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Droughts and Corruption

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Zusammenfassung / Abstract

Natural disasters are a challenge for good governance - this is the result of recent research investigating the effects of natural disasters on one important antagonistic force to good governance, public corruption. However, a specific analysis of droughts is so far neglected in this young strand of the literature. This paper fills that gap by analysing the short- and long-term influence of droughts on corruption within a unified panel estimation approach for 122 countries during the years 1985 to 2013. Relying on a meteorological drought index, we show that higher drought exposure is followed by increases in corruption. This effect holds true for subgroups of poor and rich countries although its timing and intensity is different. In addition, we identify drought-induced corruption as a phenomenon of countries yielding high per capita income in the agricultural sector.

JEL-Klassifikation / JEL-Classification: Drought; Natural Disasters; Public Sector Corruption; Institutions; Economic Development

Schlagworte / Keywords: D73, E02, Q54, Q56

1. Introduction

Corruption – "the breaking of a rule by a bureaucrat (or an elected official) for private gain" (Banerjee, Mullainathan and Hanna 2012) – requires at least two preconditions: willingness and opportunity. Both are given in the case of natural disasters. On the one hand, natural disasters raise the victims' propensity to bribe, as Hunt (2007) shows for Peruvian households. On the other hand, the commonly granted disaster relief is a type of money windfall (e.g. Leeson and Sobel 2008) that gives groups and individuals the opportunity to vie for a portion of it, most likely resulting in increased rent-seeking behaviour and corruption (Brollo et al. 2013). In addition, natural disasters are typically accompanied by an emergency situation that generates a climate of non-accountability and moral hazard. This enables bureaucrats and officials to engage in acts of corruption (Klitgaard 1988). Recent empirical research approves this relationship finding increased corruption after natural disasters in the United States (Leeson and Sobel 2008), in Vietnam (Nguyen 2017) and flood events in Bulgaria (Nikolova and Marinov 2017). International analyses of Yamamura (2014), Escaleras and Register (2016) and Rahman et al. (2017) confirm these results for many countries.

Droughts are underrepresented in this young strand of the literature, although there is evidence that related research efforts could be fruitful. Acemoglu, De Feo and De Luca (2018) give an extraordinary example that illustrates how droughts challenge good governance. They identify a severe drought at the end of the 19th century as the critical juncture that caused the rise of the Sicilian Mafia. Triggering social conflict between the socialist movement and the landowners, this drought laid a cornerstone for long-lasting negative impacts on state capacity in the affected region. Looking at corruption as an antagonistic force to good governance, anecdotal evidence of misused and distorted drought relief payments exists worldwide. Campos (2015) states in a historical survey on public drought policies in Northeast Brazil that the misuse of public resources accompanies drought relief programs since the late 18th century. An exorbitant example of abused drought aid took place during a severe drought in 1974 in Mali. At that time enormous sums of drought relief were misused to build villas for the ruling elite, whereas 300.000 nomads were left to be destitute (Hope 2016). Even recently in June 2017, a huge proportion of South African drought relief was not received by drought-distressed farmers. Most probably, the money was wasted by appointed service providers or redirected in favour of departmental officials (TimesLIVE 2017).

An important factor justifying a separate analysis of the effects of droughts on corruption is the unique and complex characteristic of this hydrometerological disaster. Droughts differ from other disasters like floods, tropical cyclones and earthquakes in at least three dimensions:

First, droughts affect areas of comparably great extents. As they generally arise out of precipitation deficiencies caused by natural climate variability (Wilhite 2000), they are not confined to specific areas like floodplains, coastal regions, storm tracks or fault zones (Svoboda and Fuchs 2017). Although they occur typically in connection with aridity (Seager et al. 2007, Dai 2011), they virtually take place all over the world regardless of whether the prevalent climate type is characterised by high or low precipitation levels (Carrao, Naumann and Barbosa 2016). In consequence, droughts usually affect much wider geographical areas than other hazardous events, implying that the drought-induced threat of corruption concerns a widely extended region.

Second, the effects of drought on water availability normally accumulate slowly over a considerable period of time and may linger for long periods after precipitation reaches back its normal level in contrast to the typically sudden onset and relatively short duration of other hazard types (Wilhite, Sivakumar and Pulwarty 2014). Figure 1 illustrates this creeping progress. Starting with a mere meteorological event, prolonged duration leads to effects on the agricultural sector. Subsequently, river streamflow and water reservoirs are reduced impacting agricultural irrigation systems, hydrological energy generation, transportation ways and tourism. Economic, social and environmental impacts and, consequently, the disaster related reasons for corruption typically exacerbate the longer a drought takes place.

Third, droughts do seldom cause structural damage like destroyed buildings or communication lines. Due to their non-structural nature, damages are much more difficult to survey and quantify (Wilhite 2000). In consequence, it is a comparatively precarious task to monitor their removal. This opens up considerable opportunities for corrupt activities.

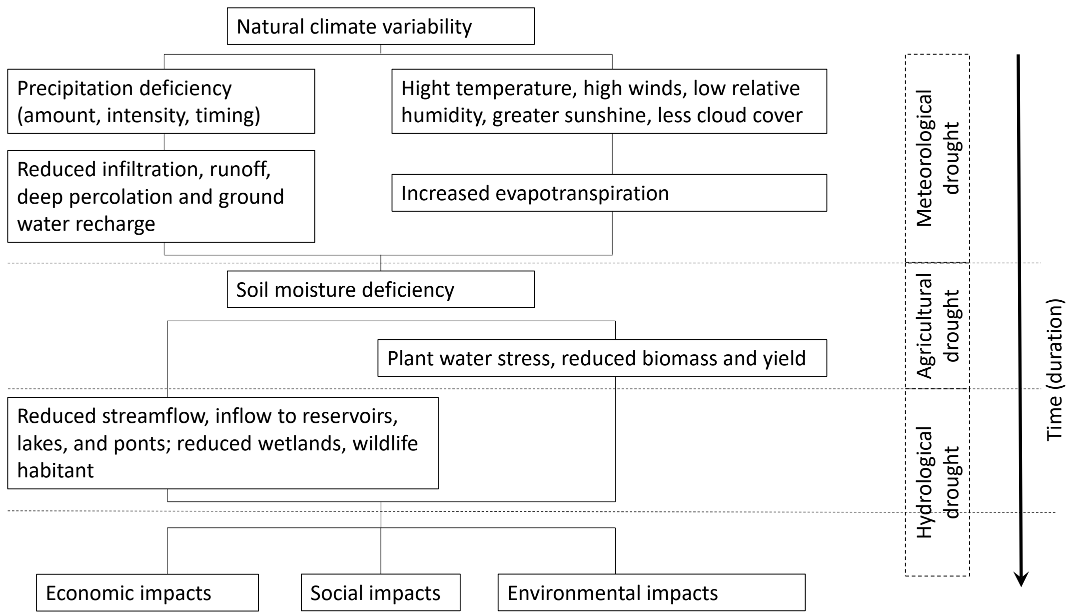


Figure 1: Drought Duration and Related Drought Types, Source: Wilhite (2000)

Wilhite (2000) concludes that these three characteristics hinder an accurate, reliable and timely quantification of drought impacts and the formulation and monitoring of governmental drought contingency plans. Therefore, information is asymmetrically distributed between the affected individuals, local officials and the central drought relief coordinators, generating a breeding ground for moral hazard behaviour.

Another fact that stresses the relevance of droughts for corruption is its close connectedness to the water sector, a branch highly affected by corruption especially in environments of scarce water availability (TPI 2008). Droughts raise the risk of corruption particularly for the operation of irrigation systems. Although only one-sixth of the farmed area worldwide is irrigated, these farms use about 70 percent of the water that humans withdraw from nature and produce 40 percent of the world's food (Rijsberman 2008). Most irrigation systems are organised in a way that allows to allocate the water very precisely to where it is needed. These manipulation possibilities are often translated into corruption opportunities (Wade 1982). Officials, responsible for operating the gates, are likely to be bribed or ask for side payments for additional or prolonged opening, especially when farmers suffer from water shortages due to droughts (Rijsberman 2008).

The threat of drought-induced corruption is expected to worsen in the future due to changing climatic conditions and more frequent, prolonged and severe precipitation deficiencies that will significantly raise the global prevalence of droughts (Dai 2011, Güneralp, Güneralp and Liu 2007). Reviewing the recent literature on drought, Dai (2011) concludes that global aridity has increased substantially since the 1970s and is likely to sustain and rise further during the 21st century in most parts of Africa, America, Australia, Southeast Asia, the Mediterranean region and the Middle East.

Against this background, we investigate whether droughts influence corruption within a unified panel estimation approach for several subgroups of an unbalanced panel of 122 countries during the years 1985 to 2013. To analyse potentially occurring long-term effects, we estimate cumulative effects of droughts on corruption over long time horizons. In order to solve the over-controlling problem (Dell, Jones and Olken 2014), we estimate a two-way fixed effects model with heteroscedasticy and autocorrelation (HAC) corrected standard errors. Due to the fact that droughts spread over large areas, we further correct the standard errors for spatial correlation. The estimation results derive from a truly exogenous drought index based on precipitation deficiencies, the standardized precipitation index (SPI). We show that high drought exposure is followed by corruption increases. This effect holds true for subgroups of poor and rich countries although its timing and intensity is different. Sampling according the per capita agricultural value added, we find that a drought-induced increase in corruption is a phenomenon of countries achieving high per capita amounts of value added in the agricultural sector. Several robustness tests show the stability of these findings.

The paper is organized as follows. The second Section delivers a review of the related literature. The third Section describes the corruption and drought data used in our analysis and explains the estimation strategy. In Section 4 we present the basic results. Section 5 reports several stability tests. Section 6 summarizes and concludes.

2. Related Literature

Empirical research on the effects of natural disasters on public corruption started only recently.[1] The limited number of existing papers allows presenting each of them, before drawing consequences that shape the research efforts of this study.

The seminal paper examining the corruption impact of natural disasters is authored by Leeson and Sobel (2008). The authors study whether Federal Emergency Management Agency (FEMA) relief payments following natural disasters in the years 1990 to 1999 increase corruption-related crime convictions in the U.S. states. By accumulating the coefficients of FEMA disbursements of the preceding three years, their two-way fixed effects regressions show that an additional $ 100 p.c. payment raises corruption at state level by almost 102 percent.

Nguyen (2017) asks whether "natural disasters open a window of opportunity for corruption". With a so-called 'consumption income gap approach' he answers this question using four years of survey data[2] on 27,050 rural Vietnamese households in 2,984 communes. He finds that natural disasters occurring in the preceding three years equally reduce the income of official[3] and non-official households but not their expenditures. Whereas consumption in non-official households is reduced significantly through natural disasters, official households show almost no change in their spending. This gap cannot be explained by different coping strategies (remittances, migration) of both household types and therefore an unreported income pointing to the existence of corruption is assumed.

The study of Nikolova and Marinov (2017) concentrates on flood events in 227 Bulgarian municipalities, caused by several torrential precipitation events in the years 2004 and 2005. The authors analyse the consequences of the related governmental disaster relief on local corruption. They find spending infringements[4] increase sizeable

[1] It should be noted that in a broader sense research to disaster related corruption consequences shares some similarities with the already more comprehensive literature on the effects of natural resource windfalls (e.g. Brollo et al. 2013,) or aid payments on corruption (e.g. Knack 2001, Djankov, Montalvo and Reynal-Querol 2008).

[2] Nguyen (2017) used data of the Vietnam Living Standard Survey (VLSS) – a survey implemented at highest World Bank standards.

[3] A household is classified as 'official' if at least one household member works for the local government (Nguyen 2017).

[4] Spending infringements are identified by the Bulgarian National Audit Agency (BNAA).

as a consequence of flood-related transfers of the central Bulgarian government. To ensure the exogeneity of their measure of locally received funds in the cross section regression approach, the authors instrument the total flood related assistance by a measure for high monthly precipitation.[5]

Yamamura (2014) conducts the first international study on the impact of natural disasters on corruption. Investigating panel estimations for 84 countries and the period of 1990 to 2010, he finds that the one and two year lagged number of natural disasters, as documented in the Emergency Database (EM-DAT), significantly increases the national corruption level, measured with the Public Corruption Index of the International Country Risk Guide (ICRG). A separate analysis of floods, storms, earthquakes, volcanic eruptions and landslides delivers effects with varying coefficient signs and significance depending on disaster type and development. Compared to estimation results of non-OECD countries, Yamamura (2014) finds a considerably larger effect of natural disasters on corruption in the OECD countries. This effect is especially high for floods.

Escaleras and Register (2016) follow a similar approach that differs from Yamamura (2014) notably by its long-term perspective. Their panel Tobit regression of 75 countries during 1984 to 2009 reveals that the number of natural disasters (floods, storms and earthquakes reported by EM-DAT) of the prior 5, 10 or 25 years raise corruption (ICRG) significantly. This result remains stable when the regression is repeated with the Transparency International (TI) corruption measure for the period of 1996 to 2009. This finding of a long-term disaster related corruption increase is robust in a disaggregated analysis for floods and storms, whereas the effects of earthquakes are insignificant and unclear in their direction.

