD provides latitude and longitude for 6,862 of the world's largest dams and reservoirs. GRanD includes all dams with reservoirs that have storage capacity greater than 0.1 km^3 and a number of dams with smaller reservoirs. The GRanD dataset also includes some information on the characteristics of the dams that we can take into account in our analysis. For example, GRanD classifies dams by primary use and provides total reservoir capacity and dam height. Table 3 reports the main use category for all the dams in GRanD. Irrigation is the most frequent use, followed by hydroelectricity; unfortunately, the data lack information on primary use for 23 percent of dams. The dam location data are purely cross-sectional and do not change over time; this should not appreciably affect the analysis, given the relatively short period of time in the panel (2000-2011).

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[6] HYDRO1k provides global coding except in polar areas and for the Australian mainland.

The three "dam presence" variables in Table 2 are dummy variables indicating the presence or absence of any dam (or dams) in a grid cell's local 4-digit Pfafstetter subbasin, in the subbasin immediately upstream, and in subbasins further upstream. About 45 percent of observations are in a subbasin with at least one local dam. The hierarchical Pfafstetter system codes basins in a way that makes it possible to traverse a network of drainage basins and identify whether an area is downstream of an area in which dams are present. We use these codes to determine areas that are immediately and more distantly downstream of large dams.[7] The upstream dam counts have far fewer observations (about 9.6 million, compared to 40 million) because most grid cells are in subbasins with no upstream subbasins (Figure 1). Conditional on having an upstream subbasin, about 24 percent of grid cells have at least one dam in the immediate upstream subbasin; about 59 percent have at least one dam in one or more subbasins further upstream.

Table 2 also summarizes other independent variables that we use as control variables in studying resilience to droughts by subbasin. First, the equations control for population density in the subbasin. The population data are from the Gridded Population of the World version 3 (GPWv3), which provides estimates of population density in 2000 (CIESIN 2005); the units are thousand people per square kilometer. Second, the physical geography of the subbasin may affect the need for dams and resilience to drought. One such measure is a subbasin's compound topographic index (CTI); this "wetness index" is a function of the slope and the upstream area contributing to a river's flow.[8] It is time invariant and highly correlated with soil moisture. HYDRO1k provides this measure at the subbasin level.

The final two variables in Table 2 are used as instruments for the placement of dams in Section 6. The average slope in subbasin, also from HYDRO1k, may indicate the suitability of the area for damming. We follow prior work in using slope as an instrument for the presence of

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[7] We are grateful to Sergey Reid for determining the full set of upstream/downstream relationships among sub-basins for each continent. We used existing VBA code (Furnans, 2001) to conduct the necessary basin traversals. The code was originally intended to serve as a tool for an earlier version of ArcGIS, but we were able to apply the VBA code in Excel. The code from Furnans (2001) identifies watersheds that are *directly* upstream and downstream of each given basin. We ran the code repeatedly by continent to identify all of the upstream or downstream subbasins for each given subbasin.

[8] Specifically, CTI = ln(flow accumulation / tan(slope)). If the slope is equal to zero, the formula uses slope = 0.001.

dams (Duflo and Pande 2007) in Section 6. Given prior work that suggests dam construction may be more intensive upstream of country borders due to free-riding in water diversions in international river basins (Olmstead and Sigman 2015), we also use the degree of local river-sharing as an instruments in Section 6. On average, subbasins comprise land belonging to 1-2 countries.

