CESifo WORKING PAPERS

7258
2018

September 2018

Precipitation and Economic Growth

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
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Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
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CESifo *Working Paper No. 7258*
Category 10: Energy and Climate Economics

Precipitation and Economic Growth

Abstract

As the ongoing process of global warming goes along with changes in both mean precipitation and precipitation extremes, the scientific interest in the effects of rainfall on economic prosperity has recently grown significantly. However, the few existing empirical studies of short-run growth effects of precipitation deliver inconclusive results. The medium- and long-run growth perspective is yet mostly unexplored. In this paper we deliver a systematic analysis of the short- and long-run growth effects of rainfall based on a large panel dataset covering more than 150 countries over the period of 1951 to 2013. We find strong and highly robust empirical evidence for long-lasting negative growth effects of rainfall shortages in poor and underdeveloped countries, which are not driven by the subsample of Sub Saharan African countries.

JEL-Codes: O440, Q540, Q560, F630.

Keywords: economic growth, precipitation.

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September 13, 2018

1 Introduction

As long as farming was the primary source of employment and income, economists strongly recognized the role of geography and climate in determining economic prosperity (Nordhaus 2006). However, as the agricultural sector became less important as a consequence of industrialization, endogenously determined production factors such as capital, labor, population growth, human capital and technology became the most discussed determinants of economic growth. In the late 1990s economists noticed that saving, investment, fertility, educational efforts and research and development, i.e. behavior leading to the accumulation of traditional factors of production, might be driven by institutions (Acemoglu, Johnson and Robinson 2001) and geography (Bloom et al. 1998). Only recently, mostly driven by the phenomenon of global warming, climatic factors were rediscovered as potential determinants of economic activity.

Global warming, i.e. the upward trend of the average surface temperature since the early 20th century, and most notably since the late 1970s, already has and will continue to change the living conditions on planet Earth. While the average annual surface temperature fluctuates only slightly around an upward trend, regional changes in climatic variables such as temperature and precipitation differ enormously. Most scientists expect global warming to continue in the future even if the climate goals of the Paris agreement of 2015 were to be met. The phenomenon of global warming is most closely related to an increase in the (regional) mean temperature. However, changes in mean temperatures often go along with changes in temperature variability and temperature extremes (Rummukainen 2012). Quite obviously, over land the number of warm days and nights increases whereas the opposite holds true for cold days and nights (Zhang et al. 2011). There is an especially strong upward trend for the occurrence of heat waves (Schär et al. 2004, Jones, Stott and Christidis 2008, Kyseli 2009), whereas cold extremes are expected to become more rare, although not necessarily less intense and long-lasting (Kodra, Steinhaueser and Ganguly 2011).

Global warming has also an effect on precipitation patterns. According to the so-called Clausius-Clapeyron relationship, an increase of one degree of temperature leads to a 7 percent rise in atmospheric moisture (Rummukainen 2012). More water in the atmosphere generates changes in the hydrological cycle. In combination with increasing temperature (and thus rising evaporation), a rise in atmospheric moisture results in an increase of global precipitation. However, precipitation has developed quite heterogeneously in the spatial dimension. In the mid and the high latitudes of the Northern Hemisphere precipitation increased by between 0.5 and 1 percent per decade since 1910 (mostly in autumn and winter) whereas in the sub-tropics precipitation decreased by about 0.3 percent per decade (Walther et al. 2002).

Not only mean precipitation is subject to change in consequence of global warming, but also precipitation extremes (Kharin et al. 2007, Westra et al. 2014). While average precipitation is restricted by evaporation from a global perspective and thus is only loosely connected to atmospheric moisture, precipitation extremes are much more closely linked to the total water content of the atmosphere. In particular, convective precipitation[1] contributes to this phenomenon (Berg, Moseley and Haerter 2013). Lehmann, Coumou and Frieler (2015) show that between 1980 and 2010 the number of record-breaking precipitation events per year has significantly increased on the global level. Especially over land areas of the Northern Hemisphere and in some regions close to the equator precipitation extremes are becoming more prevalent (Orlowsky and Seneviratne 2012, O'Gorman and Schneider 2009). Notably, strong increases in extreme precipitation events are expected for South-East Asia (Lehmann, Coumou and Friehler 2015). Global warming will most likely also increase the number of droughts (Dai 2011), extreme periods of unusually dry conditions, relative to trends. Drought prevalence is mostly increasing in large parts of Africa, the Mediterranean region, parts of North- and South America and Southeastern Asia (Rummukainen 2012).