Analysing transmission channels of hazardous rainfall on democratic change, Rahman et al. (2017) examine the impact of extreme precipitation events on the level of corruption (ICRG) in 130 countries during the years 1984 to 2009. They find no direct corruption effect of their measure of extreme rainfall that captures precipitation variations at the upper scale of the rainfall volume distribution. After introducing an

[5]In detail Nikolova and Marinov (2017) use the average precipitation of all months of the years 2004 and 2005 for which the monthly rainfall percent change relative to a monthly historical average equals or exceeds 30 percent.

additional regression stage explaining total flood affected persons (EM-DAT) by extreme precipitation (stage 1), a strong significant contemporary effect of the number of flood affected persons on corruption (stage 2) is detected.

Reviewing the literature concerning the effects of natural disasters on public sector corruption reveals three important facts that influence the research efforts of this paper.

First, the absence of any specific investigation about the consequences of droughts on public corruption is obvious, especially in contrast to the broad consensus of four studies that state floods raise the level of corruption (Nikolova and Marinov 2017, Yamamura 2014, Escaleras and Register 2016 and Rahman et al. 2017).

Second, five of six reviewed studies analyse only contemporary or short-term disaster-related corruption effects. The sole exception are Escaleras and Register (2016), examining whether disasters of the prior 5, 10 or 25 years affect corruption. This might be appropriate when studying disasters with a sudden onset and a comparatively fast progress, however, for droughts long-term studies are highly recommended.

Third, surveying the existing literature testifies some efforts to use a truly exogenous source of variation for disaster occurrence and severity.[6] Escaleras and Register (2016) refrain explicitly from using values of damages or the amount of total affected persons as disaster measure in favour of the less endogenous number of disasters. The argument behind doing so is the broad consensus that low levels of corruption (Anbarci, Escaleras and Register 2005) and good institutions and governance (Raschky 2008, Noy 2009) mitigate or even prevent natural hazards[7] from becoming natural disasters[8] by reducing the number of deaths, affected persons or economic damages. However, the number of disasters reported by EM-DAT may also be at least partly endogenous, because the admission criteria to enter this database rely on the number of deaths, affected persons

[6]This efforts can be observed in other stands of disaster literature, as well. See for example Felbermayr and Gröschl (2014) and Berlemann and Wenzel (2018) for economic growth investigations and Smirnov et al. (2018) for disaster consequences on political leader survival.

[7]Natural hazards can be defined as "a dangerous phenomenon [...] that may cause the loss of life, injury or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage." (UNISDR 2009)

[8]Natural disasters can be defined as "a serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources." Disasters are often described as "a result of the combination of: the exposure to a hazard; the conditions of vulnerability that are present; and insufficient capacity or measures to reduce or cope with the potential negative consequences." (UNISDR 2009)

or an announced state of emergency.[9] In addition, simply counting the number of droughts comes at the price that no information on the severity of the recorded events is given. Therefore, Nikolova and Marinov (2017) as well as Rahman et al. (2017) go one step further and use truly exogenous precipitation measures to instrument flood consequences. We follow this attempt and use a drought index based on meteorological data to indicate drought severity.

3. Data and Estimation Strategy

To enhance the understanding of the estimation approach, we begin this section with a detailed description of the data used to measure the existence and severity of droughts and corruption. A complete overview of all data sources and the summary statistics is provided in Tables A.1 and A.2 in the Appendix.

3.1. Drought Data

In order to use a truly exogenous measure characterizing the occurrence and severity of droughts, we prefer an index based on meteorological data to the number of droughts recorded by EM-DAT. In general, drought indices are quantitative measures describing droughts by assimilating information on precipitation or, if appropriate, other variables into a single numerical number (Zargar et al. 2011). The purpose of this study requires an index with global coverage and international comparability. Both demands are met by the standardized precipitation index (SPI) developed by McKee, Doesken and Kleist (1993). First, the computation of the SPI is solely based on precipitation data globally available from several rainfall datasets. We base this study on monthly area-weighted[10] country means of precipitation available for the years 1901 to 2013 from one of the most prominent datasets, the CRU CY 3.22 dataset published by the Climate Research Unit of

[9] A disaster enters the EM-DAT Database 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. (EM-DAT 2018)

[10] In order to construct internationally comparable data either area or population weights are used. This study relies on area weights as agriculture is likely a major field where drought-induced corruption takes place.

the University of East Anglia.[11] Second, the calculation methodology of the SPI ensures its comparability between different locations and even climate zones, as it transforms the distribution of each precipitation record into a standard normal distribution with a mean value of zero. Therefore, negative SPI values indicate relatively dry periods and positive values point to excessively wet periods. A concrete SPI value can be interpreted as the number of standard deviations that precipitation deviates from its normalized average (Zargar et al. 2011).

Another favourable characteristic of the SPI is its ability to monitor different types of droughts. The monthly SPI value can be calculated in consideration of the fallen amount of precipitation of the preceding 1, 3, 6, 9, 12 or 48 months.[12] Referring back to Figure 1 in Section 1, the 1-month SPI reflects overly meteorological drought conditions, 3- to 9-month SPI values denote to phenomena of agricultural droughts and the 12-month SPI refers to hydrometeorological droughts (Zargar et al. 2011). The drought measure we apply in this study bases on 12-month SPI values. We choose this timescale to cover long-term precipitation patterns related to river streamflow and reservoir and groundwater levels which play an important role for water dependent production and irrigation systems.

Relying on the SPI, McKee, Doesken and Kleist (1993) identify a drought event as "a period in which the SPI is continuously negative and the SPI reaches a value of -1.0 or less". According to this definition, we calculate the drought measure of this study following three steps: First, we identify all months of a drought event. Second, we set all SPI values of months not being part of a drought to zero. Third, we calculate the modulus of the annual sum of all 12-month SPI values belonging to drought events for each country. We refer to this measure later on as Drought SPI. Compared to the number of droughts recorded by EM-DAT, it captures not only the mere frequency but also the severity of droughts, and it is exogenous to the corruption situation and institutional conditions of the countries.

[11] The CRU CY 3.22 precipitation time series are derived from the CRU Time Series (TS) gridded dataset, which uses meteorological station observations covering the global land surface (except Antarctica) to obtain 0.5 degree latitude/longitude grid cell data. For a more details to the data see Harris and Jones (2014).

[12] Timescales of 1, 3, 6, 9, 12 and 48 months are typical used periods. In principle, the SPI can be calculated for each timescale in between, as well.

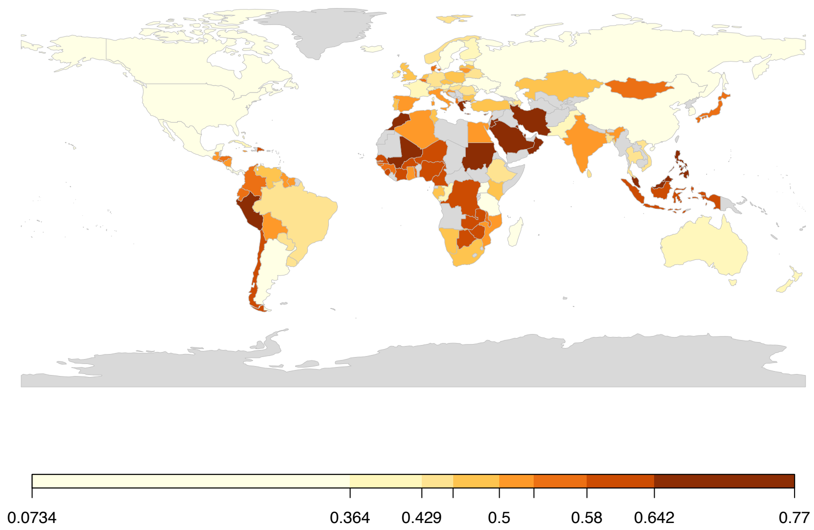


Figure 2: Country Standard Deviations of Drought SPI (1965-2013), 8 Quantiles, Source: CRU CY 3.22

Figure 2 maps the variability of the Drought SPI for all analysed countries over the period of 1965 to 2013. This sample period comprises all years the drought measure is later on included in the estimations.[13] The colour categories refer to eight quantiles of the standard deviations of the Drought SPI variable. Countries with high standard deviations of Drought SPI are located on the African continent and in the equatorial regions. Analysing the average Drought SPI over this period, the countries Burkina Faso, Gambia and Guinea faced the most severe drought situations (see Table A.4 in the Appendix).

3.2. Public Corruption Data

Measuring corruption is a quite challenging task (Banerjee, Mullainathan and Hanna 2012). The very nature of this phenomenon, being illicit and secretive, causes great efforts to hide it rather than to give the opportunity to quantify it correctly. Therefore, most attempts to deliver consistent measures of corruption across countries rely on the perceptions of individuals or experts. Although these subjective measures have their limitations, they are the most useful available tool for cross-country analysis (Banerjee,

[13]Data on corruption change is not available before 1985, however, as the drought measure enters the estimation equation with a lag up to 20 years, the drought data is including earlier observations.

Mullainathan and Hanna 2012).

We use data of the International Country Risk Guide (ICRG) rating, published by the Political Risk Group (PRS), assessing corruption within the political system. It is based on experts' perceptions of different forms of corruption, among them special payments, bribes, nepotism or patronage. This data is available for a comparable broad sample of 140 countries during the years 1984 to 2016. The original scoring of the ICRG corruption index reaches from 0 (indicating the highest corruption risk) to 6 (lowest possible risk). Theoretically, every value within these two bounds can be achieved (not only integer numbers). To enhance the understanding of the estimation results, we use an inverted scale in this analysis with 0 denoting low corruption risk and 6 high corruption risk.

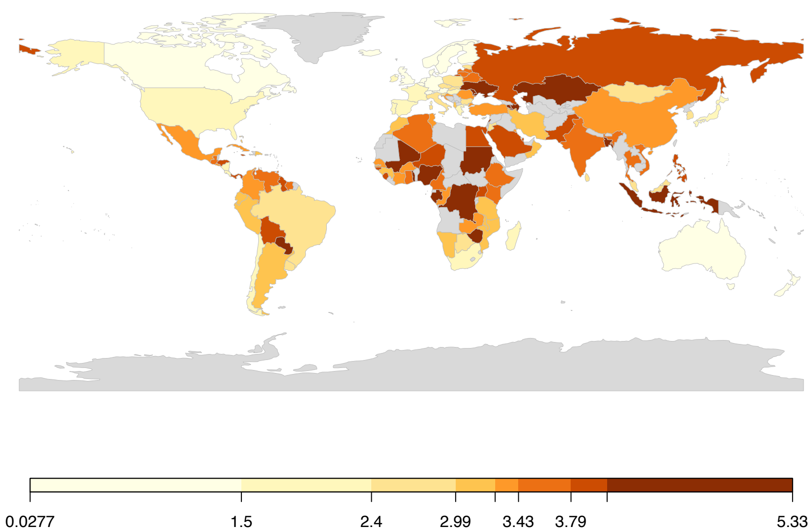


Figure 3: Country Averages of Corruption (1984-2013), 8 Quantiles,
Source: ICRG (2017)

Figure 3 shows the average corruption of all 122 countries included in this study over the analysed time period of 1984 to 2013. The average corruption level is low in Northern America and in most parts of Europe. Canada, Denmark and Finland show the lowest level of average corruption ranging from 0.03 to 0.31. In contrast, countries like Gabon, the Democratic Republic of Congo, Bangladesh, Azerbaijan or Armenia have an average corruption level between 4.28 and 5.33 (see Table A.5 in the Appendix).

This picture changes when we analyse the development of corruption over time.

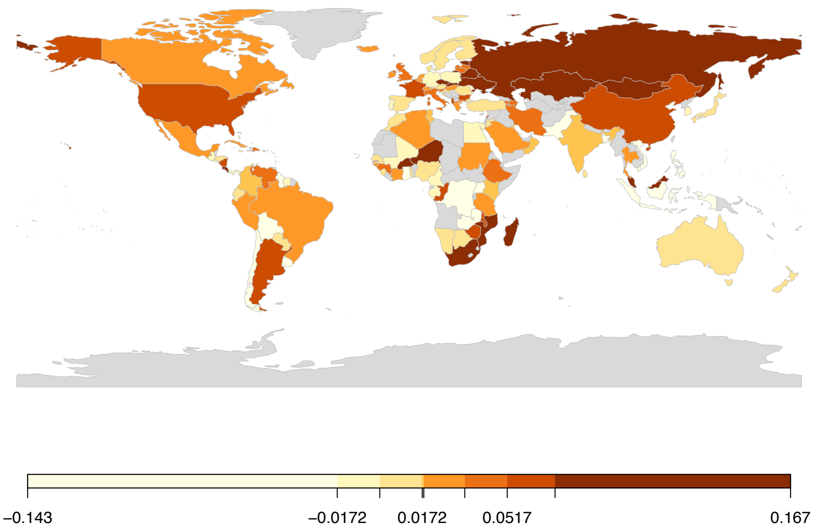


Figure 4: Country Averages of Corruption Change (1985 -2013), 8 Quantiles, Source: ICRG (2017)

Figure 4 shows the average change of the ICRG corruption index during the years 1985[14] to 2013 for all studied countries. Some countries, among them Bangladesh, Chile or the Democratic Republic of the Congo, improved their corruption situation whereas the corruption level in European countries like France, Italy or the United Kingdom and the United States increased. In addition, Figure 4 points out the dramatic rise of corruption in most of the former Warsaw Pact states.[15]

The distribution of the level and the change of the ICRG corruption index is shown in Figures A.9 and A.10 in the Appendix. Figure A.9 points to the censored characteristic of the ICRG corruption index by high frequencies at both ends of its distribution. This is an important fact that has to be considered when choosing an appropriate estimation strategy.