5. Preliminary results: Impact of drought on economic activity

Table 4 reports results from estimating equation (2), with varying definitions of DSI bins. Each column also includes fixed effects for 3.3 million grid cells and 12 years (2000-2011); standard errors are clustered by subbasin. Column 1 uses three DSI categories, comparing dry conditions and wet conditions to "near normal" conditions (the excluded category is $-0.3 < \text{DSI} < 0.3$). Compared to normal conditions, DSI values below -0.3 reduce the value of the lights index, but wet conditions have no statistically significant effect. Column (2) re-estimates equation (2) with K=11, using all of the DSI bins defined in Mu et al. (2013). Compared to normal conditions, the estimated DSI coefficients are negative and statistically significant for conditions of severe and extreme drought. They are negative, but insignificant, for all of the other "non-normal" categories, both dry and wet. The magnitude of DSI impacts appears to grow with drought severity. This is true for all of the DSI coefficients moving away from normal on the dry side of the index, though only the two most severe categories have significant coefficients. Compared to normal conditions, severe drought reduces the lights index (at the mean value of 2.16) by about 1.4 percent, and extreme drought reduces lights by about 4.6 percent.

Column (3) demonstrates that these results are insensitive to condensing the "wet" categories into a single bin containing all observations with DSI values above 0.3. In column (4), we combine all categories with DSI values above -1.2 (the boundary for "severe drought"), and compare lights outcomes for areas experiencing severe or extreme drought to all others. Compared to all other categories, the lights index in areas experiencing severe or extreme drought is reduced by about 3.2 percent. Given its simplicity and consistency with the prior specifications in Table 4, we use this specification to explore the impacts of dams in Section 6.

6. Preliminary results: Influence of dams on drought sensitivity

This section explores the effects of dams on estimated drought sensitivity. To estimate the effects of dams and reservoirs on resilience to drought, we use a two-stage procedure. The first stage analysis estimates separate drought sensitivity for each subbasin, j, using grid-level data. The second stage then examines the determinants of this estimated drought sensitivity. The estimated first-stage equations have the form:

$$L_{it} = \varphi_j D_{it} + \mu_i + \rho_c \delta_t + \epsilon_{it} \tag{3}$$

As in column (4) of Table 4, these equations restrict attention to the response to severe or extreme drought, so D_{it} is an indicator for a DSI value less than or equal to -1.2, and it is interacted with a subbasin fixed effect to produce an estimate of the subbasin level sensitivity to droughts, φ_j. Grid-cell fixed effects, μ_i, are included, so the identification is from the change in drought status over time in a specific location. In addition, the equations are estimated separately by country, so the year effects, δ_t, vary by country.[9] These country-year effects mean that only within-country effects of drought are exploited: drought may have national consequences especially in small countries, so our estimated drought sensitivities may be too conservative with inclusion of these effects.[10]

The estimated values of the coefficients φ_j — representing drought sensitivity by river subbasin — are then used as the dependent variable in a second stage equation to represent the reduction in economic activity from a drought in a given subbasin. These second stage equations have the form:

$$\hat{\hat{\varphi}}_j = \beta X_j + \theta_j + \epsilon_j \tag{4}$$

where X_j are characteristics of the subbasin that may affect its sensitivity to drought, such as the presence of a dam in the subbasin or in an upstream subbasin, and θ_i are geographic effects

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[9] For tractability, equations for the Russian Federation were run separately for European and Asian areas, effectively allowing the country-year effects to vary within Russia across this divide. All other countries have a single set of year effects.

[10] We hope to work with continent-year effects in the future, but have chosen this country-year approach for now because it facilitates use of our current computing resources by reducing the dimensionality of individual equations.

(continent or country). The dependent variable is an estimate, so the second-stage equations are weighted by the number of grid-cells in each subbasin that form the basis of this estimate.

At present, limitations in computing power have restricted the analysis to 3-digit Pfafstetter subbasins, of which there are 3,414 globally that meet the restriction of having some lights in all years. We can only obtain estimates of drought sensitivity for subbasins that experienced severe or extreme drought during the 12-year study period. This exclusion reduces the number of subbasins from 3,414 to 1,889. Tables 5 and 6 report coefficients for equation (4) estimated by Weighted Least Squares (WLS) and Table 7 contains Instrument Variables (IV) estimates to address the possibility of endogenous dam placement.

