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# Droughts and corruption

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## Abstract

Natural disasters are challenges for good governance. That conclusion follows from recent research investigating the effects of natural disasters on one important force hostile to good governance: public sector corruption. However, a specific analysis of droughts is so far neglected in the still-young relevant strand of the literature. The present paper fills that gap by analyzing the short- and long-term influence of droughts on public sector corruption within a unified panel estimation approach for 120 countries during the period 1985–2013. Relying on a meteorological drought measure, the Standardized Precipitation Index, we show that more severe drought exposure is followed by more corruption. The effect holds for subsamples of developing and developed countries. The robustness of the results is supported by a variety of stability tests. Furthermore, we provide initial evidence on the transmission paths of drought-induced corruption, which differ depending on the countries' level of development. Whereas droughts increase corruption risk in developing countries by triggering significantly larger aid inflows and less democratic accountability and transparency, corruption in developed countries rises as a consequence of governmental drought relief payments.

**Keywords** Drought · Economic development · Institutions · Natural disasters · Public sector corruption · SPI

**JEL Classification** D73 · E02 · Q54 · Q56

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## 1 Introduction

Corruption—“the breaking of a rule by a bureaucrat (or an elected official) for private gain” (Banerjee et al. 2012)—requires at least two preconditions: willingness and opportunity. Both preconditions are present in the case of natural disasters. Natural disasters may increase victims’ propensity to bribe public officials, as Hunt (2007) shows for Peruvian households.<sup>1</sup> Furthermore, taxpayer-financed disaster relief payments represent monetary windfalls (e.g., Leeson and Sobel 2008) that give groups and individuals opportunities to compete for shares of them, most likely resulting in more rent-seeking behavior and corruption (Brollo et al. 2013). In addition, natural disasters typically create emergency situations that generate a climate of non-accountability and moral hazard. “Crisis” enables bureaucrats and officials to engage in acts of corruption (Klitgaard 1988). Recent empirical research supplies evidence for the disaster-corruption relationship in the United States (Leeson and Sobel 2008), Vietnam (Nguyen 2017) and flood events in Bulgaria (Nikolova and Marinov 2017). The international analyses of Yamamura (2014), Escaleras and Register (2016), and Rahman et al. (2017) provide additional confirmation of those results for many countries.

Droughts are underrepresented in the emerging strand of the relevant literature, although evidence exists that related research efforts could be fruitful. Acemoglu et al. (2018) provide a notable example illustrating how droughts challenge good governance, identifying a severe drought at the end of the nineteenth century as the critical juncture resulting in the rise of the Sicilian Mafia. Triggering social conflict between the socialist movement and landowners, that drought led to long-lasting negative impacts on state capacity in the affected region. Viewing corruption as a force antagonistic to good governance, anecdotal evidence of misused and distorted drought relief payments exists worldwide. In a historical survey of public drought policies in northeastern Brazil, Campos (2015) notes that the misuse of public resources has accompanied drought relief programs since the late eighteenth century. A prominent example of diverted disaster aid took place in 1974 during a severe drought in Mali. At that time, enormous sums of drought relief were misappropriated to erect villas for the ruling elite, while nearly 300,000 nomads were left destitute (Hope 2016).

An important factor justifying an analysis of the effects of drought on corruption is the unique and complex characteristics of such hydrometeorological disasters. In particular, droughts differ from other natural disasters, such as floods, tropical cyclones and earthquakes, along three primary dimensions.

First, as droughts generally arise as rainfall deficiencies caused by natural climate variability (Wilhite 2000), they are not confined to specific areas such as floodplains, coastal regions, storm tracks or fault zones (Svoboda and Fuchs 2017). Although they typically occur in more arid locations (Seager et al. 2007; Dai 2011), they are prevalent throughout the world (Carrao et al. 2016). Consequently, droughts usually affect considerably wider geographical areas than other hazardous events, meaning that a drought-induced threat of corruption could span a broad region.

Second, the effects of drought related to water availability normally accumulate over a considerable time span and may linger for long periods after precipitation returns to normal levels. The effects of drought thus contrast starkly with the typically sudden onset and relatively short

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<sup>1</sup> The effect depends on entering household fixed effects in the estimation approach (Hunt 2007).

duration of other hazard types (Wilhite et al. 2014). Therefore, its economic, social and environmental impacts, and hence the disaster-related reasons for corruption, typically become more salient the longer a drought persists.

Third, droughts mainly cause non-structural damage, e.g., crop or forest failures. Compared with structural damage such as destroyed buildings or communication lines, the negative effects of a drought are far more difficult to survey and quantify (Wilhite 2000). Therefore, it is much more difficult to monitor their alleviation, creating considerable opportunities for corrupt activities.

Another aspect substantiating the relationship between droughts and corruption is that fact that the water sector is prone to corruption to begin with, especially in situations of scarce water availability (TPI 2008). Droughts raise the risk of corruption, particularly in the operation of channel irrigation systems. Irrigation research often informs technical solutions for irrigation systems, which are characterized by numerous manipulation possibilities under the guise of precise water allocation. However, such manipulation options translate into corruption opportunities (Rijsberman 2008; Wade 1982) Officials responsible for operating the gates may be bribed or request side payments for additional or prolonged opening, especially when farmers experience drought-related water shortages (Rijsberman 2008).

For some regions of the world, the threat of drought-induced corruption is expected to become more prevalent in the future owing to changing climatic conditions. Although recent assessments of projected droughts differ substantially depending on the drought definition applied and the projection model, some consensus exists that drought duration and intensity tend to increase in southern Africa, central and southern Europe including the Mediterranean region, central North America, Central America and Mexico, and northeastern Brazil (Seneviratne et al. 2012).

Against that background, we investigate whether droughts influence public sector corruption within a unified estimation approach on an unbalanced panel of 120 countries from 1985 to 2013. To analyze potential long-term consequences, we estimate the cumulative effects of droughts on corruption over long time horizons of up to 20 years. In order to avoid an overcontrolling problem (Dell et al. 2014), we estimate a two-way fixed-effects model with heteroscedasticity and autocorrelation (HAC)-corrected standard errors. Because droughts often extend over large geographic areas, we further correct our estimated standard errors for spatial autocorrelation. Our estimation results rely on the Standardized Precipitation Index (SPI), a truly exogenous drought index based on precipitation deficiencies. We show that high levels of drought exposure are followed by corresponding increases in public sector corruption. The effect holds true for subsamples of both developing and developed countries, although the timing and intensity may vary. After conducting a variety of stability tests, we find initial evidence for possible transmission paths of drought-induced corruption.

The paper is organized as follows. The second section provides a review of the related literature. The third section explains the estimation strategy, and Sect. 4 describes the data used in our analysis. In Sect. 5, we present our estimation results and test their stability. In addition, we offer initial evidence on the transmission paths of drought-induced corruption. Lastly, Sect. 6 summarizes and concludes the paper.

## 2 Related literature

Empirical research on the effects of natural disasters on corruption started only recently.<sup>2</sup> Given a limited number of existing papers, we present each before drawing conclusions that shape the research efforts of the present study.

The seminal paper of Leeson and Sobel (2008) examines the corruption impact of natural disasters. They study whether relief payments dispersed by the Federal Emergency Management Agency (FEMA) following natural disasters from 1990 to 1999 increased corruption-related criminal convictions in US states. Their two-way fixed-effects regressions show that an additional \$100 relief payment per capita increased average corruption at the state level by just over 100% when considering its total effect during the 3 years after disbursement.

Nguyen (2017) asks whether natural disasters create “a window of opportunity for corruption.” He answers that question using survey data from 2002, 2004, 2006 and 2008 on 27,050 rural Vietnamese households in 2984 communities.<sup>3</sup> He finds that while natural disasters occurring in the 3 years prior to each survey reduced the incomes of official<sup>4</sup> and non-official households equally, the same was not true for their expenditures. Whereas the consumption spending of non-official households was reduced significantly by natural disasters, official households exhibited almost no change in spending. That gap could not be explained by different coping strategies (e.g., remittances or migration) of the two household types; therefore, unreported income pointing to the existence of corruption was suspected.