In the light of rising mean precipitation (and especially of the growing number and intensity of extreme precipitation events and droughts) a renewed interest in the effect of precipitation on economic growth evolved. The effects of extreme weather events might go well beyond the direct effects on agriculture. Heavy precipitation events, but also extremely dry periods, might affect the tourism sector (Becken and Wilson 2013). Whenever countries use hydroelectric or other sorts of energy production that

[1]Convective precipitation occurs when air rises vertically rather than diagonally. Convective precipitation is typically more intense and short-termed than other forms of precipitation such as stratiform and orographic precipitation.

use water as secondary input, precipitation might affect the energy sector (Solaun and Cerda 2017). Heavy precipitation and related flood events might destroy capital goods and public infrastructure (Berlemann, Steinhardt and Tutt 2017). Both effects often result in interruptions of business activity (Berlemann and Vogt 2008). Precipitation events, especially droughts, might also lower school attendance (Alderman, Hoddinott and Kinsey 2006, Alston and Kent 2006, Sacerdote 2012). Extreme rainfall events and droughts might also impact fertility (Schultz 1997, Guarcello, Mealli and Rosati 2010). Last but not least, emergency help and reconstruction support for the affected population typically binds fiscal resources which are then unavailable for different, potentially more productive utilizations.

Numerous empirical studies have considered the effect of rainfall on agricultural productivity, either in the form of case studies, single country time-series analyses or, more rarely, in panel studies.[2] However, they almost exclusively focus on the very short-run and on countries with a comparatively high importance of the agricultural sector. Interestingly enough, they nevertheless fail to deliver a clear picture as various studies find a positive effect of precipitation while others find the opposite or no effect. To a significant extent, this is due to the enormous variety in sample countries, sample periods, data sources, empirical methodologies and time horizons. Moreover, one might suspect that one of the major sources of heterogeneity is the employed rainfall indicator.

In this paper we contribute to the literature by delivering a systematic empirical analysis of the short- but especially potentially occurring long-run effects of precipitation on economic growth. Our (unbalanced) sample covers the period of 1951 to 2013 and more than 150 countries around the globe, allowing us to deliver results in a worldwide perspective but also for certain subgroups of countries. In order to solve the over-controlling problem (Dell, Jones and Olken 2014) we run our estimations in a two-way fixed effects setting with heteroscedasticity and autocorrelation (HAC) corrected standard errors. We also control for spatial dependencies which likely play an important role in the context of spatially correlated rainfall. We make use of three advanced measures of precipitation, standardized rainfall anomalies (SPA), the standardized pre-

[2]We summarize the related literature in Section 3.

cipitation index (SPI) and the standardized precipitation and evapotranspiration index (SPEI), which have yet rarely been used in the related literature. Besides using the indicators in their classical linear version in our regression approach, we also allow for asymmetric effects for comparatively dry and overly wet periods. Besides numerous stability tests, we also deliver results for three alternative rainfall datasets to study whether our results depend on the source of precipitation data.

Our major findings, which turn out to be robust in a large number of stability tests, is that rainfall primarily matters only in the group of less developed and comparatively poor countries. For this country group we find a systematically negative impact of rainfall shortages on economic growth which last for more than a decade, indicating that the effects of overly dry periods go well beyond the short-term effect of crop-failure. Interestingly enough, rainfall surpluses turn out to have no significant growth effects. We also show that the effects for poor countries are not driven by the group of Sub Saharan African countries.

The paper is organized as follows. The second section introduces the measurement of precipitation and discusses various existing precipitation indices. The third section summarizes the existing literature. Section 4 explains our estimation approach and the employed data. In Section 5 we deliver and discuss our estimation results. Section 6 delivers numerous stability tests. Section 7 summarizes and concludes.