6.1 Weighted least squares estimates

Table 5 reports the results from the most basic estimates of equation (4) with the role of dams captured by a simple dummy for the presence of a dam in the local subbasin. Column 1 includes just the dam dummy and continent fixed effects. The point estimate on the presence of a dam has a positive coefficient, suggesting that areas with dams may experience less severe effects of drought. Column 2 replaces the continent fixed effects with country effects; 121 countries are included in the analysis. Country effects adjust for country-level variability in economies and institutions that may affect resilience in the face of droughts and may be correlated with the presence of dams, our variable of interest. However, they may also absorb some of the variation of interest: especially for small countries, the presence of dams may affect the ability of the entire country to withstand a drought. We continue to include country effects as our base case, but note that their inclusion may dampen the estimated effects of dams. In practice, however, as Column 2 reports, adding country level effects increases the point estimate on the presence of a local dam; this pattern suggests that countries with less ability to withstand drought have more dams.

The next two columns add controls for subbasin-level heterogeneity that may be correlated with the presence of dams. Column 3 adds population density in the subbasin in 2000 (the first year of our analysis) as a control. Dams tend to be in populated places, where the level and thus the potential change in lights are higher. The population variable has a statistically significant positive coefficient, suggesting that more populated places suffer less absolute reduction in economic activity when droughts occur. Populated subbasins do more frequently have dams and inclusion of this variable reduces the point estimate (and statistical significance) of coefficient on the presence of a dam. Column 4 adds the CTI, the hydrologically-based wetness index described in Section 4. The CTI measures soil suitability for agriculture and may address the need for dams as a substitute for other sources of freshwater. The wetness index is not itself statistically significant, but the presence of a dam has a coefficient that is positive and statistically significant when we include the index.

Table 6 considers a wider set of explanatory variables for the drought sensitivity of a subbasin. First, Column 1 considers the heterogeneity in effects by different types of dams.[11] The equation adds a variable for the presence of a hydroelectric dam in the subbasin. Areas that depend on electricity from their dams might suffer more dramatic declines in lights than areas that use the dams for irrigation or water supply, where the dams may provide a substitute for precipitation. The point estimate on hydroelectric dams is negative as expected, but it is not statistically significant. Many dams have multiple or missing uses, so the data may be too noisy to isolate the effect of hydroelectric dams.

Column 2 of Table 6 explores another dimension of heterogeneity, the quantity of water impounded by the dam. The variable is the estimated reservoir capacity of dams in the subbasin (summed over all dams present, when there are multiple dams).[12] It has a positive and statistically significant effect, suggesting that a large amount of reservoir capacity has strong beneficial effect on the ability of economic activity in the subbasin to withstand the effect of droughts.

The final column of Table 6 explores of the role of upstream dams. Upstream dams may result in reduced water flow (or differently timed flow) that can reduce the resilience of areas to droughts. To examine their effect, we separate upstream dams into two groups: those in the immediately adjacent upstream basin and those that are farther upstream. Immediately upstream dams may be quite close to the basin in question and thus any benefits of proximity to the dam

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[11] We plan more equations that examine heterogeneity in local and upstream dams in the future, to the extent that the characterization of dams in the GRanD dataset allows.

[12] The GRanD Project calculated reservoir capacity and provided it for all but a very few dams in the data, making this variable our preferred measure of dam size. It does, however, have a very pronounced upper tail, so a few observations may be very influential. The variable as entered in our equation is the maximum storage capacity in thousands of million cubic meters.

may mix with the costs that dams impose downstream. We expect dams farther upstream to generate costs more exclusively. To estimate the effects of upstream dams, the equations must address the location of subbasins in the river system. Some subbasins have many upstream subbasins (see Figure 1) and thus are at greater risk for an upstream dam than those with few or no subbasins. Subbasins with more upstream subbasins likely have larger rivers and thus are also likely to be less sensitive to droughts, potentially confounding the apparent effect of upstream dams. To address this concern, column 3 adds a variable for the number of upstream subbasins.[13]