3.3. Estimation Approach

Comparable papers examining the corruption effects of natural disasters (Yamamura 2014, Escaleras and Register 2016) refer to the empirical literature studying the causes and determinants of corruption (Treisman 2000, Pellegrini and Gerlagh 2008). They

[14]Data of annual changes can be calculated the first time for the year 1985.
[15]This study refers to that special country group in a stability test in Section 5.

explain the level of corruption with a set of typical control variables and add the number of natural disasters to the estimation equation. Taking the censored characteristic of the ICRG corruption index into account, Escaleras and Register (2006) apply a (random effects) Tobit model.

However, it is worth reconsidering the choice of the dependent variable of the estimation model as the occurrence of natural disasters should primarily affect the change of the corruption level.[16] Knack (2001) employs the change of the ICRG corruption index as dependent variable when studying the impact of foreign aid on corruption. This approach has two convenient implications. First, invariant or slowly evolving determinants of the corruption level, like roots of the existing legal system, colonial heritage, ethnical division or religious traditions (Treisman 2000, La Porta et al. 1999), are unlikely to matter much in this specification (Knack 2001). Second, using the change of corruption as dependent variable allows to conduct a standard fixed effects estimation as the censored characteristic of the ICRG index does not play a role anymore. In consequence, the dependent variable we study in this analysis is the annual change of the ICRG corruption index.

Regarding the independent variables of the estimation model, the increasingly considered over-controlling problem should be avoided. Dell, Jones and Olken (2014) discuss this issue for the climate-economy literature extensively. It arises when possibly endogenous control variables are included in the estimation equation. As an example, this might be the case if we would adopt the control variables applied by Knack (2001) in the estimation approach of this paper, because both GDP p.c. growth as well as population growth can be considered as endogenous to droughts (Berlemann and Wenzel 2016). In consequence, their inclusion in the estimation equation will likely lead to an insignificant coefficient of the disaster variables because at least parts of the drought effects on corruption change are captured by the coefficients of GDP p.c. or population growth. Additional control variables may also be endogenous to disaster effects, as Berlemann and Wenzel (2016) show for education and Rahman et al. (2017) for democracy. Therefore, the most reliable approach to capture the true

[16] North (1990) gives approval to this by including natural disasters beside wars, revolutions and conquest among the "sources of discontinuous institutional change".

net effect of drought-induced corruption change is to conduct a two-way fixed effects panel estimation without possibly endogenous time-variant controls. However, we include a variable covering pure temperature effects on corruption in the estimation equation following the proposal of Auffhammer et al. (2013). Therefore, we use annual standardized temperature anomalies (STA)[17] as temperature measure in the basic approach.[18]

Furthermore, the estimation approach should allow to study long-term effects of a drought. 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 informs about the full impact a drought has on corruption change.

The applied estimation equation is therefore

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

with α being country fixed effects, β being time fixed effects, D being the drought measure and STA being the temperature variable. L defines the maximal number of years, drought (and temperature) is allowed to influence the future corruption change. We calculate the cumulative effect of a drought on corruption change as

$$\Gamma_{cum,L} = \sum_{l=0}^{L} \gamma_l \tag{2}$$

Calculating HAC standard errors (Newey and West 1987), the confidence intervals of the estimations are corrected for heteroscedasticity as well as autocorrelation of the residuals.[19] Moreover, the great spatial extent of droughts requires to account for spatially correlated error terms. Therefore, we implement the procedure of Conley (1999)[20], correcting spatial correlation up to a distance of 1000 km from the centre of a country.

[17]The STA is calculated as the deviation of the annual average temperature from its long-term mean, divided by its long-term standard deviation. Temperature data is also available from the CRU CY 3.22 dataset.

[18]Figures A.13 and A.12 in the Appendix show that estimating the model without temperature variable or applying the annual mean temperature in degree Celsius does not change the results considerably.

[19]Standard errors are corrected for autocorrelation up to 10 years.

[20]An adapted version of the Conley correction procedure, proposed by Fetzer (2015), is used.

As a first step, we analyse drought-related effects on corruption change for the whole sample of 122 countries for the time period of 1985 to 2013. We include the drought measure with up to 20 lags so that the considered drought events reach back to the year 1965.

The following two steps of the estimation strategy aim to identify whether the relation between droughts and corruption change depends on special characteristics of country groups. Therefore, we form country subgroups according to development and agricultural aspects using data of the World Development Indicators (WDI). We then estimate the empirical model described earlier for these country groups. Further details on the subsamples and the subsequently conducted stability tests are given in the Sections 4 and 5.

4. Estimation Results

In this section we present the results of the two-way fixed effects model estimations in detail. As precondition for valid results, unit root tests show that the left hand variable as well as the drought measure turn out to be stationary.[21] Instead of reporting the full estimation results for every single model, we present a graphical representation of the estimated cumulative coefficients of Drought SPI and the referring 90 percent confidence intervals (based on HAC standard errors). When a coefficient differs significantly from zero on the 90 percent confidence level, it is marked in orange colour whereas it is shown in grey in the case of insignificance. The graphics show the standardized cumulative coefficients of the drought measure depending on the number of the included lags reported on the x-axis.

4.1. Full Sample

Starting point for the analysis is an examination how Drought SPI affects corruption change in the full sample of 122 countries. The overall positive signs of the estimated cumulative coefficients in the upper part of Figure 5 show that corruption change takes higher (positive) values, indicating an increase in corruption, when Drought

[21] The results of the unit root tests are reported in Table A.3 in the Appendix.

SPI rises. However, in the short run the cumulative coefficients are not significantly different from zero on conventional levels of significance. This picture changes when medium- and long-term drought impacts on corruption change are taken into account. Cumulating the effects of a drought over six and more years leads to a significant increase of corruption in the full sample. The standardized cumulative coefficient of 20 lags of Drought SPI amounts to 0.173. This value indicates that after 20 years a one standard deviation increase of the drought measure results in a 0.173 x 0.346 = 0.06 point higher drought-related increase of the ICRG corruption index, whereas 0.346 equals the standard deviation of corruption change. As the mean corruption change in this sample is 0.023, this is a quite remarkable effect. It suggests that droughts form a persistent habit of corruption in a society.

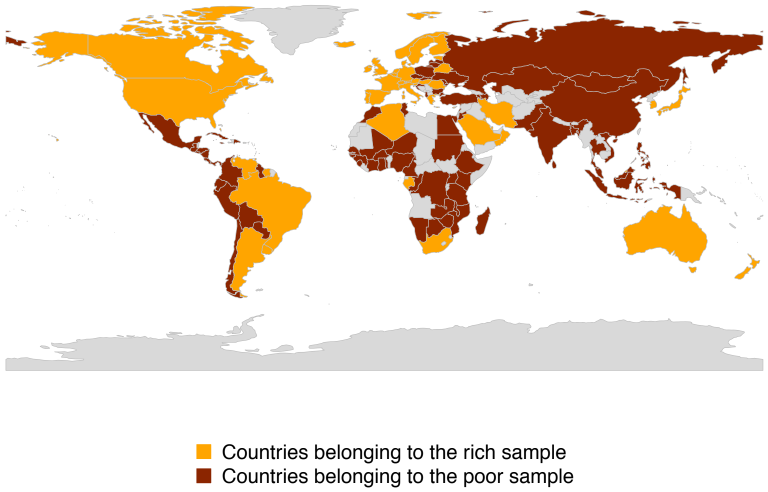
4.2. Development Subsamples

The countries analysed in the former subsection are characterized by quite different levels of development. This raises the question whether the detected effect of droughts on corruption depends on the level of development of the countries. Yamamura (2014) as well as Escaleras and Register (2016) analyse the corruption effects of natural disasters separately for developing and developed countries, but with differing results. Whereas Yamamura (2014) finds the effects of natural disasters on corruption to be much higher in OECD countries compared to non-OECD countries, Escaleras and Register (2016) detect larger effects in their developing sample.

To study the impact of the level of development, we divide the sample into two subgroups according to their initial World Bank income classification.[22] High and upper middle income countries are pooled together as a subgroup of 47 rich countries. Low and lower middle income countries form the second subgroup of 75 poor countries. The world map in Figure 5 shows the two subsamples.

The middle and lower part of Figure 5 summarizes the estimation results for the rich and poor samples. Both subsamples show a significant, positive effect of droughts

[22]The countries are grouped by their World Bank classification in the first year they appear in the World Bank dataset. If there are classification changes directly within the first three years, the predominantly classification in this years is used.



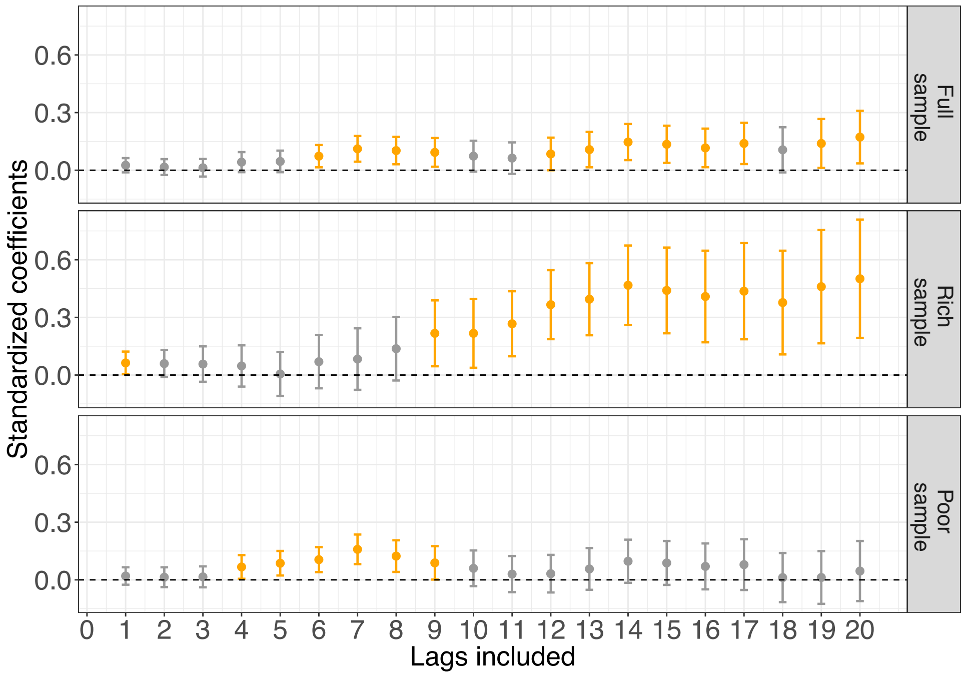


Figure 5: Cumulative Effects of Drought SPI on Corruption Change,
Full, Poor and Rich Samples,
Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

on corruption change, however, with different timing and intensity. Apart from a small significant effect of a previous-year drought, higher Drought SPI values have systematically positive effects on corruption change in the rich sample in the long run, cumulating the effects of nine and more years after a drought took place. This effect is comparatively large. The standardized cumulative coefficient of the estimation considering the drought effect of 20 preceding years is 0.501, indicating a 0.173 point higher corruption change due to a one standard deviation rise of the drought measure. The poor sample shows a different relationship between droughts and public sector corruption. Within this country group, corruption change is significantly higher in the four up to nine years following a drought event. This moderate effect diminishes in the long run. One of the reasons for the different timing and size of drought impacts in the two country groups may be due to the fact that developed countries typically possess well established and reliable systems of water resource management (Grey and Sadoff 2007). Therefore, rich countries are comparably better equipped to mitigate and overcome water supply shocks by drought conditions in the short run whereas the drought impacts in less developed countries may become crucial much earlier. In the developed countries a habit of corruption seems to establish over a long time horizon but with higher persistence and intensity. This could be triggered by granted assistance payments, which may be more easily available and higher in rich countries. Another potential reason for drought-induced corrupt behaviour in developed countries may be the high water withdrawal demand for industrial production. The water withdrawal of the industrial sector as percentage of the total water withdrawal raises with development (FAO 2011). In North America and Western and Central Europe – regions with mainly rich countries – the average industrial water withdrawal adds up to 49.5 percent of the total water withdrawal, compared to a value of 12.75 percent for the rest of the world (FAO 2011). In drought situations water dependent industries may tend to compete for scarce water resources by means of corruption (TPI 2008).

4.3. Agriculture Subsamples

Considering agriculture as the economic sector primarily affected by droughts, drought-induced corruption is supposed to be most prevalent in countries with a notably important agricultural sector.[23] We apply two different measures of agricultural importance to separate the country sample according to agricultural aspects.

The first indicator commonly used to measure the agricultural dependence of economies is the agricultural value added as percentage of GDP. It is closely related to the overall development of countries. The usually very high proportion of agricultural value added on GDP in poor countries mirrors the deficiency of value added in the industrial or service sectors of these economies. In order to separate the full sample according to this indicator, we compare the proportion of agricultural value added on GDP of the countries to the median of this variable in the year of its first available observation.[24] In consequence, a sample of 67 not agricultural dependent countries, which are characterized by an agricultural value added as percentage of GDP below or equal the median, can be compared to 55 agricultural dependent countries. We show both samples in the left world map in Figure 6. Below this map, Figure 6 summarizes the results for these two country groups. The results are very similar as those reported for the poor and rich countries in the last subsection. This is not surprising considering the earlier mentioned close relationship between development and agricultural dependence. In agricultural dependent countries droughts have a significant positive effect on corruption change in the medium run, cumulating the effects of a drought over five up to eight years. Significant corruption increases in countries not depending on agriculture take place in the first years following a drought and in the long run.