Nikolova and Marinov (2017) concentrate on flooding in 227 Bulgarian municipalities caused by several torrential rainfall events from 2004 to 2005. The authors analyze the consequences of governmental disaster-related relief payments on local corruption. They find that spending “infringements”<sup>5</sup> increase sizably in the wake of the flood-related transfers initiated by the central Bulgarian government. To ensure exogeneity of the measure of locally distributed funds in their cross-sectional regression approach, the authors instrument total flood-related assistance with a measure of high monthly precipitation.<sup>6</sup>

Yamamura (2014) conducts the first international study of the impact of natural disasters on corruption. Interpreting panel estimates for 84 countries from 1990 to 2010, the author finds that the 1- and 2-year lagged number of natural disasters, reported by the Emergency Database (EM-DAT), increases the national corruption level significantly, as measured by the corruption perception index of the International Country Risk Guide (ICRG). An additional analysis of floods, storms, earthquakes, volcanic eruptions and landslides delivers effects with varying coefficient signs and significance depending on disaster type and level

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<sup>2</sup> In a broader sense, research on the consequences of disaster-related corruption shares some similarities with the comprehensive literature on the effects of natural resource windfalls (e.g., Brollo et al. 2013) and aid payments (e.g., Knack 2001; Djankov et al. 2008) on corruption.

<sup>3</sup> Nguyen (2017) relies on data from the Vietnam Living Standards Survey (VLSS)—a survey implemented at the highest World Bank standards.

<sup>4</sup> A household is classified as “official” if at least one household member works for the local government (Nguyen 2017).

<sup>5</sup> Spending infringements are identified by the Bulgarian National Audit Agency (BNAA) and include (1) irregularities in bidding processes, (2) repair payments for undamaged buildings and (3) money paid for work not performed.

<sup>6</sup> Nikolova and Marinov (2017) define flood events between 2004 and 2005 as months in which the percentage change in rainfall, relative to a monthly historical average, equals or exceeds 30%.

of economic development. Compared to estimation results for non-OECD [Organisation for Economic Co-operation and Development] countries, Yamamura (2014) finds a considerably larger effect of natural disasters on corruption in OECD countries. The effect for floods in particular is sizable.

Escaleras and Register (2016) follow a similar approach, diverging from Yamamura (2014) by adopting a long-term perspective. Their panel tobit regression on a sample of 75 countries from 1984 to 2009 reveals that the total number of natural disasters (floods, storms and earthquakes reported by EM-DAT) from three prior years (5, 10 or 25 years before) raises the level of corruption (ICRG) significantly. That result remains stable when the regression is repeated with Transparency International's (TPI's) corruption measure for the period 1996–2009. Escaleras and Register's finding of a long-term disaster-related increase in corruption is robust in a disaggregated analysis of floods and storms, while the effects of earthquakes are insignificant.

Rahman et al. (2017) examine the impact of extreme precipitation events on the level of corruption (ICRG) in 130 countries during the period 1984–2009. Overall, they do not find a direct effect of their measure of extreme rainfall on corruption. However, when first explaining total flood-affected persons (the data were taken from the EM-DAT database) by extreme precipitation and then regressing corruption on the number of flood-affected individuals, the authors find a strong significant contemporary effect.

Our review of the related literature allows us to draw three conclusions for our own research design.

First, while four studies of floods find that they raise the level of corruption (Nikolova and Marinov 2017; Yamamura 2014; Escaleras and Register 2016; Rahman et al. 2017), somewhat surprisingly the case of droughts has up to now been neglected.

Second, five out of the six reviewed studies analyze only contemporary or short-term disaster-related corruption effects. The only exception in that respect is the analysis of Escaleras and Register (2016), which covers at least the three-year perspective. While focusing on the short term might be appropriate when studying sudden-onset disasters such as storms, long-term studies are more appropriate when analyzing the effects of slow-onset disasters such as droughts. Moreover, the long-run perspective is more relevant for the country's later development.

Third, the use of truly exogenous measures of natural disaster occurrence and severity seems to be an important issue.<sup>7</sup> Escaleras and Register (2016) explicitly refrain from using estimated damage or the total number of affected persons as disaster measures in favor of the less endogenous number of disasters. The argument behind doing so is that low levels of corruption (Anbarci et al. 2005) and good institutions of governance (Raschky 2008; Noy 2009) mitigate or even prevent natural hazards from becoming natural disasters, by reducing the number of deaths, affected persons or economic damage. However, the number of disasters reported by EM-DAT may also be at least partly endogenous, as the criteria for entering the database rely on the number of deaths, affected persons or an announced state of emergency (CRED 2018).<sup>8</sup> In addition, by simply counting the number

<sup>7</sup> Similar efforts can be observed in other strands of the disaster literature. For example, see Felbermayr and Gröschl (2014) and Berlemann and Wenzel (2018) for economic growth studies, as well as Smirnov et al. (2018) for disaster-related consequences for the survival of political leaders.

<sup>8</sup> A disaster is entered in EM-DAT if one of the following criteria is fulfilled: (1) ten or more people reported killed, (2) 100 or more people reported affected, (3) declaration of a state of emergency or (4) call for international assistance (CRED 2018).

of droughts, information on the severity of the recorded events is neglected. Therefore, both Nikolova and Marinov (2017) and Rahman et al. (2017) use truly exogenous precipitation measures to instrument flood consequences.

### 3 Estimation approach

In order to study whether and how droughts affect corruption, we apply a two-step estimation approach. In the first step, we examine whether droughts have an impact on corruption. In the second step, we focus on uncovering the likely transmission channels.

#### 3.1 Impact of droughts on corruption

In the first step, we focus on the general effect of droughts on corruption. Earlier papers examining the corruption effects of natural disasters (Yamamura 2014; Escaleras and Register 2016) refer to the literature studying the causes and determinants of corruption (Treisman 2000; Pellegrini and Gerlagh 2008). Typically, those studies explain the level of corruption with a set of standard control variables and add the number of natural disasters to the estimation equation. However, one might argue that the occurrence of natural disasters should primarily affect changes in the corruption level.<sup>9</sup> As an example, Knack (2001) employs the change in the corruption index as the dependent variable to assess the impact of foreign aid on corruption. That approach has two implications. First, invariant or slowly evolving determinants of corruption, e.g., roots of the existing legal system, colonial heritage, ethnic fractionalization or religious traditions (Treisman 2000; La Porta et al. 1999), are unlikely to be statistically significant (Knack 2001). Second, using the change in corruption as the dependent variable allows for a standard fixed-effects estimation, since the censored characteristic of the left-hand variable no longer is a concern. We follow that approach and employ the annual change in ICRG's corruption index as dependent variable in our study.

Another important aspect of the estimation approach is the choice of independent variables. The estimation controls should be chosen in order to avoid the well documented "over-controlling problem"<sup>10</sup> (Dell et al. 2014), which arises when endogenous control variables are included in the estimation equation. For example, when employing growth in GDP per capita or population as controls in our regression approach (see, e.g., Knack 2001), both might be endogenous to droughts (Berlemann and Wenzel 2016). The inclusion of those variables in the estimation equation likely will lead to downward-biased or insignificant coefficients on the drought variable, because at least part of the drought's effects on corruption are already captured by the coefficients on GDP per capita or population growth. Additional control variables likewise may be endogenous to disaster effects (e.g., democracy; see Rahman et al. 2017). In order to capture the true net effect of drought-induced corruption, the most reliable approach is to conduct a two-way fixed-effects panel estimation excluding possibly endogenous time-variant controls in our baseline analysis.

<sup>9</sup> North (1990) includes natural disasters alongside wars, revolutions and conquests among the "sources of discontinuous institutional change."

<sup>10</sup> Dell et al. (2014) discuss the over-controlling problem in depth as it pertains to the climate-economy literature.

However, following the proposal of Auffhammer et al. (2013), we enter annual standardized temperature anomalies (STA)<sup>11</sup> as an explanatory variable accounting for pure temperature effects on corruption in the estimation equation. In stability tests, we add further standard control variables.

As discussed earlier, the estimation approach should allow for an evaluation of the long-term effects of droughts. Therefore, we simultaneously include several lags of the drought measure in the estimation equation. Cumulating the estimated contemporaneous and lagged effects of a drought over the time horizon of interest allows us to measure the full impact a drought has on corruption.