The estimated effect of upstream dams in Column 3 of Table 6 conforms to these expectations. The presence of a dam two or more subbasins upstream has a negative coefficient, suggesting that these subbasins experience more severe negative effects from droughts than similar basins without upstream dams. However, the coefficient is only weakly statistically significant. The coefficient for local upstream dams is negative, but small and not statistically significant, perhaps because it blends the positive effect of local dams with the negative effect of farther upstream dams. The coefficient on the count of upstream subbasins is statistically significant and positive as expected, suggesting that places to which more water may flow in from outside fare relatively better in droughts.[14]

6.2. Instrumental variables estimates of the effect of dams

One concern about the interpretation of the estimates of equation (4) is potential endogeneity of dam locations. For example, if dams strengthen resilience against drought, they might preferentially be built in places that expect strong effects of drought. The presence of dams may also simply be correlated with other factors that affect resilience, such as access to

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[13] To address the concern that the presence of upstream dams is capturing position in the river system, we also estimated equations that included ”flow accumulation, the catchment area that is upstream of a given point. We used the maximum flow accumulation in the subbasin calculated from the HYDRO1k Streamlines file. This variable did not enter with a statistically significant coefficient in any equation, nor did its inclusion affect the major results.

[14] The estimated equations include subbasins with zero upstream subbasins (with zeros for both upstream dam variables as well). If we exclude subbasins without upstream subbasins, the number of subbasins in the analysis falls to 584 (from 1889) and the number of countries falls from 121 to 72. None of the dam coefficients are statistically significant with this exclusion, but this may result from the decline in the sample size and number of countries identifying the results.

capital. To address concerns about endogeneity, this subsection reports instrumental variable estimates of equation (4).

The estimates rely on two different sorts of instruments. First, Duflo and Pande (2007) use slope as an instrument for the construction of dams in India. Our equations include average and maximum slope in the subbasin, constructed from the HYDRO1k data.[15] Second, our prior research (Olmstead and Sigman, 2015) suggests that dams are more likely to be located on shared rivers. Thus, we use as instruments the presence and number of different countries downstream from this subbasin. These instruments have the advantage of relating to conditions downstream of the location, not to local geographic heterogeneity (which could plausibly also affect economic activity). In addition, the number of countries that share the subbasin is included as another measure of the water resource commons problem.

Table 7 presents the IV estimates. The first two columns are the estimates for the main equation and first stage with continent fixed effects; the second two columns are the estimates with country effects. Using instrumental variables dramatically alters the estimated effects of dams. With the instrumental variables, local dams have a negative and statistically significant effect on drought sensitivity in column 1. With country effects in column 3, the point estimate is negative, but is imprecisely estimated.

The instrument variable analysis thus implies that dams may make areas more vulnerable to drought. Earlier evidence suggesting greater resilience may be an artifact of other factors in the distribution of dams. We plan to explore the robustness of this result, whether it generalizes to less severe drought conditions, and whether it varies systematically with other factors in the future.

7. Conclusions

The results of this analysis suggest that droughts have a significant effect on local economic activity. In fixed effects models, we estimate that severe drought reduce the lights index (at the mean value of 2.16) by about 1.4 percent, and extreme drought reduces lights by about 4.6 percent.

[15] Some authors express concern that slope variables may be related to the suitability of the land for agriculture and thus not satisfy the exclusion restriction for instrument. Our results are robust to using just the political boundaries instruments, although the estimates are less precise and less statistically significant.

We find mixed evidence on the role of dams in the reduction in economic activity with drought. In analyses with some control for dam placement (and country fixed effects), we find evidence that supports the view that local dams help areas withstand severe and extreme drought. However, when we use instrumental variables to treat the presence of a dam as endogenous, the effect reverses and evidence suggests that areas with dams actually experience more harm. This negative effect may suggest that the presence of a large dam encourages irrigators to plant more water-intensive crops and businesses and households to install more water-intensive technologies, increasing their vulnerability to severe water shortages. We also find some evidence that upstream dams inflict harm on downstream areas, leaving them with less resilience in the face of drought, presumably from water diversion and changes in river flow from upstream dams and reservoirs.