The second variable used to measure the importance of the agricultural sector is the per capita volume of agricultural value added. It takes into account that a lot of industrialized and highly developed countries, as Australia, Finland or Greece, are among the big producers of agricultural products.[25] To divide the sample referring to the median of per capita agricultural value added, we follow the same procedure

[23]Table A.6 in the Appendix summarizes the manifold effects of droughts on agriculture in detail.
[24]This proceeding and the fact, that the years of the first observation differ between countries, lead to samples of diverging size even when the median is used as separation criterion.
[25]Compare Table A.5 in the Appendix.

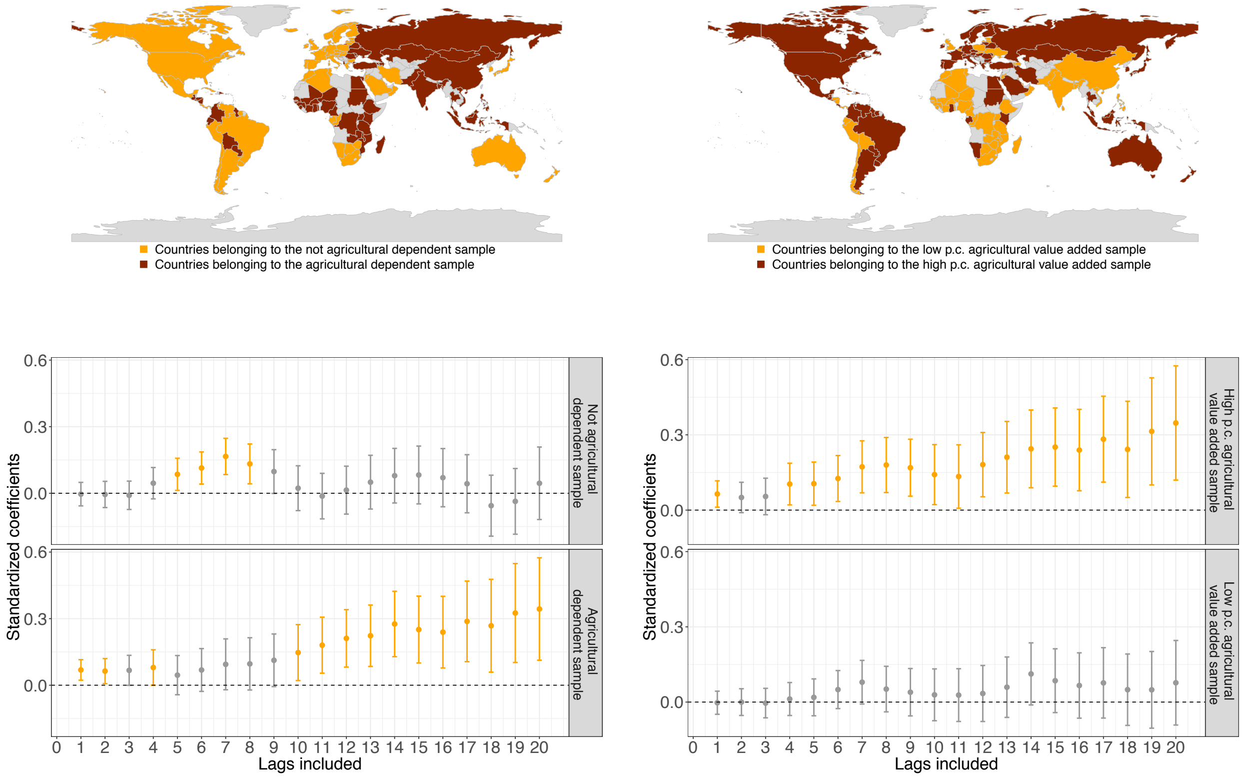


Figure 6: Cumulative Effects of Drought SPI on Corruption Change, Samples According Agricultural Dependence and Per Capita Agricultural Value Added (in 2010 US$), Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

described for the first measure. As a consequence, 58 countries characterized by a per capita agricultural value added below or equal the median, face 64 countries with a per capita agricultural value added higher than the median. The right part of Figure 6 presents these country groups in a world map and summarizes the estimation results. The results show that drought-induced corruption increases appear in countries with high per capita agricultural value added. The cumulative coefficients of the estimations are significantly different from zero on conventional levels of significance for all but two cumulation horizons. This shows that drought exposure has a positive effect on corruption change up to 20 years following a drought event in this subsample. In contrast, we do not find any effects of droughts on corruption in countries characterized by low per capita agricultural value added. Therefore, drought-related corruption is primarily a threat to countries yielding high per capita income in the agricultural sector.

5. Stability Tests

5.1. Exclusion of Former Warsaw Pact States

In the post-cold war era, former Warsaw Pact states[26] experienced a deep institutional transformation (Savoia and Sen 2016), affecting the perceived corruption in this country group. In Figure 7 we compare the average corruption change of the former Warsaw Pact states and the other countries included in this study during the analysed time period of 1985 to 2013.[27] Recognizing the special development of corruption during the 1990s in the former Warsaw Pact states raises the question whether the estimation results of this study are driven by this country group. Therefore, we test the stability of the results by re-estimating all models excluding the 16 former Warsaw Pact states. As Table A.14 in the Appendix shows, the presented results remain virtually unchanged by this sample variation.

[26]The following countries included in the country sample of this study are referred to as former Warsaw Pact states: Armenia, Azerbaijan, Belarus, Bulgaria, Czech Republic, Estonia, Hungary, Kazakhstan, Latvia, Lithuania, Poland, Republic of Moldova, Romania, Russian Federation, Slovakia, Ukraine.

[27]In addition, Figure 7 reveals a peak corruption increase in the years 2001/2002. This is common for most of the analysed countries shown in detail in Figure A.11 in the Appendix.

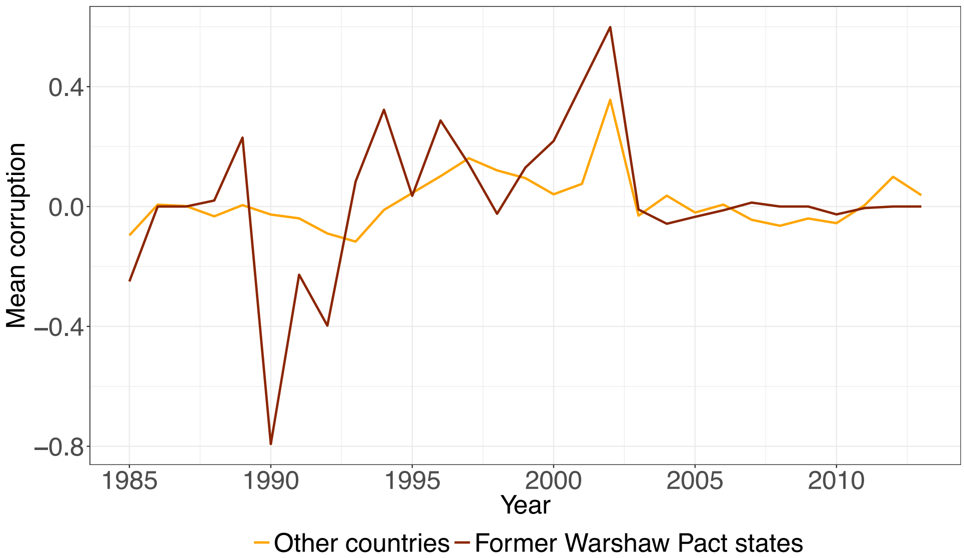


Figure 7: Yearly Averages of Corruption Change,
Source: ICRG (2017)

5.2. Inclusion of Corruption Level

An often employed control variable in estimations of the determinants of corruption change is the level of corruption (see e.g. Knack (2001)). Corruption is generally expected to rise the more, the lower the initial level of corruption is (Knack 2001, Savoia and Sen 2016). Therefore, we include the one-year lagged level of corruption in the estimation model of this study. However, this approach is problematic due to the over-controlling problem already discussed in Section 3. The corruption level of the previous year is influenced by the included lags of Drought SPI of the preceding two and more years. In consequence, comprising the level of corruption in the estimation should lead to less significant effects of the drought measure. Figure A.15 in the Appendix shows that this is the case when estimating the model with the one-year lagged corruption level as additional control variable.

A different approach to control for the effect of the current level of corruption on the occurrence of drought-induced corruption change is to separate the countries according to their prevalent corruption level. In order to do so, we group two country samples according to the median corruption in the year of its first available observation. In consequence, 74 countries with an initial corruption below or equal the median can be compared to 48 countries with above median corruption as shown in the world map in Figure A.16 in the Appendix. Analysing the effects of Drought SPI on corruption change in the corrupt and non-corrupt samples gives no clear difference between these two country groups, as the results in Figure A.16 in the Appendix show. Consequently, we find the influence of the prevalent corruption level of the countries is of minor importance for the research question of this study.

5.3. Standardized Precipitation Evapotranspiration Index

Based on the previously used SPI, Vincente-Serrano, Begueria and Lopez-Moreno (2010) recently proposed an extended drought index considering potential evapotranspiration (PET) as a further determinant of drought severity. Their standardized precipitation evapotranspiration index (SPEI) also incorporates the water demand arising from temperature increases, a feature particularly relevant for studying future drought severity in an environment of climate change (Vincente-Serrano, Begueria and Lopez-Moreno 2010). To test the stability of the earlier reported results, we calculate Drought SPEI analogously to the Drought SPI measure described in Section 3. We derive the PET data from the CRU CY 3.22 dataset.[28]

Figure 8 compares the averages of Drought SPI and Drought SPEI for all analysed countries, during all years droughts are considered in the estimations of this study. Over a long time period both measures correlate strongly. However, beginning in the early 1990s, Drought SPEI shows steadily higher average drought severity than Drought SPI. As both measures are based on the same precipitation data, this gap occurs due to risen PET, probably caused by climate change. The variability of Drought SPEI in Figure A.17 in the Appendix shows that its standard deviation is highest in the countries located in the arid climate zones, where the PET typically reaches its maximum values.

The results of this study remain stable when Drought SPEI is applied as a measure for drought occurrence and severity in the estimation approach.[29] Figure A.18 in the Appendix shows a less significant long-term drought-induced corruption change in the full sample and fewer significant impacts in the poor and agricultural dependent coun-

[28]The PET values refer to the theoretical evaporative demand of the atmosphere, calculated for a reference surface.

[29]It should be discussed if it is appropriate to estimate the model with Drought SPEI and an additional temperature control because temperature is a main determinant of PET. Therefore, Figure A.19 in the Appendix shows the estimation results with Drought SPEI but excluding the temperature control. However, the results remain nearly unchanged.

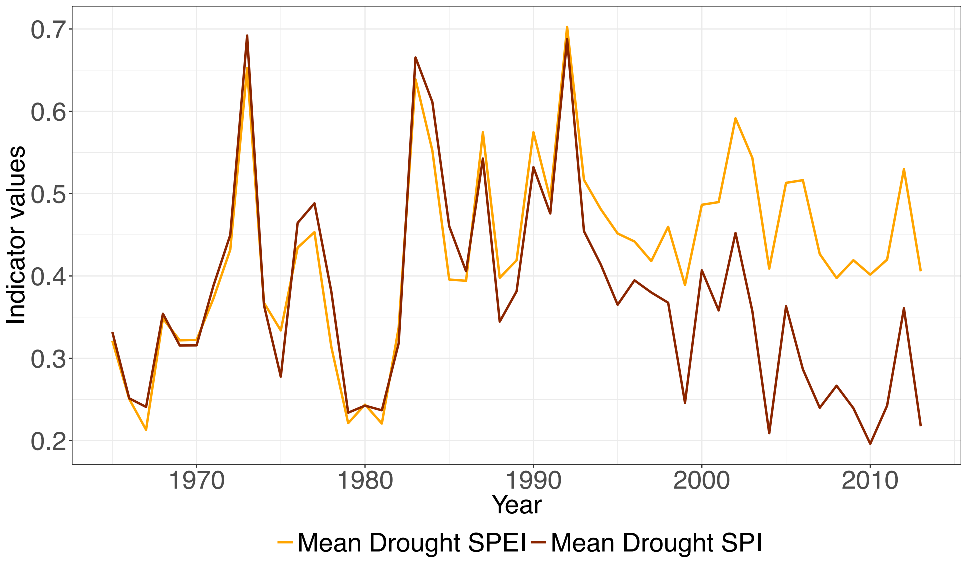


Figure 8: Yearly Averages of Drought SPEI and Drought SPI for the Full Sample, Source: CRU CY 3.22

try groups. However, the clear evidence that droughts raise corruption in countries with high per capita agricultural value added remains unchanged. A closer examination shows that the cumulative effects of droughts on corruption change are slightly lower, perhaps due to the fact that the SPEI emphasizes droughts in arid countries with high PET values, which typically have less agricultural production. This is expected to change when climate change raises PET also in more humid countries.