Summing up, our estimation equation for the first step of our analysis reads

$$C_{i,t} - C_{i,t-1} = \alpha_i + \beta_t + \sum_{l=0}^L (\gamma_l \cdot D_{i,t-l}) + \sum_{l=0}^L (\delta_l \cdot T_{i,t-l}) + \varepsilon_{i,t}, \quad (1)$$

with  $\alpha$  being country fixed effects,  $\beta$  being time fixed effects,  $D$  being the drought measure and  $T$  being the temperature variable. The maximal number of years that drought (and temperature) can influence future corruption is denoted by  $L$ . We calculate the cumulative effect of a drought on the change in corruption as

$$\Gamma_{cum,L} = \sum_{l=0}^L \gamma_l. \quad (2)$$

The corresponding standard error for the cumulative coefficient is computed as

$$SE_{cum,Spatial-HAC} = \sqrt{\sum (w^T \times VAR_{Spatial-HAC}(\gamma) \cdot w)}, \quad (3)$$

where  $w$  is a weighting vector.<sup>12</sup> We calculate the variance–covariance matrix (VAR) correcting for HAC<sup>13</sup> (Newey and West 1987) as well as spatial correlation of the residual values<sup>14</sup> (Conley 1999).

Yamamura (2014) and Escaleras and Register (2016) evaluate the corruption effects of natural disasters for both developing and developed countries and obtain differing results for those country groups. Yamamura (2014) finds the effects of natural disasters on corruption to be considerably larger in OECD countries than in non-OECD countries, while Escaleras and Register (2016) detect larger effects in their sample of developing countries. To study whether the relationship between droughts and the change in corruption depends on the level of economic development, we construct subsamples according to the World Development Indicators (WDI) income classifications.<sup>15</sup> Low-, lower-middle- and

<sup>11</sup> The STA is calculated as the deviation in the annual average temperature from its long-term mean divided by its long-term standard deviation. Temperature data in degrees Celsius also are available in the CRU CY 3.22 data set.

<sup>12</sup> We use equal weights.

<sup>13</sup> Standard errors are corrected for autocorrelation up to 10 years.

<sup>14</sup> We apply an adapted version of the Conley procedure, proposed by Fetzter (2015), correcting spatial correlations up to a distance of 1000 km from the center of a country. Data on longitudes and latitudes of countries' centers are taken from the Central Intelligence Agency's *World Factbook* (CIA 2015).

<sup>15</sup> The countries are grouped by their World Bank classification in the first year they appear in the World Bank data set. If classification changes occur within the first 3 years, the predominant classification in those years is used.



upper-middle-income countries are pooled together to the first subsample of 92 developing countries, while high-income countries comprise the second subsample of 28 developed countries. We then estimate the empirical model described earlier for these subsamples.

Subsequently, we conduct a variety of stability tests to investigate the robustness of our findings. Details on the tests are presented in Sect. 5.

### 3.2 Transmission channels

The second step of our estimation strategy aims at revealing possible transmission channels. To this end, we derive a macroeconomically testable transmission hypothesis from Klitgaard's (1988) corruption formula

$$\text{Degree of Corruption} = \text{Monopoly} + \text{Discretion} - \text{Accountability} \quad (4)$$

Droughts likely influence the first two determinants of corruption risk: monopoly and discretion. In particular, they may increase aid inflows or encourage the local government to finance disaster relief payments (Shughart 2011). Public officials are actively involved in the targeting and distribution of such funds, which is often characterized by monopolistic supply structures and discretionary power of individuals (Ewins et al. 2006). Furthermore, accountability and transparency of public agencies may be reduced owing to a drought, as governments are likely to become more autocratic in the aftermath of disasters (Rahman et al. 2017), and a concurrent atmosphere of disorder may arise. Those considerations lead to the following transmission hypotheses.

#### 3.2.1 Transmission hypothesis

Droughts have an effect on four factors which determine the degree of corruption: they increase aid inflows and government spending, and they lower democratic accountability and create an atmosphere of disorder.

We test the hypothesis for each transmission factor ( $TF$ ),<sup>16</sup> applying the two-way fixed-effects estimation approach we adopted already in step 1 of our empirical analysis

$$TF_{i,t} - TF_{i,t-1} = \alpha_i + \beta_t + \sum_{l=0}^L (\gamma_l \cdot D_{i,t-l}) + \sum_{l=0}^L (\delta_l \cdot T_{i,t-l}) + \varepsilon_{i,t}. \quad (5)$$

We then calculate the cumulative effect of a drought on the specific transmission factor as

$$\Lambda_{cum,L} = \sum_{l=0}^L \gamma_l. \quad (6)$$

Each step of our baseline estimation strategy is conducted with the same data sample to ensure consistent and comparable results.

<sup>16</sup> Because transmission through “received aid” is not characterized by time persistence like the level of corruption or the level of democratic accountability, as an exception to Eq. 5, we enter the level instead of the difference in received aid as the dependent variable.

## 4 Data

In the following, we explain the data we employed in our empirical analysis. Basically, we need data on droughts, corruption indicators and additionally macroeconomic data.

### 4.1 Drought data

In order to rely on a truly exogenous measure characterizing the occurrence and severity of droughts, we utilize an index based on meteorological data. In general, drought indices are quantitative measures describing droughts by assimilating information on precipitation (or, if appropriate, other variables) into a single numerical value (Zargar et al. 2011). For our study, an index with global coverage and international comparability is required. Both items are fulfilled by the SPI, developed by McKee et al. (1993). First, the computation of the SPI is based solely on globally available precipitation information from several rainfall data sets. We base our study on monthly area-weighted<sup>17</sup> country means of precipitation. The data are available for the period 1901–2013 from one of the world’s most prominent sources, the CRU CY 3.22 data set published by the Climate Research Unit of the University of East Anglia (Harris and Jones 2014).<sup>18</sup> Second, the calculation of the SPI ensures comparability across different locations and climate zones, as it transforms the distribution of each precipitation record into a standard normal distribution with a mean of zero. Therefore, negative values of the SPI indicate relatively dry periods, while positive values point to excessively wet periods. An SPI value can be interpreted as the number of standard deviations by which precipitation diverges from its normalized average (Zargar et al. 2011).

In our application, we calculate the SPI over the preceding 12 months. We opted for that time horizon to account for long-term precipitation patterns related to river stream flows as well as reservoir and groundwater levels, both of which are important factors in water-dependent production and irrigation systems.

Our drought measure follows the drought definition developed by McKee et al. (1993), which defines drought as “a period in which the [monthly] SPI is continuously negative, and the SPI reaches a value of  $-1.0$  or less.” In order to calculate our drought measure, which we refer to as “Drought SPI” in the following, we first check whether each sample month qualifies as belonging to a drought according to McKee et al.’s definition. We calculate the modulus of the annual sum of all 12-month SPI values being part of drought for each country. The SPI’s values for all months that do not qualify as drought are set to zero. Compared to the number of droughts recorded by EM-DAT, our Drought SPI captures not only the frequency but also the severity of droughts and is exogenous to the corruption level and the institutional conditions of the sample countries.

Figure 1 maps the mean of the Drought SPI for all analyzed countries from 1965 to 2013. As we enter the drought measure with up to 20 lags in our estimation approach, the

<sup>17</sup> In order to construct internationally comparable data, either area weights or population weights are used. Our study relies on the former, as agriculture is likely a major sector in which drought-induced corruption takes place.

<sup>18</sup> The CRU CY 3.22 precipitation time series is derived from the CRU Time Series (TS) gridded data set, which collects meteorological station observations covering the Earth’s land surface (except for Antarctica) to obtain 0.5-degree latitude–longitude grid cell data. For more details on the series, see Harris and Jones (2014).

sample comprises all years in the baseline estimations.<sup>19</sup> The color categories refer to eight quartiles of the Drought SPI's mean. Countries with high Drought SPI means are located in Africa and in the equatorial regions.