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Table 1. Summary statistics: lights by drought severity index values

DSI value range	N	Mean	Standard deviation	Minimum	Maximum
Extreme drought (DSI ≤ -1.5)	2,523,306	2.26	6.29	0	63
Severe drought (-1.5 < DSI ≤ -1.2)	2,017,739	2.10	6.25	0	63
Moderate drought (-1.2 < DSI ≤ -0.9)	2,804,888	2.10	6.30	0	63
Mild drought (-0.9 < DSI ≤ -0.6)	3,555,744	2.10	6.27	0	63
Incipient drought (-0.6 < DSI ≤ -0.3)	4,214,057	2.11	6.23	0	63
Near normal (-.0.3 < DSI < 0.3)	9,322,090	2.18	6.27	0	63
Incipient wet spell (0.3 ≤ DSI < 0.6)	4,427,061	2.23	6.26	0	63
Slightly wet (0.6 ≤ DSI < 0.9)	3,836,693	2.21	6.21	0	63
Moderately wet (0.9 ≤ DSI < 1.2)	2,996,601	2.15	6.15	0	63
Very wet (1.2 ≤ DSI < 1.5)	2,070,107	2.10	6.09	0	63
Extremely wet (DSI ≥ 1.5)	2,253,394	2.11	6.14	0	63
All values	40,021,680	2.16	6.24	0	63

Table 2. Summary statistics: major independent variables and instruments

Variable	N	Mean	Std. dev.	Min.	Max.
DSI values					
Extreme drought	40,021,680	0.06	0.24	0	1
Severe drought	40,021,680	0.05	0.22	0	1
Moderate drought	40,021,680	0.07	0.26	0	1
Mild drought	40,021,680	0.09	0.28	0	1
Incipient drought	40,021,680	0.11	0.31	0	1
Near normal	40,021,680	0.23	0.42	0	1
Wet	40,021,680	0.39		0	1
Population density in 2000	40,021,680	0.0623	0.134	0	4.062
Dams present, local subbasin	40,021,680	0.45	0.50	0	1
Dams present, next upstream subbasin	9,595,092	0.24	0.43	0	1
Dams present, 2+ subbasins upstream	9,595,092	0.59	0.49	0	1
Wetness index in local subbasin	40,021,680	6.06	1.25	2.47	15.10
Slope in local subbasin	40,021,680	1.74	1.85	0	17.55
Number of countries in local subbasin	39,961,368	1.69	1.43	1	12

Table 3: Main uses of dams in GRanD

Main use	Number	Share
Irrigation	1,781	25.95
Missing	1,577	22.98
Hydroelectricity	1,541	22.46
Water supply	847	12.34
Flood control	547	7.97
Recreation	293	4.27
Other	206	3.00
Navigation	56	0.82
Fisheries	14	0.20
Total	6,862	100.00

Source: Authors' calculations based on data from GRanD (Lehner *et al*., 2011).
Notes: A few dams also have major or secondary uses indicated, but most do not. "Other" includes dams with primary uses of livestock watering and water pollution control, in addition to those labeled in GRanD as "other".

Table 4. Impact of drought severity index on lights, using various DSI bins

	(1)	(2)	(3)	(4)
Variable	**3 bins**	**11 bins**	**6 bins**	**2 bins**
DSI < -0.3 (dry)	-0.0256**			
	(0.0075)			
DSI > 0.3 (wet)	-0.00297			
	(0.00658)			
Extreme drought		-0.1031**	-0.1031**	
		(0.0172)	(0.0172)	
Severe drought		-0.0301**	-0.0301**	
		(0.0106)	(0.0106)	
Severe or extreme drought				-0.0688**
				(0.0128)
Moderate drought		-0.0109	-0.0109	
		(0.0080)	(0.0080)	
Mild drought		-0.0022	-0.0022	
		(0.0060)	(0.0060)	
Incipient drought		-0.0021	-0.0021	
		(0.0043)	(0.0043)	
Incipient wet spell		-0.0063		
		(0.0039)		
Slightly wet		-0.0029		
		(0.0059)		
Moderately wet		-0.0050		
		(0.0081)		
Very wet		-0.0038		
		(0.0110)		
Extremely wet		-0.0025		
		(0.0157)		
Wet			-0.0027	
			(0.0066)	
R^2	0.080	0.080	0.080	0.080
Clusters	7,832	7,832	7,832	7,832
Observations	40,021,680	40,021,680	40,021,680	40,021,680