5.4. EM-DAT Drought Number Indicator

Comparable studies analysing the effects of natural disasters on corruption measure natural hazards by the number of disasters reported in EM-DAT (Yamamura 2014, Escaleras and Register 2016). This raises the question whether and how the presented estimation results would change if we would apply the EM-DAT Drought Number to measure the occurrence of droughts.[30] Figure A.20 in the Appendix compares the results of estimations applying the Drought SPI and the Drought Number. In the full sample a higher drought exposure leads to corruption increases regardless of the measure used. However, the results for several subgroups differ clearly. Estimating with the Drought Number measure undermines drought-induced corruption effects in high developed countries and emphasizes them in poor and, consequently, in agricultural dependent

[30]We normalize the reported number of droughts for the different size of countries by dividing it by the area of the countries (in million sq. km) derived from the WDI database.

countries. The first reason for these differences might be the already discussed possible endogeneity of the Drought Number indicator referring to development aspects. An identical meteorological drought event might reach the EM-DAT admission criteria thresholds, depending on deaths, the total of affected persons, the announcement of a state of emergency or a call for international assistance, much earlier in the socially more vulnerable poor countries. Therefore, the EM-DAT Drought Number might over-report droughts in developing countries. Second, the number of droughts in developing countries is suggested to be exaggerated to obtain international aid (Albala-Bertrand 1993, Skidmore and Toya 2002). Third, it should be considered that the Drought Number indicator gives no information about the severity of the reported droughts. It simply counts drought events not distinguishing whether they are of moderate or even devastating magnitude. The lack of information on drought severity when estimating with Drought Number may additionally explain the few negative significant cumulative coefficients in the short run in the rich and high per capita agricultural value added country groups.

6. Conclusions

To the best of our knowledge, this paper gives first evidence of short- and long-term effects of droughts on corruption. Therefore, we use a truly exogenous measure for drought occurrence and severity based on the SPI, consider the over-controlling problem and correct for spatial correlation within a unified panel analysis of 122 countries during the years 1985 to 2013. Estimation results for the full sample show that countries experience more corruption the more drought prone they have been in the preceding years. This effect holds true for subgroups of poor and rich countries although its timing and intensity distinguishes. Whereas in poor countries a drought if followed by significant higher corruption change in the medium run, rich countries experience long-term drought-induced corruption increases of comparable high size. Considering that agriculture is the economic sector primarily affected by droughts, we show that drought-related corruption threatens countries yielding high per capita income in the agricultural sector. This finding is of special importance as climate change is expected to raise drought frequency and intensity for humid regions such as Northwest France, Southeast England, Southeast Brazil, Uruguay, and Southeast United States, which are extensively used for agriculture and livestock farming (Carrao, Naumann and Barbosa 2016, Russo et al. 2013).

The results of this analysis should encourage governments and institutions to review common practices in drought management. The typical drought crisis management is often uncoordinated and disintegrated and increases future vulnerability as it reduces self-reliance and leads to higher dependence on government and donor organizations due to drought relief and assistance (Wilhite, Sivakumar and Pulwarty 2014). In addition, the findings of this study suggest that such policies prepare a convenient breeding ground for corruptive behaviour. This underlines the relevance of recent efforts to establish a more pro-active and self-relying drought management (Sivakumar et al. 2012, Wilhite, Sivakumar and Pulwarty 2014, Carrao, Naumann and Barbosa 2016). Further research, based on sub-national or micro-level data, analysing detailed diffusion ways of drought-induced corruption especially in high developed countries and in the agricultural sector, should accompany and support these policy efforts.

Furthermore, the findings of this paper suggest another possible transmission channel of drought effects on economic growth (see Berlemann and Wenzel 2016, Berlemann and Wenzel 2018) that should be explored by further research.

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A. Appendix

Table A.1: Data Sources

Variable	Description	Source
Corruption	Assesment of corruption within the political system	ICRG (2017)
Agriculture, value added	Percent of GDP	WDI (2016)
Agriculture, value added	Constant 2010 US$	WDI (2016)
Population	De facto total population	WDI (2016)
Area	Land area (sq. km)	WDI (2016)
Precipitation	Area weighted monthly mean of precipitation (in mm)	CRU CY 3.22
Potential Evapotranspiration	Area weighted daily mean of potential evapotranspiration (in mm)	CRU CY 3.22
Temperature	Area weighted monthly mean of temperature (in degree Celsius)	CRU CY 3.22
Drought Number	Number of registered drought events	EM-DAT (2018)

Table A.2: Summary Statistics

Variable	N	Mean	St. Dev.	Min	Max
Corruption	3435	2.951	1.356	0.000	6.000
Change of corruption	3313	0.023	0.346	−3.170	2.580
Agriculture, value added (% GDP)	3205	14.694	13.352	0.034	65.973
Agriculture, value added p.c. (US$)	3167	406.181	368.525	16.504	3799.123
Drought SPI	5978	0.373	0.527	0.000	3.305
Drought SPEI	5978	0.429	0.521	0.000	2.507
Drought Number	5978	0.544	5.485	0.000	194.932
Temperature	5978	17.993	8.531	−7.400	29.800
Standardized Temperature Anomaly	5978	0.402	1.047	−3.671	4.521

Table A.3: Augmented Dickey-Fuller Unit Root Test

Variable	lags (1)	lags (2)	lags (3)
Drought SPI	-51.8837	-29.7454	-24.9600
	(0.0000)	(0.0000)	(0.0000)
Drought SPEI	-52.0377	-27.9302	-22.3588
	(0.0000)	(0.0000)	(0.0000)
Drought Number	-57.5310	-37.3822	-30.6558
	(0.0000)	(0.0000)	(0.0000)
Temperature	-40.8956	-27.5934	-21.3543
	(0.0000)	(0.0000)	(0.0000)
Std. Temperature Anomaly	-47.2829	-30.0567	-24.5900
	(0.0000)	(0.0000)	(0.0000)
Corruption	-9.3858	-6.0875	-4.4691
	(0.0000)	(0.0000)	(0.0000)
Change of corruption	-33.5241	-20.3470	-14.9323
	(0.0000)	(0.0000)	(0.0000)

Notes: Inverse logit t test-statistic (L*). Calculated for demeaned variables. P-values reported in parenthesis.

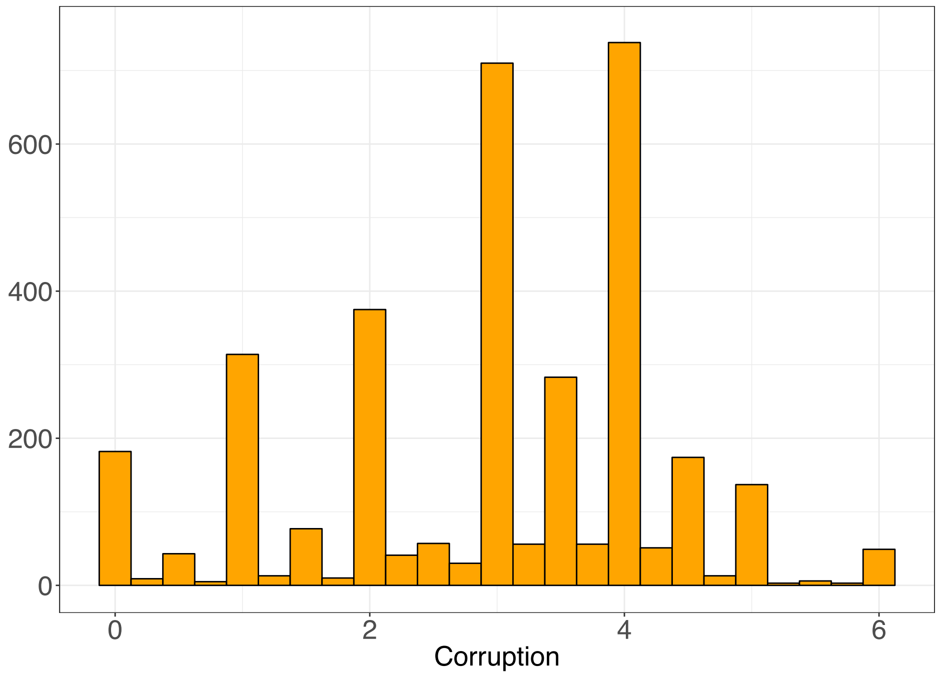


Figure A.9: Histogram of Corruption, Source: ICRG (2017)

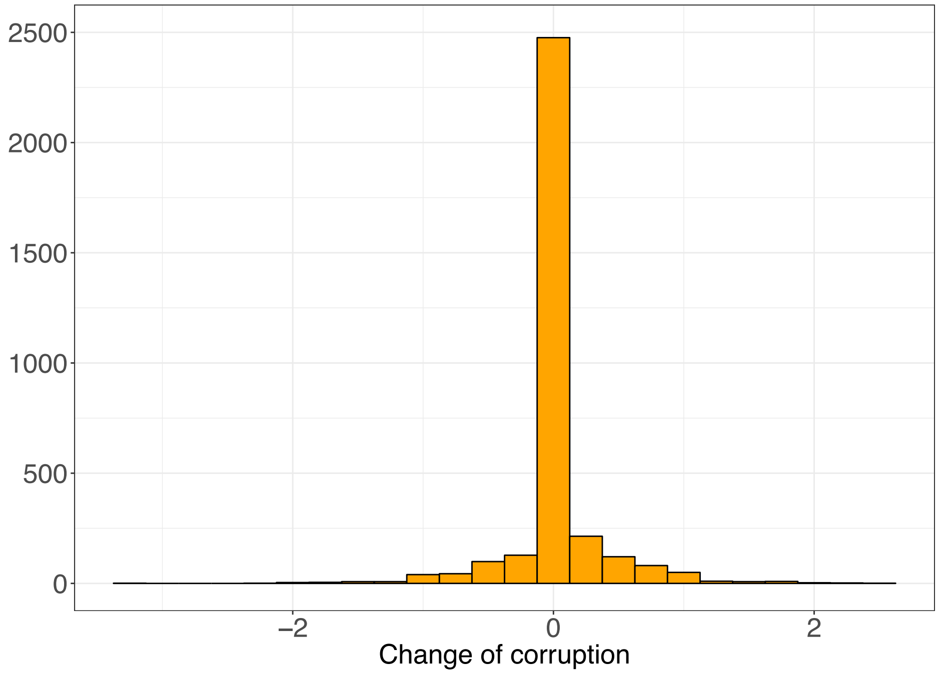


Figure A.10: Histogram of Corruption Change, Source: ICRG (2017)

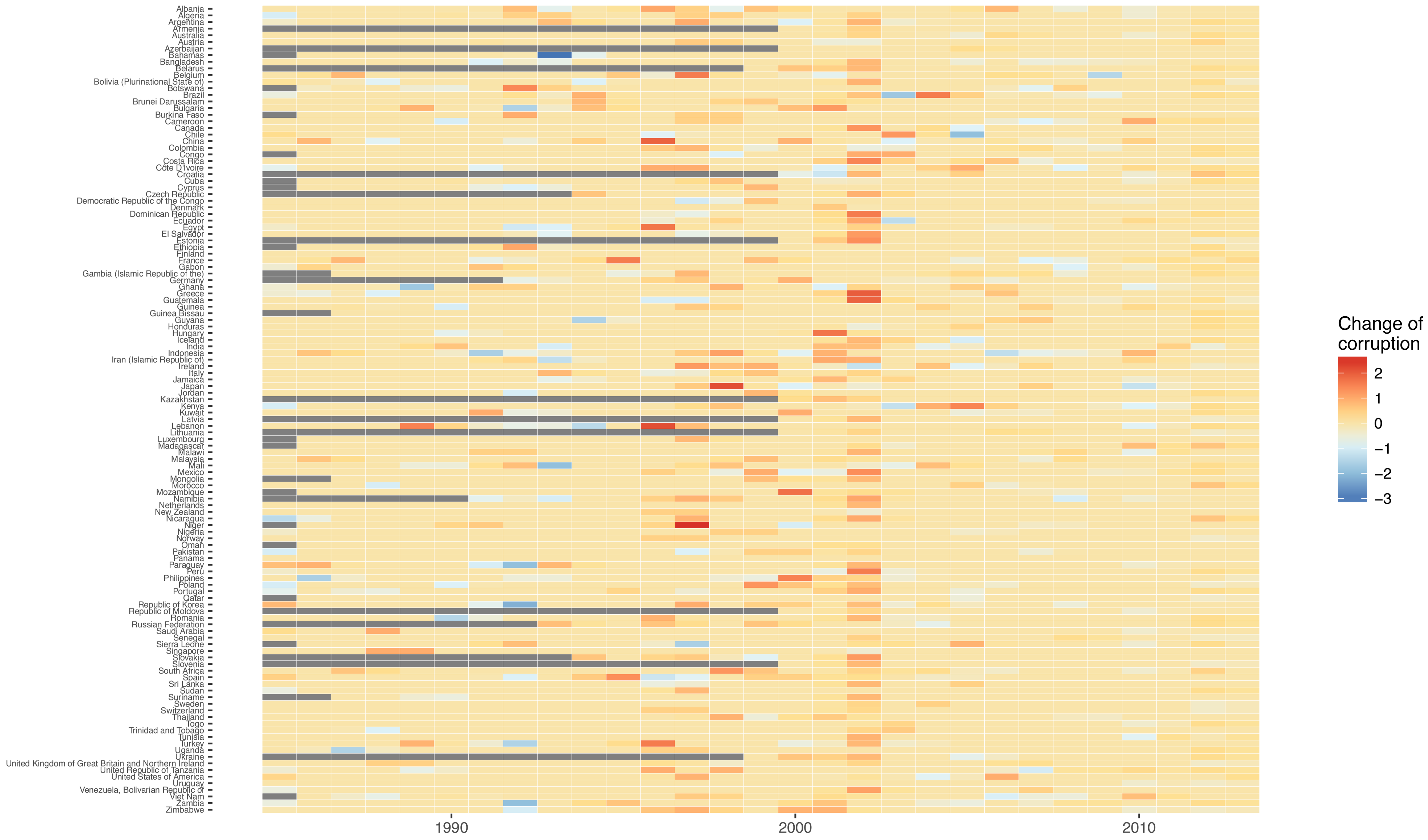


Figure A.11: Heatmap of Corruption Change, Source: ICRG (2017)