## 4.2 Corruption data

Measuring corruption is a rather challenging task (Banerjee et al. 2012). The very nature of the corruption phenomenon, being illicit and secretive, necessitates great effort to conceal it rather than affording the opportunity to quantify it accurately. Therefore, most attempts to deliver consistent measures of corruption across countries rely on the perceptions of individuals or experts. Although subjective measures have their limitations, they are the most viable tools for cross-country analysis (Banerjee et al. 2012).

We rely on data from the ICRG rating, published by the PRS Group, to assess corruption within the political system (ICRG 2017). The ICRG's corruption measure is based on experts' perceptions of different forms of corruption, among them special payments, bribes, nepotism and patronage. The data are available for a comparably broad sample of 140 countries over the period 1984–2016. The original scoring of the ICRG index ranges from 0 (indicating the highest corruption risk) to 6 (lowest possible risk).<sup>20</sup> To simplify the interpretation of the estimation results, we invert the scale in the subsequent analysis, with 0 denoting low and 6 high corruption risk.

Based on a comparison of the average corruption level of all 120 sample countries from 1984 to 2013, North America and most parts of Europe are characterized by low corruption. Canada, Denmark and Finland show the lowest average levels of corruption (0.03, 0.22 and 0.31 index points, respectively). In contrast, countries such as Armenia, Azerbaijan and Bangladesh exhibit average corruption levels of 5.33, 4.71 and 5.33, respectively.

However, a different picture emerges when we evaluate the development of corruption over time. Figure 2 shows the average annual change in the ICRG corruption index from 1985 to 2013<sup>21</sup> for all sample countries. Some countries, such as Bangladesh and Chile, reduced their corruption levels, whereas the United States and European countries (including France, Italy and the United Kingdom) experienced increasing levels. In addition, Fig. 2 points to the considerable rise of corruption in most of the former Warsaw Pact states.

## 4.3 Other institutional and macroeconomic data

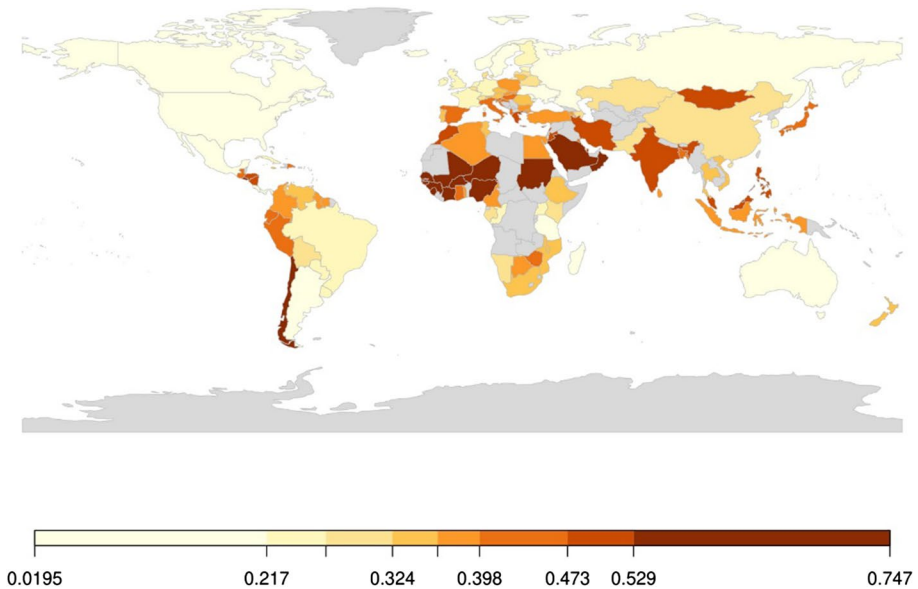
Testing our transmission hypotheses requires appropriate measures of the candidate transmission factors affecting the determinants of corruption. Global data sources for drought relief in the form of foreign aid or as government spending are unavailable. Therefore, we approximate the variables of interest with more general measures.<sup>22</sup> Specifically, we enter

<sup>19</sup> ICRG data for computing changes are not available prior to 1985; however, as the drought measure enters the estimation equation with up to a 20-year lag, the drought data in our sample contain observations from 1965 on.

<sup>20</sup> Theoretically, every value within the two bounds can be achieved (not only integers), which allows us to handle the measure as a continuous variable.

<sup>21</sup> Annual changes can be calculated the first time for the year 1985.

<sup>22</sup> The limited global availability of appropriate data emphasizes the need for microeconomic or regional analyses to shed further light on the transmission channels of drought-induced corruption.



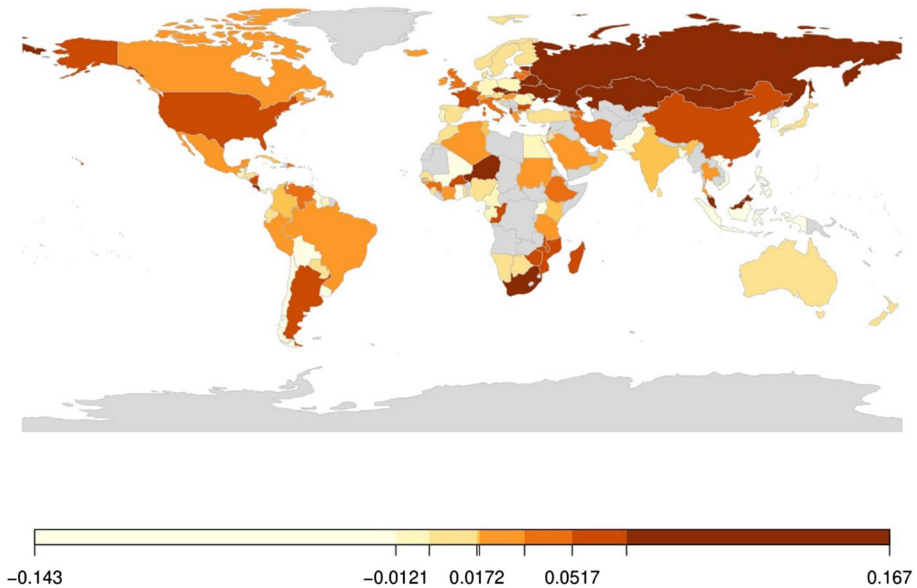
**Fig. 1** Country mean of Drought SPI (1965–2013), eight quantiles; data source: CRU CY 3.22

(i) received per capita net official development assistance and official aid to approximate foreign drought aid (WDI 2019) and (ii) the change in the share of government consumption (WDI 2016) to account for governmental drought relief payments, although admittedly drought relief constitutes only a small portion of those two variables. We measure the extent to which droughts affect the accountability and transparency of public officials' behavior by means of three ICRG indices: political risk associated with (1) democratic accountability, (2) law and order and (3) internal conflict. Table 1 summarizes the measures and data sources for the transmission channels examined.

To conduct our stability tests, we enter additional climatic and macroeconomic data. We discuss the empirical measures in Subsection 5.2. A summary of all data sources and summary statistics can be found in “Appendices 1 and 2”.

Considering all necessary climatic, institutional and macroeconomic data, we end up with an unbalanced panel of 120 countries for the period 1985–2013 in our baseline estimations.<sup>23</sup> Because the climate variables are included in the estimation equation with up to 20 lags, our sample comprises observations of climatic measures from 1965 on.

<sup>23</sup> However, when estimating our baseline regressions with all 136 countries for which we have ICRG and climate data, the results remain nearly unchanged. The results are available from the author upon request.



**Fig. 2** Country averages of corruption change (1985–2013); eight quantiles; data source: ICRG (2017)

## 5 Estimation results

In this section, we present the results of estimating the two-way fixed-effects model. Unit root tests indicate that the left-hand variables, drought measures and other control variables are stationary.<sup>24</sup> Thus, the results presented do not suffer from spurious regression problems.

Instead of reporting the full estimation results for every model, we offer a graphical representation of the estimated cumulative coefficients of the Drought SPI and the corresponding 90% confidence intervals (based on HAC standard errors).<sup>25</sup> Coefficients differing significantly from zero at the 90% confidence level are marked in color, whereas insignificant coefficients are shown in gray. The graphs depict the standardized cumulative coefficients of the drought measure for up to 20 lags.