2 Precipitation Measurement and Precipitation Indicators

Constructing adequate precipitation measures is a rather complex task. The amount of precipitation reaching the ground during a certain period of time is equal to the depth to which it would cover a horizontal projection of the Earth's surface, provided any part of the precipitation falling as snow or ice were melted. Over larger areas, precipitation is hard to measure precisely. To a large extent this is due to the fact that precipitation exhibits comparatively low degrees of spatial and temporal correlation. Moreover, regional variations in topography can affect precipitation amounts significantly. These properties make it hard to interpolate rainfall between the units of measurement. In practice, precipitation is either measured by gauge stations, weather radar or satellite imagery. Numerous local and regional precipitation datasets are available. Even on the global scale, various datasets are accessible. In our subsequent empirical investigations we mostly rely on one of the most prominent datasets, the CRU CY dataset published by the Climate Research Unit of the University of East Anglia.[3]

The Central Research Unit Country (CRU CY) dataset (Version 3.22) provides monthly area weighted[4] country means of precipitation (P) and potential evapotranspiration (PET)[5] in mm for the period of 1901 to 2013. The referring time series are derived from the CRU Time Series (TS) gridded dataset,[6] which uses meteorological station observations covering the global land surface (except Antarctica) to obtain 0.5 degree latitude/longitude grid cell data.

Figure 1 maps the mean of the annual area-weighted precipitation averages of all countries which are later included into our estimations.[7] We show the mean over the period of 1931 to 2013, which is the sample period for our subsequent empirical study.[8] The color categories refer to eight quantiles of the rainfall variable. It is easy to see that mean rainfall is high in the tropics and low in the arid climate zone. Similarly, Figure 2 shows eight quantiles of the mean annual area-weighted PET averages. The PET values are rather theoretical than actual, as they indicate the evaporative demand of the atmosphere, calculated for a reference surface (a well-watered hypothetical grass reference crop with specific characteristics). As the figure reveals, potential evapotranspiration is highest in the arid climate zones.

[3] In Section 6.1 we show the results which are derived when using two alternative precipitation datasets with worldwide coverage.

[4] In order to construct internationally comparable data, either area or population weights are used in the related literature (see Dell, Jones and Olken 2014). We opt for area weights in our study as agriculture is likely a major factor in determining the impact of rainfall on economic growth.

[5] The reported PET values are calculated in accordance with the Food and Agricultural Organization (FAO) grass reference evapotranspiration equation, a variant of the Penman Monteith method, developed by Elkstrom et al. (2007). It is based on Allen et al. (1994) and takes into account the daily mean temperature, monthly average daily minimum and maximum temperature, vapor pressure and cloud cover.

[6] For a more detailed description of the data see Harris and Jones (2014).

[7] We only consider countries for which CRU CY 3.22 provides rainfall and PET data. Moreover we restrict ourselves to countries for which data on economic growth is available. This leads to a country sample of 153 countries.

[8] Data on economic growth is not available before 1951, however, as rainfall indicators enter our estimation equations with a lag of up to 20 years, the rainfall dataset is including earlier observations.

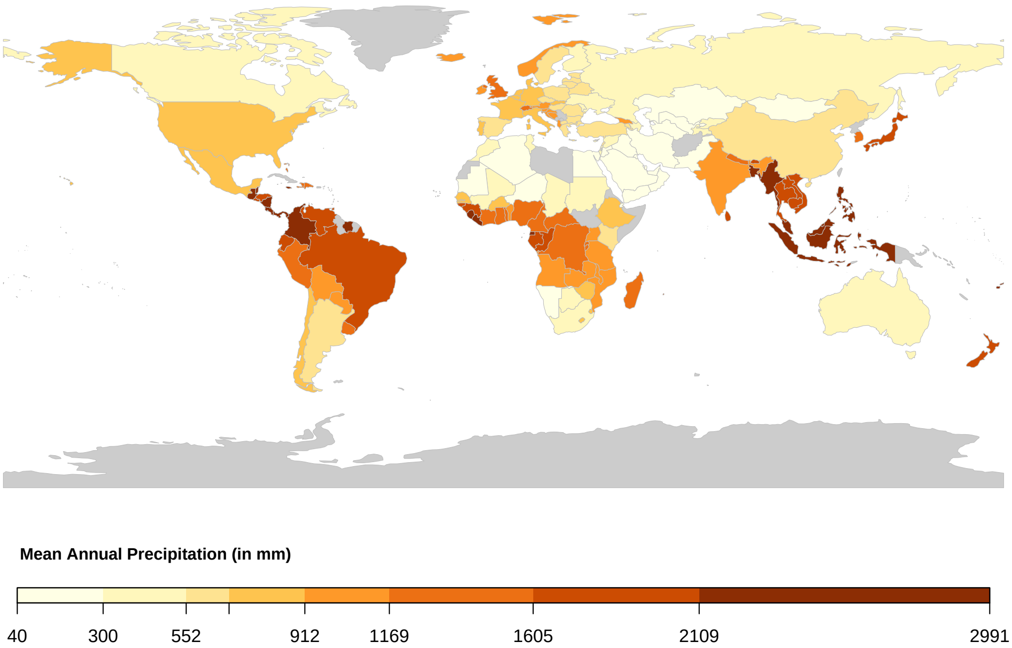

Figure 1: Long-run Average of Mean Annual Precipitation (1931-2013), 8 Quantiles, Source: CRU CY 3.22