Table A.4: Top and Bottom 10 Countries - Drought Data

Top 10 countries			**Bottom 10 countries**		
Rank	Country name	Value	Rank	Country name	Value
		Average Drought SPI (1965-2013)			
1	Burkina Faso	0.75	122	Argentina	0.02
2	Gambia (Islamic Republic of the)	0.73	121	Canada	0.04
3	Guinea	0.72	120	Costa Rica	0.08
4	Guinea Bissau	0.70	119	Iceland	0.13
5	Mali	0.67	118	Madagascar	0.13
6	Oman	0.64	117	Republic of Moldova	0.16
7	Saudi Arabia	0.61	116	Russian Federation	0.17
8	Senegal	0.60	115	Sweden	0.17
9	Sierra Leone	0.60	114	Ukraine	0.18
10	Sudan	0.58	113	United States of America	0.18
		Average Drought SPEI (1965-2013)			
1	Algeria	0.77	122	Australia	0.11
2	Gambia (Islamic Republic of the)	0.74	121	Brazil	0.12
3	Guinea	0.73	120	Canada	0.13
4	Guinea Bissau	0.72	119	Costa Rica	0.19
5	Mali	0.72	118	Iceland	0.20
6	Mongolia	0.69	117	Madagascar	0.20
7	Oman	0.69	116	Norway	0.20
8	Saudi Arabia	0.65	115	Panama	0.23
9	Senegal	0.65	114	Sweden	0.23
10	Sierra Leone	0.65	113	United States of America	0.26
		Average Drought Number (1965-2013)			
1	Cyprus	12.10	122	Austria	0.00
2	El Salvador	5.65	122	Bahamas	0.00
3	Gambia (Islamic Republic of the)	4.92	122	Belarus	0.00
4	Guinea Bissau	4.42	122	Brunei Darussalam	0.00
5	Honduras	3.98	122	Czech Republic	0.00
6	Jamaica	2.93	122	Egypt	0.00
7	Malawi	2.90	122	Estonia	0.00
8	Republic of Moldova	1.86	122	Finland	0.00
9	Sri Lanka	1.82	122	Germany	0.00
10	Trinidad and Tobago	1.52	122	Switzerland	0.00

Table A.5: Top and Bottom 10 Countries - Other Data

Top 10 countries			**Bottom 10 countries**		
Rank	Country name	Value	Rank	Country name	Value
Average corruption (1984-2013)					
1	Armenia	5.33	122	Canada	0.03
2	Azerbaijan	4.71	121	Denmark	0.22
3	Bangladesh	4.62	120	Finland	0.31
4	Dem. Rep. of the Congo	4.52	119	Iceland	0.34
5	Gabon	4.48	18	Luxembourg	0.38
6	Kazakhstan	4.40	117	Netherlands	0.41
7	Nigeria	4.38	116	New Zealand	0.47
8	Paraguay	4.29	115	Norway	0.56
9	Republic of Moldova	4.29	114	Sweden	0.58
10	Sudan	4.28	113	Switzerland	0.76
Average change of corruption (1985-2013)					
1	Belarus	0.17	122	Bahamas	-0.14
2	Costa Rica	0.12	121	Bangladesh	-0.10
3	Czech Republic	0.12	120	Chile	-0.08
4	Estonia	0.11	119	Cyprus	-0.07
5	Kazakhstan	0.11	118	Dem. Rep. of the Congo	-0.05
6	Niger	0.11	117	Indonesia	-0.04
7	Russian Federation	0.11	116	Pakistan	-0.04
8	Slovakia	0.10	115	Philippines	0.10
9	South Africa	0.09	114	Qatar	-0.04
10	Ukraine	0.09	113	Zambia	-0.03
Average per capita agricultural value added (in 2010 US$) (1984-2013)					
1	Australia	3191.75	122	Bangladesh	40.78
2	Finland	2405.62	121	Congo	78.84
3	Greece	1044.47	120	Dem. Rep. of the Congo	83.40
4	Iceland	1021.36	119	Ethiopia	89.55
5	Malaysia	980.29	118	Guinea	99.61
6	New Zealand	909.49	117	Jordan	101.64
7	Norway	864.25	116	Mozambique	102.15
8	Spain	855.46	115	Qatar	107.98
9	Turkey	782.58	114	Singapore	111.57
10	Uruguay	763.62	113	Trinidad and Tobago	114.83
Average agricultural value added (percent of GDP) (1984-2013)					
1	Ethiopia	50.46	122	Belgium	0.17
2	Ghana	49.49	121	Brunei Darussalam	0.23
3	Guinea Bissau	49.44	120	Germany	0.37
4	Malawi	39.79	119	Kuwait	0.58
5	Mali	39.31	118	Luxembourg	0.94
6	Niger	37.87	117	Qatar	1.00
7	Sierra Leone	37.85	116	Singapore	1.09
8	Togo	37.56	115	Switzerland	1.10
9	Uganda	37.20	114	United Kingdom	1.20
10	United Republic of Tanzania	36.22	113	United States of America	1.20

Table A.6: Drought Effects on Agriculture

Crop and timber production	Livestock and dairy production	Fishery
Decreased amount and quality of harvest due to: • reduced plant growth • abnormal insect infestations • higher disease vulnerability • lower nutrient availability and uptake • soil changes	High feeding and watering costs due to: • scarce water resources • reduced pasture growth • need of supplemental feeding	Loss of fish population due to: • desiccation of lakes and rivers • decreased river streams (especially affecting young fish)
Decreased soil fertility (e.g. wind erosion)	Reduced conception rate, health conditions and milk production (cattle)	
Loss of perennial plants	Increased animal slaughter	
Price changes with complex effects (partly loss-compensating) due to supply reductions		
Effects on agricultural dependent and processing industry		
Reduced tax revenue		

Sources: Wilhite 1992, Al-Kaisi et al. 2013, Leister, Paarlberg and Lee 2015, Stewart et al. 2013

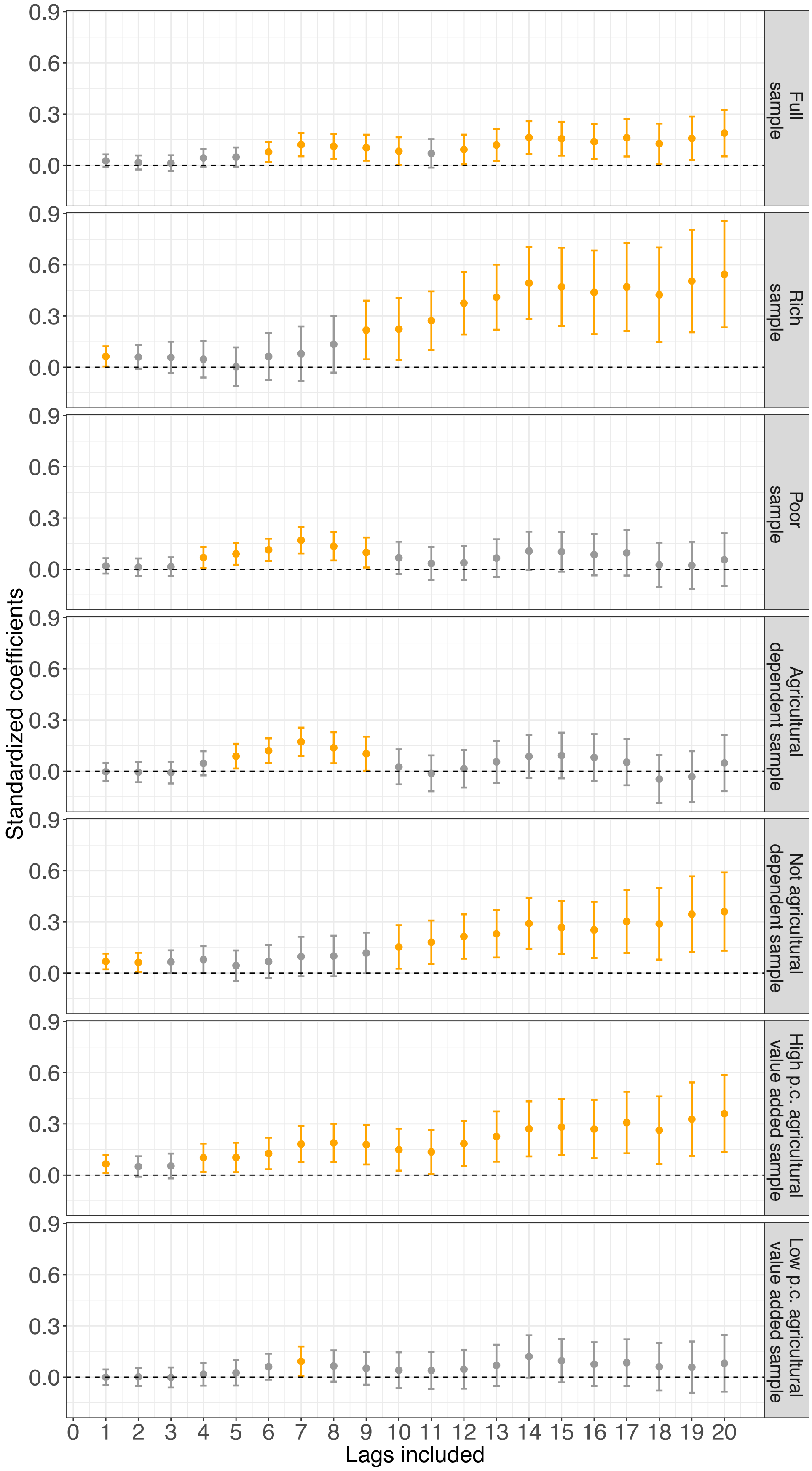


Figure A.12: Cumulative Effects of Drought SPI on Corruption Change, Average Monthly Temperature (in Degree Celsius) Instead of Standardized Temperature Anomaly as Control Variable Included, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

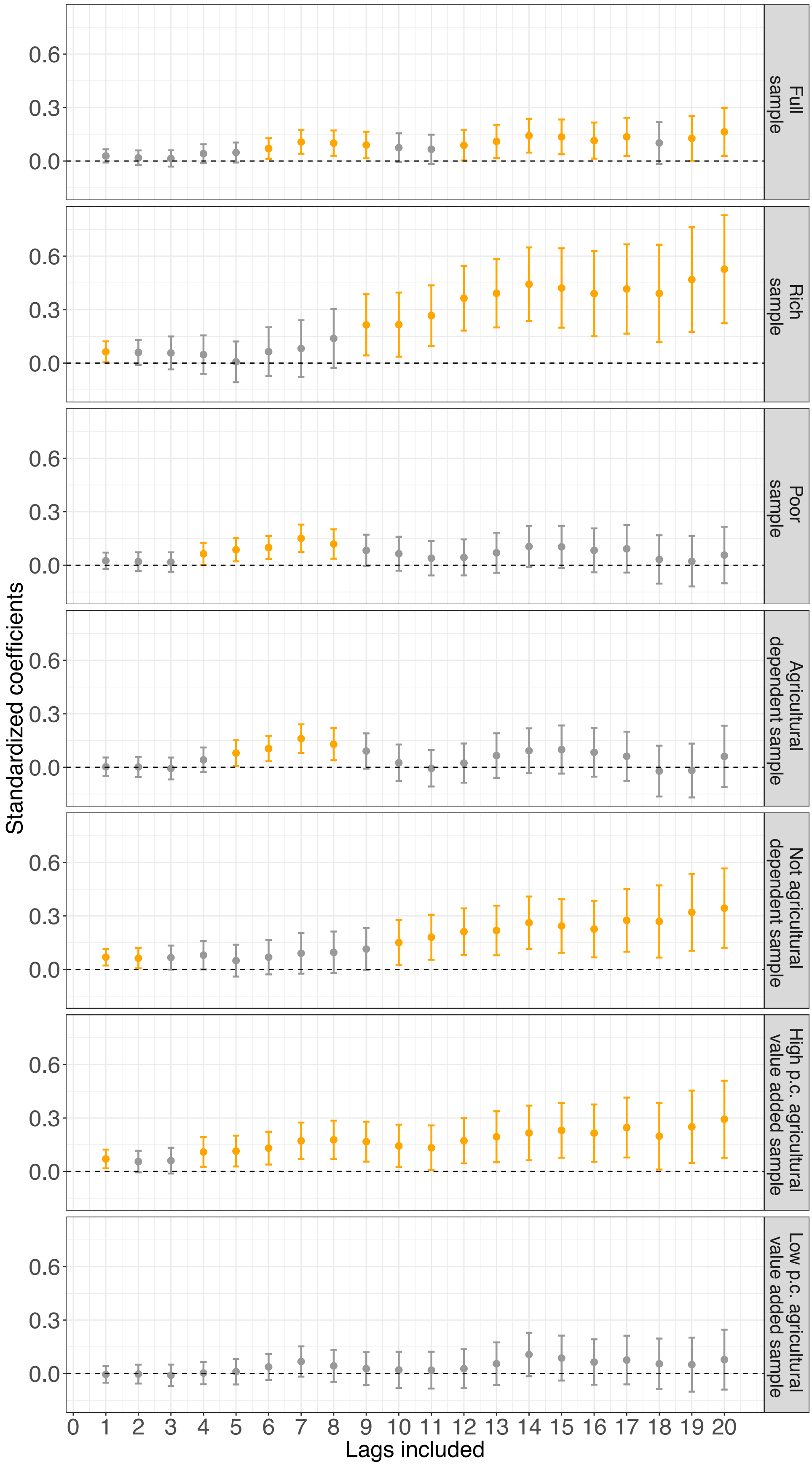


Figure A.13: Cumulative Effects of Drought SPI on Corruption Change, Without Temperature Control Variable, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