### 5.1 Baseline results

#### 5.1.1 Full sample and economic development subsamples

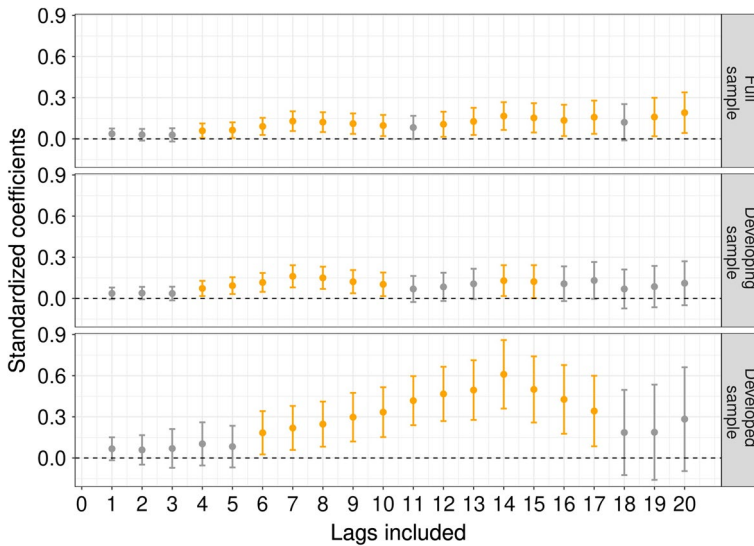
The starting point for our analysis is how the Drought SPI affects the change in corruption for the full sample of 120 countries. The overall positive signs of the estimated cumulative coefficients in the upper part of Fig. 3 indicate that corruption increases with a rising Drought SPI. In the short term, the cumulative coefficients are not significantly different

<sup>24</sup> The results of the unit root tests are reported in “Appendix 3”.

<sup>25</sup> Graphical representations of the stability test results are available from the author upon request.

**Table 1** Transmission factors and data sources

Determinants of corruption	Related transmission factor	Approximative measures	References
Monopoly + Discretion	Foreign disaster aid	Net official development assistance and official aid received (in constant 2015 US\$), per capita	WDI (2019)
Accountability	Government drought relief payments	Share of government consumption at current PPPs (change)	WDI (2016)
	Autocratic disaster management	Risk arising from democratic accountability (change)	ICRG (2017)
	Environment of disorder	Risk from law and order (change)	ICRG (2017)
		Risk from internal conflicts (change)	ICRG (2017)
<i>PPP purchasing power parity</i>			



**Fig. 3** Cumulative effects of Drought SPI on *corruption change*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)

from zero at conventional levels of significance. However, in the medium and long run, droughts have a significant impact on corruption. Cumulating the effects of the Drought SPI over four or more years leads to a significant increase in corruption in the full sample. The standardized cumulative coefficient at 20 lags of the Drought SPI amounts to 0.101. Thus, after 20 years, a one-standard-deviation increase in the drought measure results in a  $0.101 \times 0.345 = 0.035$ -point larger drought-related increase in the ICRG corruption index. Because the mean change in corruption in our sample is 0.024, the effect is sizable.

The sample countries are characterized by markedly different levels of development; therefore, we ask whether the detected effect of droughts on the increase in corruption differs depending on a country's level of development. The middle and lower parts of Fig. 3 display the estimation results for the developing and developed subsamples, respectively. Both subsamples show a significant, positive effect of the Drought SPI on corruption, yet with different timings and intensities. Within the developing subsample, the change in corruption is significantly larger in response to the cumulative effect of four up to ten as well as 14 and 15 lags of our drought measure. However, the corruption-increasing effect of severely drought-prone years becomes insignificant in the long term. In the developed-country subsample, larger Drought SPI values increase corruption in the medium and the long term. The cumulative coefficients of six up to 17 lags of our drought measure are significantly different from zero at the 10% level. The effects of drought on corruption in developed countries are comparatively large. The standardized cumulative coefficient at 14 lags of the Drought SPI is 0.342, indicating a 0.118-point larger change in corruption from a one-standard-deviation rise in the drought measure. That large effect in developed countries does not come as a surprise, as corruption is expected to rise more with lower initial levels of corruption (Knack 2001; Savoia and Sen 2016). Another explanation for the difference in timing and size of drought impacts in the two subsamples is that developed countries typically possess well-established and reliable water resource management systems (Grey and Sadoff 2007). Therefore, developed countries are comparably better equipped

to mitigate and overcome water supply shocks in the short term, while drought impacts in developing countries might be more severe. At the same time, corruption in developed countries seems to become more established in the medium term but with greater persistence and intensity. That effect could be triggered by drought relief payments, which may be more readily available and also more generous in developed countries. We shed some further light on the issue in the analysis of transmission channels, later in this section.

## 5.2 Stability tests

We conduct a variety of stability tests to investigate the robustness of our findings: we enter standard control variables in our baseline estimations and vary the applied (1) corruption measure, (2) drought measure and (3) country sample.

Although we refrained from entering standard control variables in our baseline estimations to avoid the over-controlling problem, one might be interested in the results we find when considering common control variables. As a first stability test, we control for the initial level of ICRG corruption risk (ICRG 2017) as well as the growth rates of GDP per capita and population, as proposed by Knack (2001). Furthermore, we include natural resource rents as shares of GDP and net official development assistance and official aid received<sup>26</sup> (WDI 2019) in our estimation equation to address the “resource curse” (Brollo et al. 2013) and the “aid curse” (Djankov et al. 2008) scenarios. Both “curses” raise the prevalence of corrupt behavior by opening manifold opportunities for rent-seeking behavior (Brollo et al. 2013; Djankov et al. 2008; Knack 2001). To control for common factors lowering the risk of corruption, we also add the change in the share of the Protestant population taken from the Association of Religion Data Archives (ARDA) (ARDA 2018), as well as changes in ICRG measures of democratic accountability and law and order (Aidt 2011; ICRG 2017). To account for government size and government spending (Dimant and Tosato 2017), we control for the change in government consumption (WDI 2016). In addition, we control for internal conflicts and enter the change in the ICRG internal conflict risk index (ICRG 2017) in our estimation equation. All control variables enter our estimation equation with a 1-year lag. Including the previous year’s level of corruption—which is most likely influenced by lags of the Drought SPI of the preceding two or more years—and other potentially endogenous control variables in the estimation equation should lead to less pronounced and significant effects of the drought measure on corruption. In fact, we find such an effect in the medium term in both the full sample and the developed subsample. In our estimations with control variables, corruption-increasing effects of the Drought SPI remain significant only over extended time horizons of 12 years or more.

As a second stability test, we ask whether our baseline results are robust to a different measure of public sector corruption and a considerably longer estimation period. Owing to its comprehensive sample and comparability over time, the ICRG corruption index is a standard measure of public sector corruption in empirical studies based on panel estimations.<sup>27</sup> All international studies of disaster-induced corruption presented in Sect. 2 rely on that measure (Yamamura 2014; Escaleras and Register 2016; Rahman et al. 2017). However, the recent Varieties of Democracy (V-Dem) initiative provides a large database of

<sup>26</sup> Most developed countries do not receive official development assistance. Therefore, we replace missing values for these countries with zero when conducting the stability test to avoid a sample reduction.

<sup>27</sup> The well-known Corruption Perception Index of Transparency International (TPI) is not appropriate for time series analyses prior to 2012 (TPI 2017).



social science indicators with worldwide coverage starting as early as 1900. The database also contains an index of public sector corruption (McMann et al. 2016).<sup>28</sup> We first estimate the effect of the Drought SPI on the change in V-Dem public sector corruption for the 120 countries in our baseline sample from 1901 to 2013. We find positive cumulative coefficients for the Drought SPI particularly in the full sample and the developing subsample; however, none are different from zero at conventional levels of significance. That finding might be explained by the possibility that the relevant transmission channels on which our baseline results rest are not stable over more than a century. We therefore repeat the estimations for the period 1950–2013, thus restricting the sample to the likely more homogeneous period after World War II. The results generally confirm the evidence of drought-induced increases in public sector corruption. In particular, the findings for the developing countries differ only marginally from our baseline results. In the developed country subsample, the positive cumulative coefficients on the Drought SPI are significantly different from zero in the long term, when cumulating the effects of 12 and more lags of the drought measure.