Notes: Dependent variable is value of nighttime lights index. Excluded DSI "normal" category in columns (1)-(3) is 0 +/- 0.3. Excluded category in column (4) is DSI > -1.2. Standard errors in parentheses are clustered by 4-digit Pfafstetter subbasin. All models include fixed effects for cells and years, and a constant. $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.

Table 5. WLS estimates: Effects of presence of a dam on drought sensitivity

	(1)	(2)	(3)	(4)
Dam present	0.0545	0.142^{**}	0.0916^{+}	0.0984^{*}
	(0.0385)	(0.0541)	(0.0497)	(0.0494)
Population density in 2000			0.703^{**}	0.679^{**}
			(0.219)	(0.216)
Wetness score				0.0217
				(0.0144)
R^2	0.010	0.152	0.180	0.181
Geographic effects	Continent	Country	Country	Country
Observations	1889	1889	1889	1889

Notes: Dependent variable is $\widehat{\varphi_j}$ from equation (4), sensitivity of the nighttime lights index to severe or extreme drought at the subbasin level. Robust standard errors in parentheses. Estimates are weighted by number of grid cells in a subbasin. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 6. WLS estimates: Effects of dams on drought sensitivity

	(1)	(2)	(3)
Dam present	0.131*		0.0978*
	(0.0643)		(0.0450)
Hydro dam present	-0.0642		
	(0.0560)		
Reservoir capacity		0.00757*	
		(0.00357)	
Dam just upstream			-0.0433
			(0.0694)
Dam farther upstream			-0.0890^{+}
			(0.0535)
Population density in 2000	0.694**	0.533**	0.679**
	(0.219)	(0.199)	(0.212)
Wetness score	0.0149	0.0288^{+}	0.0132
	(0.0159)	(0.0153)	(0.0158)
Count of upstream subbasins			0.0178^{+}
			(0.00932)
R^2	0.184	0.258	0.258
Observations	1889	1889	1889

Notes: Dependent variable is $\widehat{\varphi_j}$ from equation (4), sensitivity of the nighttime lights index to severe or extreme drought at the subbasin level. All equations include country fixed effects. Robust standard errors in parentheses. Estimates are weighted by number of cells in a subbasin. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 7. Instrumental variables estimates of effects of dams on drought sensitivity

	(1) Drought sensitivity	(2) First stage: Dam Present	(3) Drought sensitivity	(4) First stage: Dam present
Dam present	-0.274*		-0.471	
	(0.113)		(0.321)	
Population density in 2000	0.785**	0.978**	1.356*	1.068**
	(0.286)	(0.141)	(0.533)	(0.198)
Wetness score	-0.00856	-0.0216	-0.0170	-0.0742*
	(0.0163)	(0.0355)	(0.0304)	(0.0378)
Mean slope		-0.0170		-0.0781*
		(0.0372)		(0.0337)
Maximum slope		0.0296*		0.0443**
		(0.0138)		(0.0109)
Num. foreign downstream countries		0.0253		0.0350
		(0.0210)		(0.0257)
Number of countries in subbasin		0.0302*		0.0320
		(0.0135)		(0.0258)
Geographic effects	Continent	Continent	Country	Country
Observations	1889	1889	1889	1889

Notes: Dependent variable is $\widehat{\varphi_J}$ from equation (4), sensitivity of the nighttime lights index to severe or extreme drought at the subbasin level. Robust standard errors in parentheses. Estimates are weighted by number of cells in a subbasin. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Figure 1. Number of upstream subbasins for each level 4 Pfafstetter subbasin