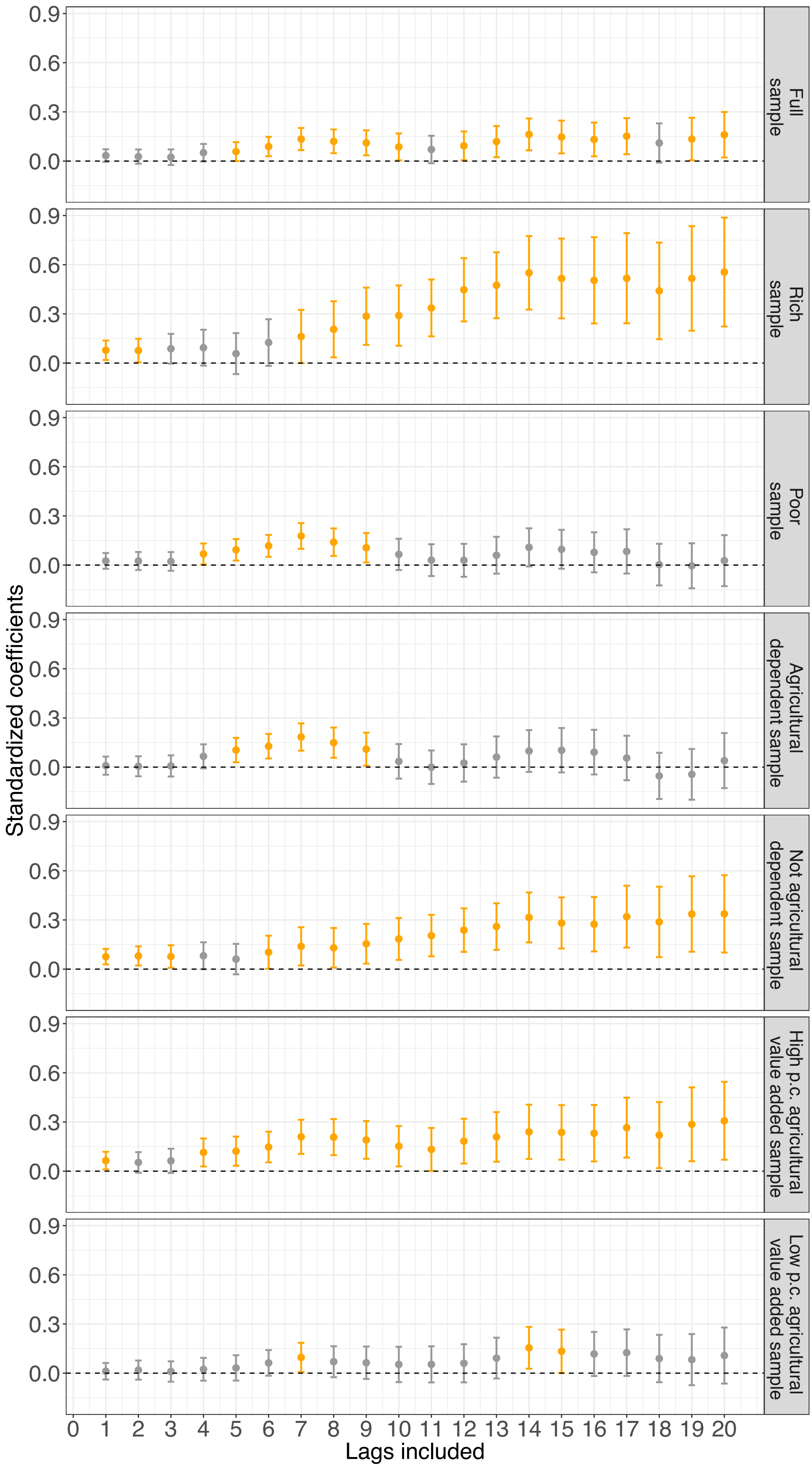


Figure A.14: Cumulative Effects of Drought SPI on Corruption change, Samples Without Former Warsaw-Pact States, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

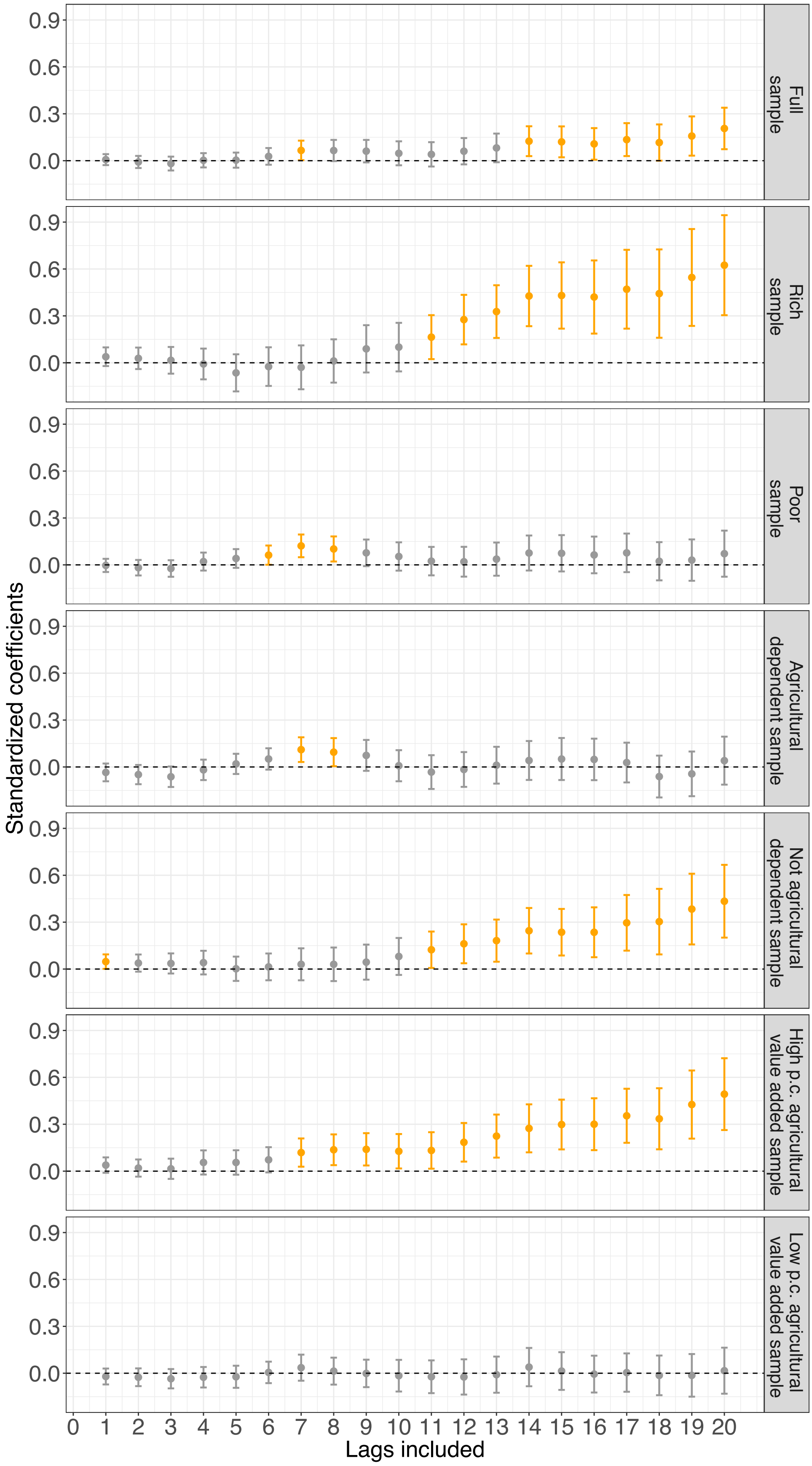
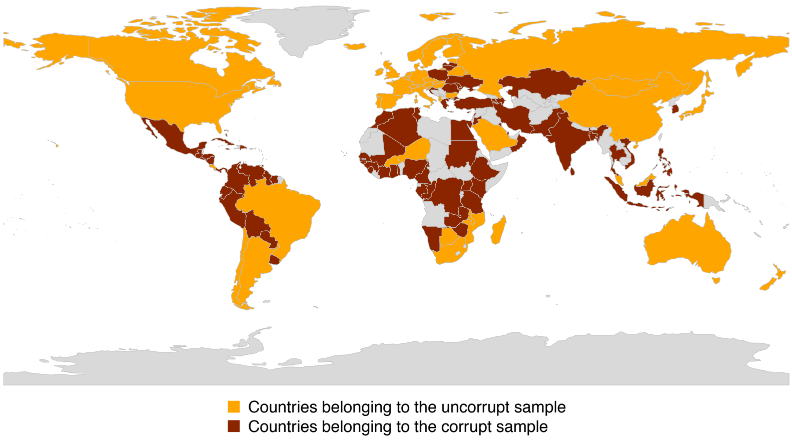


Figure A.15: Cumulative Effects of Drought SPI on Corruption Change, With One Year Lagged Corruption Level as Additional Control Variable, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)



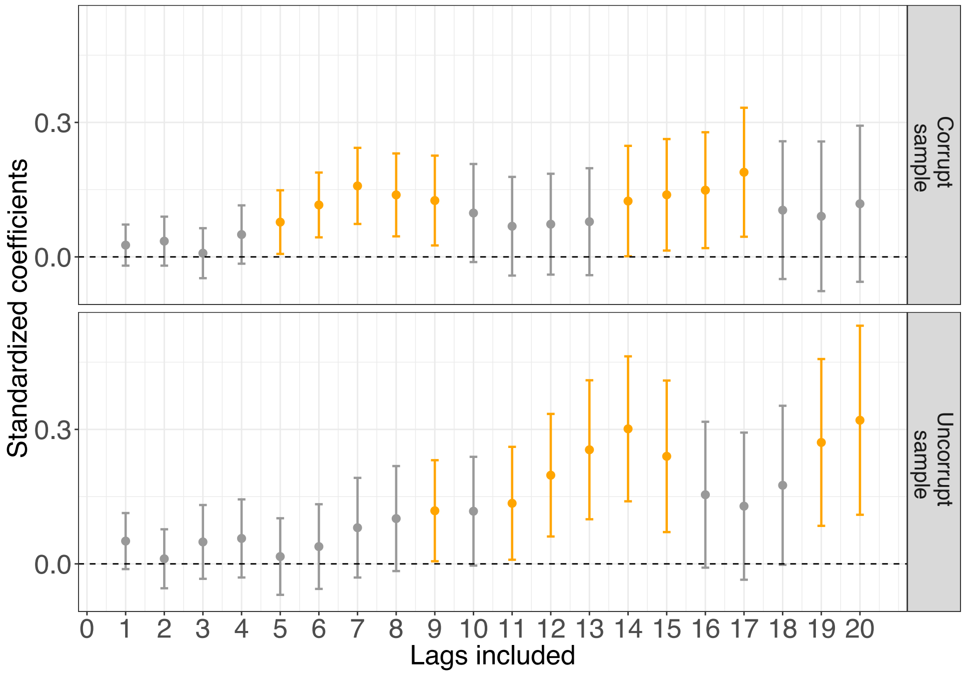
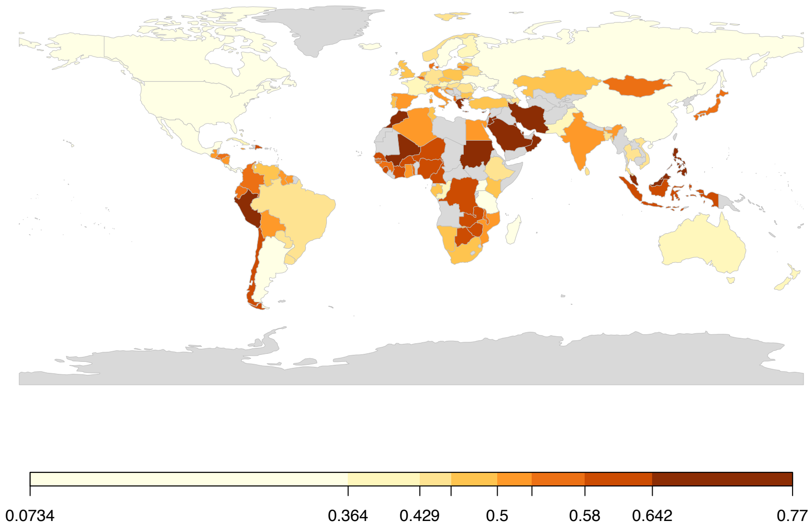
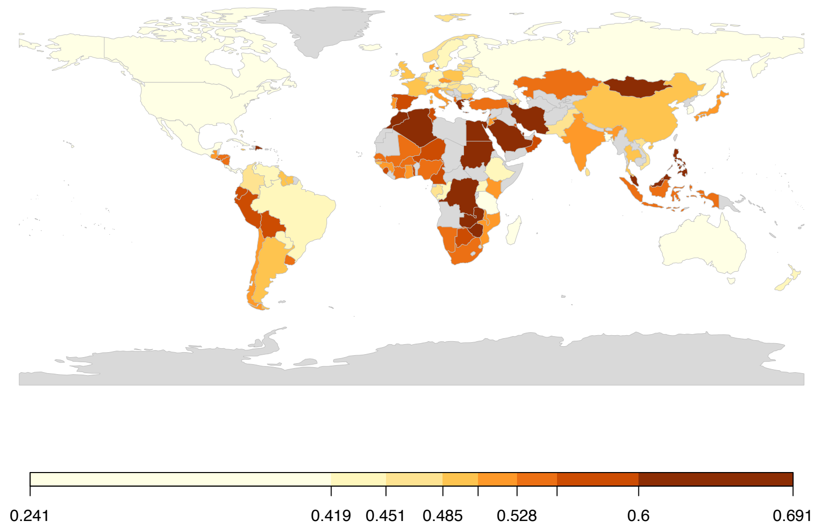