Furthermore, we consider two different variations of our drought measure. First, we ask whether and how our estimation results change when using the number of droughts reported in EM-DAT to measure the occurrence of droughts (CRED 2018).<sup>29</sup> While that measure is problematic, as discussed earlier, comparable studies analyzing the effects of natural disasters on corruption typically rely on the number of disasters reported in EM-DAT (Yamamura 2014; Escaleras and Register 2016). When estimating with the EM-DAT drought numbers, the results for the full sample and the developing subsample do not differ markedly. In both samples, higher drought exposure leads to increased corruption in the medium term. Positive significant effects of droughts on corruption change endure over very extended time horizons. However, the results for the developed country subsample clearly differ; here we find that additional droughts lead to a significant reduction in corruption in the short and medium term and have no long-term effects. The first explanation for the differences is the potential endogeneity of the EM-DAT drought number. An identical meteorological drought might fulfill EM-DAT's admission criteria thresholds, depending on deaths, the total number of affected persons, a declaration of a state of emergency or a call for international assistance, far earlier in the more vulnerable developing countries than in developed countries. Therefore, the EM-DAT drought number might over-report droughts in developing countries. Second, the number of droughts in developing countries might be overstated in order to obtain international aid (Albala-Bertrand 1993; Skidmore and Toya 2002). Third, it should be noted that the EM-DAT drought numbers do not provide information about the severity of the reported droughts. The lack of such information may help to explain the significant negative cumulative coefficients we find in the developed subsample.

As a second variation of our drought measure, we employ an extended drought index considering potential evapotranspiration (PET) being a further determinant of drought severity. Based on the SPI relied on herein, Vicente-Serrano et al. (2010) developed the

<sup>28</sup> Although V-Dem's public sector corruption index comprises interval data (McMann et al. 2016), asymptotic considerations associated with the large data sample allow for incorporating it into our two-way fixed-effects regression approach.

<sup>29</sup> We normalize the reported number of droughts for the different sizes of countries by dividing it by the land areas of the countries (in million sq. km) derived from the WDI database (WDI 2016).

Standardized Precipitation Evapotranspiration Index (SPEI). It also incorporates water demand associated with temperature increases, which is a particularly relevant feature for studying future drought severity in an environment marked by climate change (Vicente-Serrano et al. 2010). We calculate the Drought SPEI analogously to the Drought SPI measure described in Sect. 4 and repeat all estimations. The PET data were taken from the CRU CY 3.22 data set (Harris and Jones 2014).<sup>30</sup> The estimation results largely remain stable when the Drought SPEI is adopted as a measure of drought occurrence and severity in the estimation approach.<sup>31</sup> However, we see less significant long-term effects on corruption in both the full sample and the developing subsample.

Finally, we vary the country sample our estimations rely on. In the post-Cold War era, former Warsaw Pact states<sup>32</sup> experienced deep institutional transformations (Savoia and Sen 2016), affecting the perceived corruption in that country group. After a sharp decline in the average change in corruption during the early 1990s, corruption increased dramatically until 2002. Recognizing the variations in corruption in the former Warsaw Pact states raises the question of whether our estimation results are driven by developments in those countries. Therefore, we re-estimated all models excluding the 16 former Warsaw Pact states from our sample. Evidence of drought-induced corruption increased as a result of the sample change, especially in the short term for the developing country subsample.

### 5.3 Transmission channels

After presenting robust evidence for drought-induced corruption, this subsection delivers some insights into possible transmission channels.<sup>33</sup> According to our transmission hypotheses stated in Sect. 3, we ask whether droughts affect transmission factors influencing the determinants of corruption risk.

#### 5.3.1 Monopoly and discretion

Droughts may affect the determinants of corruption related to monopoly and governmental discretion in providing drought relief, which may be available in the form of foreign aid or domestic public spending. That transmission channel plays a central role in most disaster-corruption studies (Leeson and Sobel 2008; Nikolova and Marinov 2017). However, a separate analysis is advisable because of two characteristics of drought that differ from those of other natural disasters. First, the slow onset of droughts may allow for better preparation and planning of relief measures. That might lower the risk of corruption; however, at the

<sup>30</sup> PET values refer to the theoretical evaporative demand of the atmosphere calculated for a reference surface.

<sup>31</sup> It should be discussed whether it is appropriate to include Drought SPEI together with a temperature control in the estimation equation, since temperature is a main determinant of PET. However, when estimating without a temperature control, the results remain nearly unchanged. The results are available from the author upon request.

<sup>32</sup> The former Warsaw Pact states include Armenia, Azerbaijan, Belarus, Bulgaria, Czech Republic, Estonia, Hungary, Kazakhstan, Latvia, Lithuania, Poland, Republic of Moldova, Romania, Russian Federation, Slovakia and Ukraine.

<sup>33</sup> In general, droughts may increase corruption through channels that are not amenable to macroeconomic analysis. Scarce water availability may lead directly to acts of corruption, e.g., when competing for irrigation water (Wade 1982), which underscores the need for microeconomic analyses of drought-induced corruption.

same time, droughts might offer time to develop efficient corruption schemes (Ewins et al. 2006). Second, because droughts typically span longer time horizons, established corruption schemes are repeatable and defense mechanisms can be developed (Ewins et al. 2006).

Figure 4 shows that an increase in the Drought SPI significantly increases per capita development assistance and official aid received in the full and developing country subsample after three and more lags. In the developed country subsample, we find no significant influence of the Drought SPI on received aid, as external disaster aid should not be very relevant for developed countries.<sup>34</sup>

The results presented in Fig. 5 provide evidence that the second transmission factor, government spending, has an important influence in developed countries. In particular, we find that droughts lead to significant increases in government spending, especially in the short and medium terms in developed countries. We suggest that the effect is explained by taxpayer-financed drought relief payments, which typically are more generous and more readily available in developed countries.

### 5.3.2 Accountability and transparency

Droughts may increase corruption by reducing the accountability and transparency of the public sector's behavior. More autocratic governance—both during and in the aftermath of a drought—may ensure an efficient distribution of drought relief and avoid plunder and unrest in the disaster situation (Rahman et al. 2017).<sup>35</sup>

Figure 6 shows that a higher Drought SPI leads to significant short- and medium-term reductions in democratic accountability in the full sample and especially in the developing subsample.<sup>36</sup> In the developed country subsample, we find no significant effect of drought exposure on democratic accountability.

Furthermore, we find that droughts lead to an atmosphere of disorder by significantly weakening law and order in a country.<sup>37</sup> The results presented in Fig. 7 show that the effect is especially prevalent in the developing country subsample: the cumulative coefficients considering five or more lags of the Drought SPI are significantly different from zero at conventional levels of significance. In developed countries, we do not find any effects of droughts on law and order.

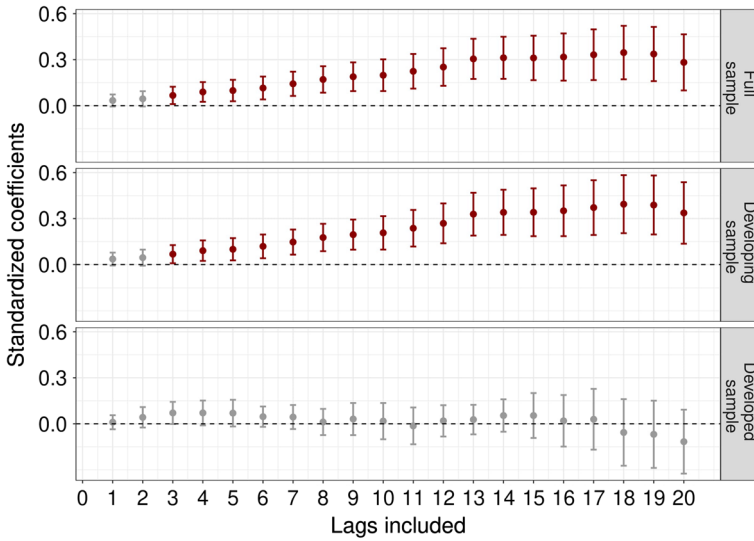
The risk of internal conflict may further contribute to an atmosphere of disorder. Figure 8 shows significant increases in the risk of internal conflict in the developing subsample when cumulating the effects of 13 or more lags of the Drought SPI. Because the effect clearly starts later than the drought-induced corruption effect found in our baseline estimations, internal conflicts do not seem to contribute to the atmosphere-of-disorder transmission factor. In developed countries, the risk of internal conflict declines significantly in the aftermath of a drought; that result might be explained by stronger social cohesion and solidarity in reaction to disasters in the developed subsample.

<sup>34</sup> In our aid estimations, the developed country subsample consists of seven countries. No other developed countries report information on net official development assistance and official aid received.

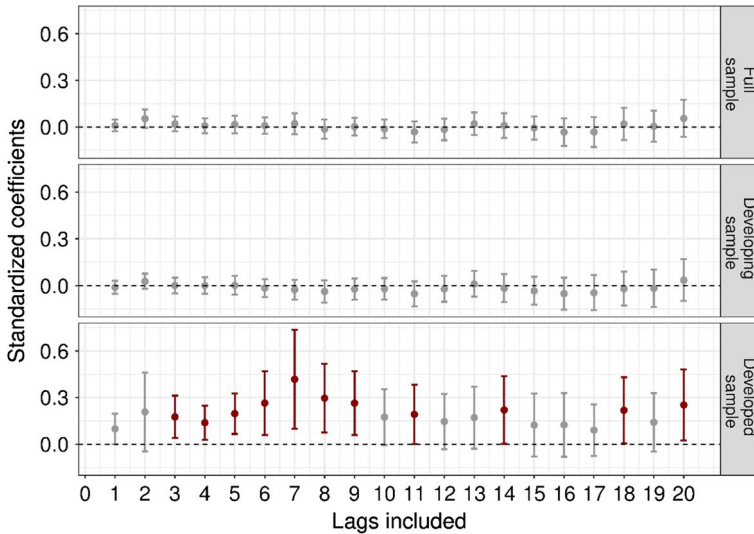
<sup>35</sup> Rahman et al. (2017) distinguish two opposing effects of floods on democracy: first, autocratic tendencies are strengthened by governmental repression to avoid plunder and to manage the relief distribution efficiently; second, greater democracy following revolts caused by citizens' dissatisfaction with disaster-induced corruption.

<sup>36</sup> A positive cumulative coefficient shows an increase in risk from less democratic accountability; we inverted the scale of the original ICRG democratic accountability measure.

<sup>37</sup> A positive cumulative coefficient shows an increase in risk from weaker law and order; we again inverted the scale of the original ICRG law and order index.

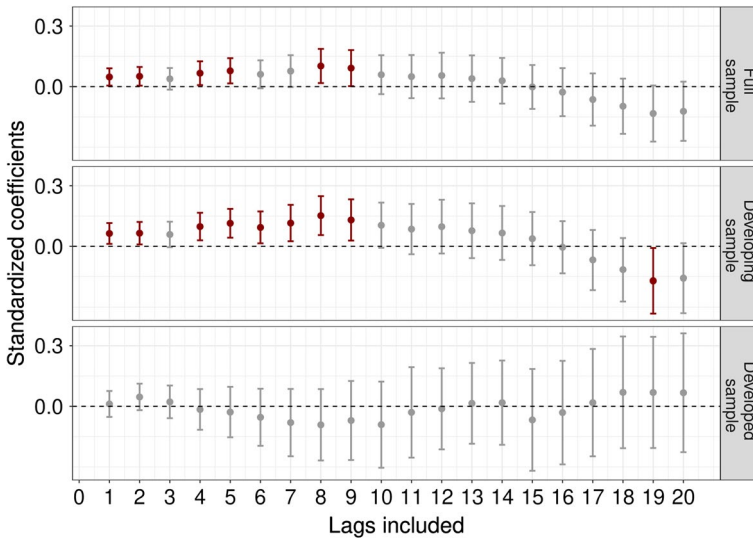


**Fig. 4** Cumulative effects of Drought SPI on *received aid*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)

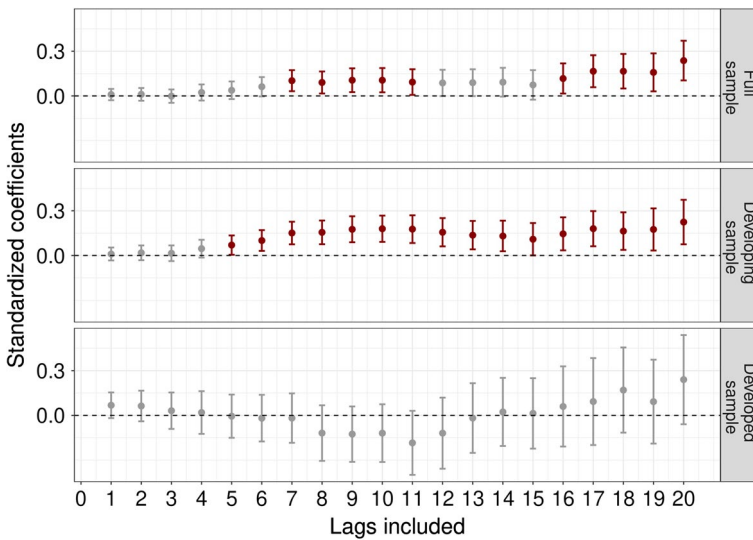


**Fig. 5** Cumulative effects of Drought SPI on *government consumption share change*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)

We conclude that droughts increase corruption risk in developing countries by triggering significantly larger aid inflows, less democratic accountability and deteriorating law and order. In developed countries, corruption rises as a consequence of governmental drought relief payments.



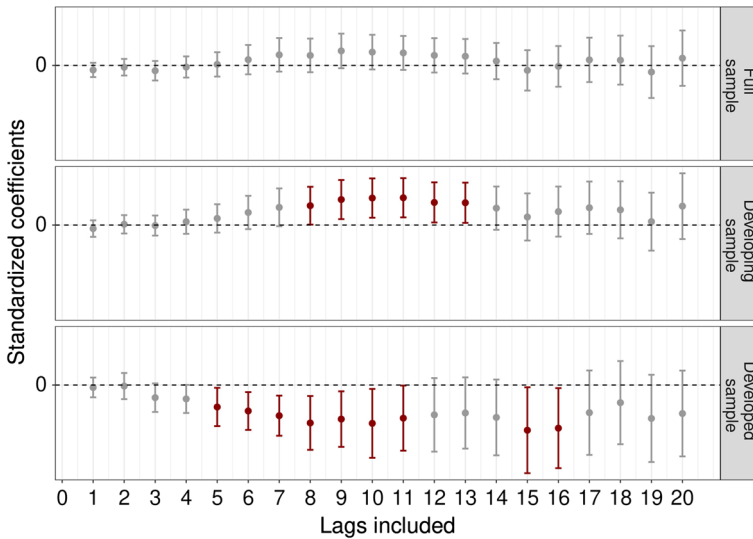
**Fig. 6** Cumulative effects of Drought SPI on *democratic accountability change*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)



**Fig. 7** Cumulative effects of Drought SPI on *law and order change*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)

## 6 Conclusions

The present paper provides a study of short-, medium- and long-term effects of droughts on public sector corruption on the basis of a panel analysis of 120 countries over the period 1985–2013. We rely on a truly exogenous measure of drought occurrence and severity,



**Fig. 8** Cumulative effects of Drought SPI on *internal conflict change*; full, developing and developed subsamples; point estimator and 90% confidence interval (1985–2013)

based on the Standardized Precipitation Index, and explicitly consider the over-controlling problem. Furthermore, we correct for spatial correlation of the regression residuals. Our estimation results for the full sample show that drought-prone countries experience more corruption in the medium and long terms. The effect holds for subsamples of developing and developed countries. In developing countries, a drought is followed by significant increases in corruption, especially in the medium term, whereas developed countries experience stronger and more long-term corruption increases. We test the robustness of the results in a variety of stability tests. In addition, we find evidence of transmission channels of drought-induced corruption that clearly differ depending on a country's level of development. In the developing subsample, droughts increase corruption risk by significant larger aid inflows, less democratic accountability and weaker maintenance of law and order. Drought-induced corruption in the developed subsample is caused by more government spending, which we suggest can be explained by more generous disaster relief payments.