Figure A.16: Cumulative effects of Drought SPI on Corruption Change, Corrupt and Uncorrupt Samples, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)



Drought SPI



Drought SPEI

Figure A.17: Country Standard Deviations of Drought SPI and Drought SPEI (1965-2013),
8 quantiles, Source: CRU CY 3.22

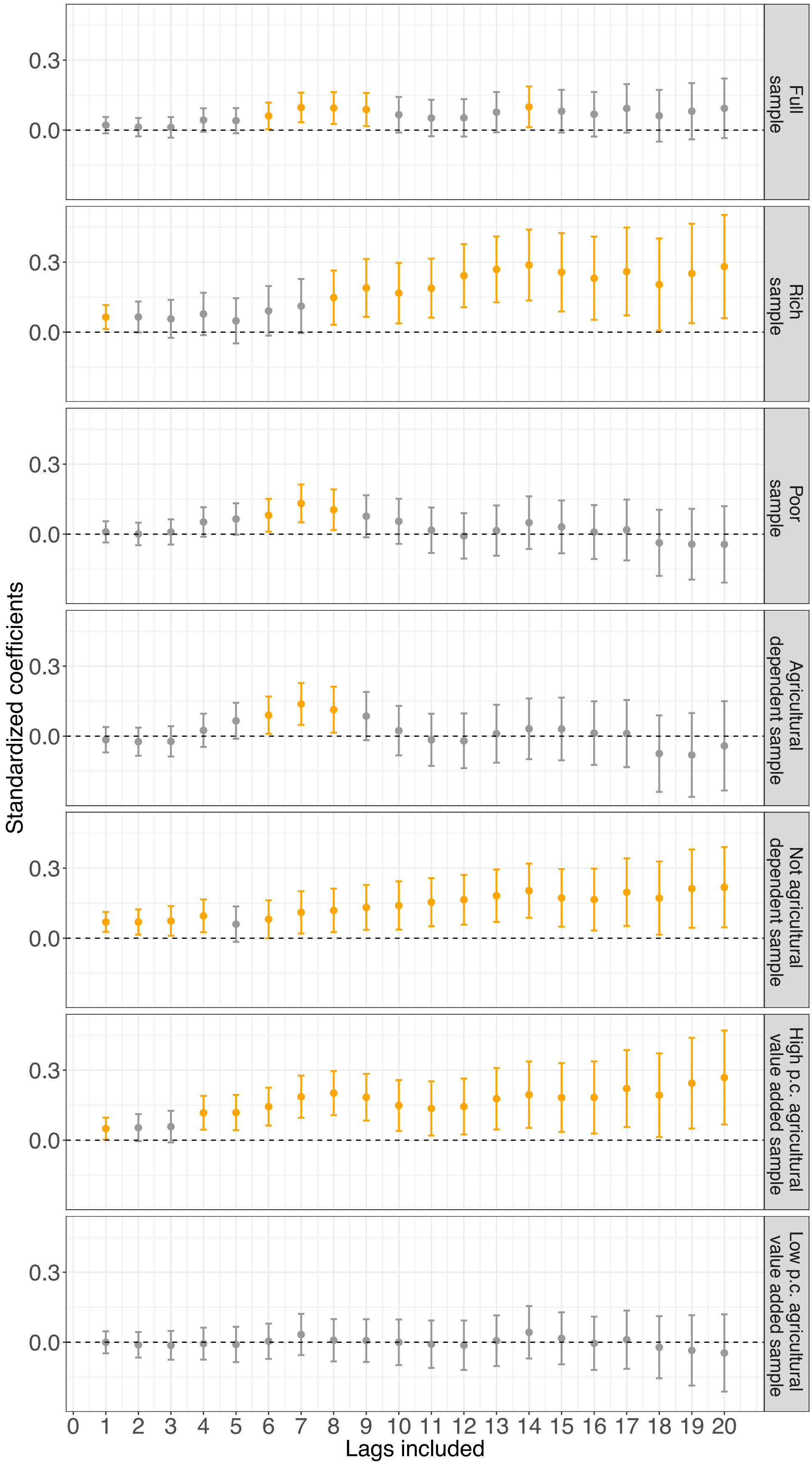


Figure A.18: Cumulative Effects of Drought SPEI on Corruption Change, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

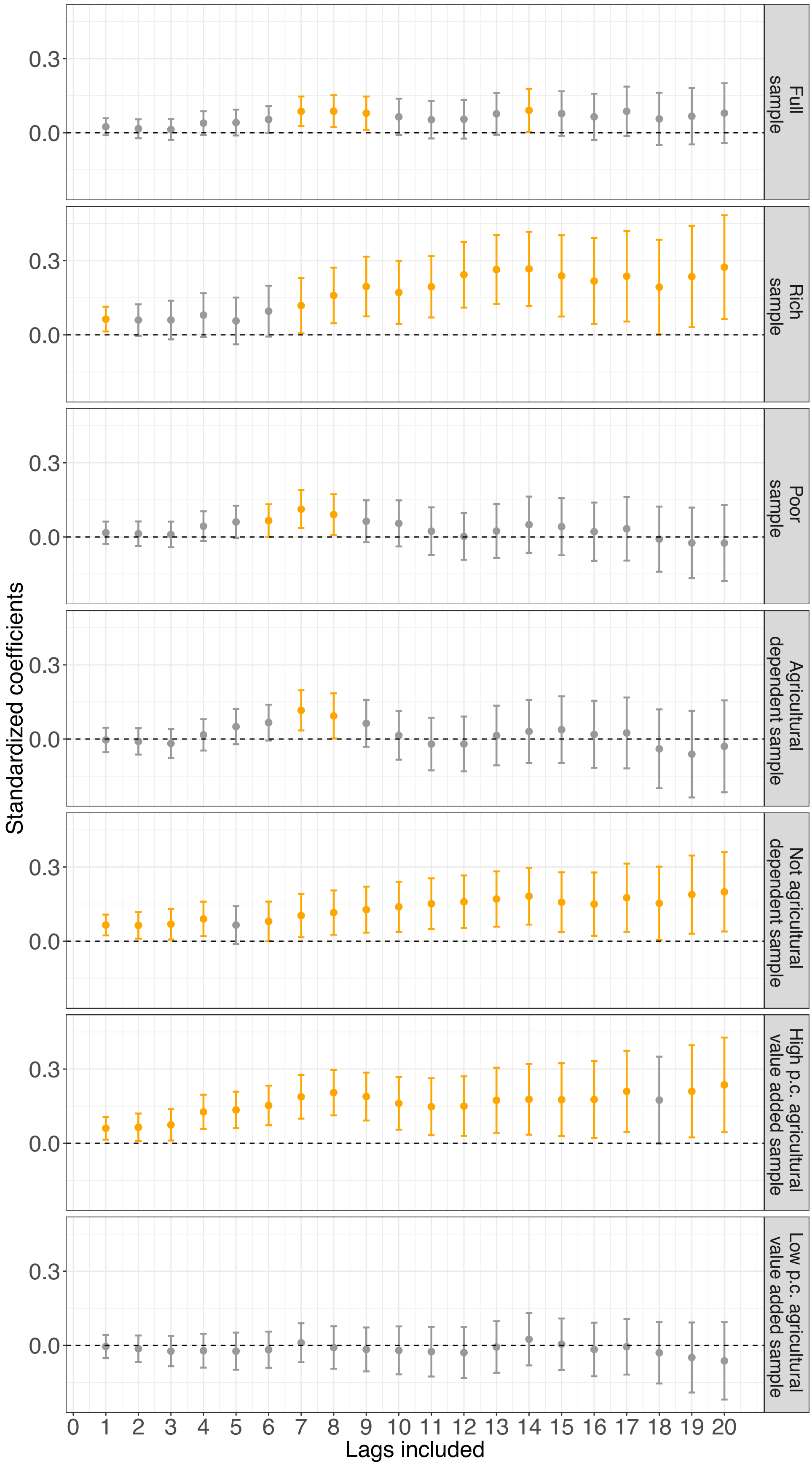


Figure A.19: Cumulative Effects of Drought SPEI on Corruption Change, Without Temperature Control Variable, Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

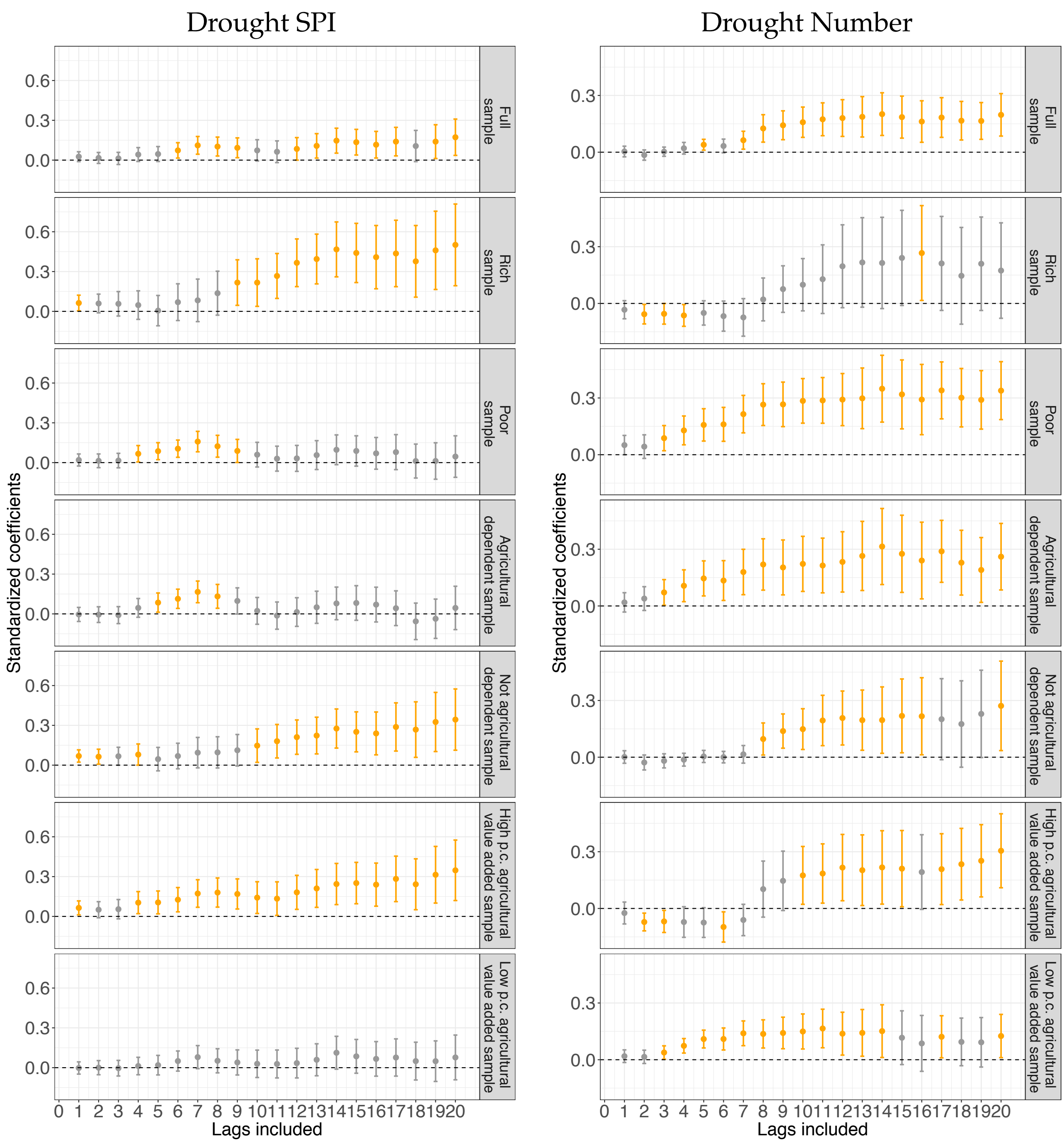


Figure A.20: Cumulative Effects of Drought SPI and Drought Number on Corruption Change,
Point Estimator and 90 Percent Confidence Interval (1985 – 2013)

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