The results of our analysis should encourage governments and institutions to review best practices for drought management. Drought relief measures that concentrate on post-disaster assistance facilitate corrupt behavior, as they are often uncoordinated (Wilhite et al. 2014) and characterized by the institutional incapability of public catastrophe responses (Shughart 2011). Instead, more proactive and self-reliant strategies could help to prevent drought-induced corruption. Such measures—including drought monitoring and early warning systems, preparedness plans and individual risk management—might mitigate or even avoid disastrous circumstances by increasing the nations' coping capacities to manage drought hazards. Furthermore, those strategies avert extensive post-impact relief windfalls provided by government and donor organizations (Sivakumar et al. 2014; Wilhite et al. 2014; Carrao et al. 2016, Shughart 2011).

Further research analyzing the transmission channels of drought-induced corruption based on subnational or micro-level data is warranted.

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## Appendix 1

See Table 2.

**Table 2** Variables and data sources

Variable	Description	References
Corruption	Assessment of corruption within the political system (inverted)	ICRG (2017)
Corruption (V-Dem)	Public sector corruption index (v2x_pubcorr)	V-Dem (McMann et al. 2016)
Precipitation	Area-weighted monthly mean of precipitation (in mm)	CRU CY 3.22 (Harris and Jones 2014)
Potential evapotranspiration	Area-weighted daily mean of potential evapotranspiration (in mm)	CRU CY 3.22 (Harris and Jones 2014)
Temperature	Area-weighted monthly mean of temperature (in degrees Celsius)	CRU CY 3.22 (Harris and Jones 2014)
Drought number	Number of registered drought events (per million sq. km)	EM-DAT (CRED 2018)
Received aid	Net official development assistance and official aid received (in constant 2015 US\$)	WDI (2019)
Government consumption	Share of government consumption at current PPPs	WDI (2016)
Democratic accountability	Risk arising from responsiveness of government to its people (inverted)	ICRG (2017)
Internal conflict	Risk from internal conflicts (inverted, normalized between 0 and 6)	ICRG (2017)
Law and order	Assessment of strength and impartiality of the legal system and of popular observance of the law (inverted)	ICRG (2017)
GDP per capita	GDP per capita (constant 2010 US\$)	WDI (2016)
Resource rents	Total natural resources rents (% of GDP)	WDI (2016)
Protestant	% of Protestants	ARDA (2018)
Population	De facto total population	WDI (2016)
Area	Land area (sq. km)	WDI (2016)
Latitude	Latitude of country center point in degrees	CIA (2015)
Longitude	Longitude of country center point in degrees	CIA (2015)

PPP purchasing power parity

## Appendix 2

See Table 3.

**Table 3** Summary statistics

Variable	N	Mean	SD	Min	Max
Corruption	3375	2.926	1.3458	0	6
Corruption change	3255	0.0242	0.3451	-3.17	2.58
Corruption (V-Dem)	11666	0.4089	0.2946	0.005	0.974
Corruption change (V-Dem)	11,633	0.0003	0.0322	-0.624	0.562
Drought SPI	13,440	0.3525	0.5058	0	3.3045
Drought SPEI	13,440	0.3643	0.4876	0	2.7157
Drought number	6480	0.5019	5.2705	0	194.9318
Temperature	13,440	17.6870	8.6224	-7.4	29.8
Standardized temperature anomaly	13,440	0.0032	0.9973	-3.6713	4.5205
Received aid	2581	45.2772	53.1072	-33.2541	617.1832
Government consumption	3398	15.8780	5.8873	0	76.2221
Government consumption change	3369	-0.0384	2.1957	-38.5816	37.4729
Democratic accountability	3375	2.0737	1.6013	0	6
Democratic accountability change	3255	-0.0254	0.3915	-2.58	2.92
Internal conflict	3375	1.4967	1.1859	0	6
Internal conflict change	3255	-0.0190	0.3983	-2.98	2.02
Law and order	3375	2.2454	1.4488	0	6
Law and order change	3255	-0.0121	0.3282	-2.25	2.04
GDP per capita growth	3421	0.0179	0.0489	-0.5555	0.3054
Resource rents	3350	9.1946	13.1143	0	77.0545
Protestant	3579	10.6984	18.2072	0.0074	94.6532
Protestant change	3579	-0.0010	0.3961	-17.2150	1.8084
Population	3597	46,121,554.8	148,920,995	216,893	1,357,380,000
Population growth	3593	1.4907	1.4389	-5.8143	17.6248
Area	3600	949,606.111	2,267,446.63	670	16,389,950
Latitude	13,440	21.8952	25.4896	-41	65
Longitude	13,440	11.8734	58.7982	-102	174

*SPI* Standardized Precipitation Index, *SPEI* Standardized Precipitation Evapotranspiration Index

## Appendix 3

See Table 4.



**Table 4** Augmented Dickey–Fuller unit root test

Variable	lags(1)	lags(2)	lags(3)
Corruption	-9.4639 (0.0000)	-6.1393 (0.0000)	-4.4695 (0.0000)
Corruption change	-33.0325 (0.0000)	-20.0646 (0.0000)	-14.7289 (0.0000)
Corruption (V-Dem)	5.0424 (1.0000)	3.4062 (0.9996)	4.6271 (1.0000)
Corruption change (V-Dem)	-104.0782 (0.0000)	-71.3791 (0.0000)	-55.7439 (0.0000)
Drought SPI	-105.1917 (0.0000)	-64.9251 (0.0000)	-50.3655 (0.0000)
Drought SPEI	-102.8083 (0.0000)	-60.6376 (0.0000)	-45.8201 (0.0000)
Drought number	-58.0713 (0.0000)	-36.2133 (0.0000)	-58.0713 (0.0000)
Temperature	-75.1919 (0.0000)	-56.9569 (0.0000)	-42.0380 (0.0000)
Standardized temperature anomaly	-84.2453 (0.0000)	-60.3217 (0.0000)	-45.8728 (0.0000)
Received aid	-11.7410 (0.0000)	-7.5048 (0.0000)	-4.4614 (0.0000)
Government consumption	-6.8330 (0.0000)	-6.1335 (0.0000)	-5.9149 (0.0000)
Government consumption change	-46.3261 (0.0000)	-28.2820 (0.0000)	-18.6207 (0.0000)
Democratic accountability	-4.9473 (0.0000)	-2.5286 (0.0059)	-5.1764 (0.0000)
Democratic accountability change	-34.5060 (0.0000)	-18.9787 (0.0000)	-17.8500 (0.0000)
Internal conflict	-7.9622 (0.0000)	-3.9943 (0.0000)	-5.4098 (0.0000)
Internal conflict change	-40.7990 (0.0000)	-22.4971 (0.0000)	-17.5284 (0.0000)
Law and order	-7.3079 (0.0000)	-5.9449 (0.0000)	-5.0837 (0.0000)
Law and order change	-35.7684 (0.0000)	-19.9676 (0.0000)	-193.603 (0.0000)
GDP per capita growth	-24.8691 (0.0000)	-12.2141 (0.0000)	-9.5149 (0.0000)
Resource rents	-8.3815 (0.0000)	-1.1885 (0.1175)	-3.1992 (0.0007)
Protestant	7.6977 (1.0000)	4.6719 (1.0000)	5.0117 (1.0000)
Protestant change	-15.7618 (0.0000)	-9.3094 (0.0000)	-0.1015 (0.4596)
Population	0.1431 (0.5569)	3.2012 (0.9993)	-1.1860 (0.1181)
Population growth	-14.5524 (0.0000)	-5.9485 (0.0000)	-5.6099 (0.0000)

Inverse logit  $t$  test statistic ( $L^*$ ). Calculated for demeaned variables  
 $p$  values reported in parentheses

**Table 4** (continued)

*SPI* Standardized Precipitation Index, *SPEI* Standardized Precipitation Evapotranspiration Index

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