In principle, the rainfall level P can directly be used as precipitation indicator in empirical studies. However doing so is often inappropriate in growth regressions. While the absolute level of development of a region might depend on the rainfall level, economic growth is more likely depending on rainfall variability. The most simple measure of rainfall variability is the year-to-year fluctuation of the annual rainfall amount (PF), which can be calculated for country i and time t as

$$PF_{t,i} = P_{t,i} - P_{t-1,i}. \tag{1}$$

While this rainfall indicator is easy to construct, it has its problems. Its major disadvantage is that two subsequent years of low rainfall are treated quite differently although they most likely have quite similar effects on economic growth. In the first year of low rainfall, the PF-indicator would deliver a numerically large negative value whereas the indicator-value would be close to zero in the second year. A more advanced indicator is the standardized precipitation anomaly (SPA), which is calculated as the difference of the annual rainfall amount of country i and its long term mean, divided by its long

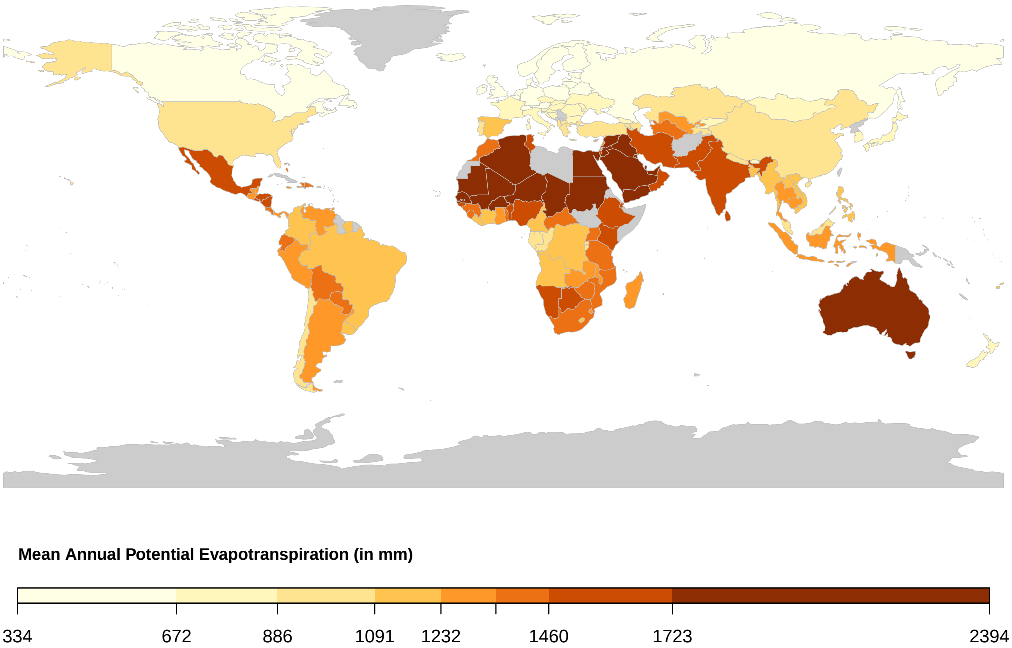

Figure 2: Long-run Average of Mean Potential Evapotranspiration (1931-2013), 8 Quantiles, Source: CRU CY 3.22

term standard deviation, i.e.

$$SPA_{t,i} = \frac{P_{t,i} - \frac{\sum_{j=t_0}^{T} P_{j,i}}{T}}{\sigma_P}. \tag{2}$$

Negative values of the indicator are associated with precipitation less than the long-term average, positive values indicate the opposite. A high fluctuation of the *SPA* indicator indicates that rainfall varies strongly around the long-run mean. In Figure 3 we show the standard deviation of the *SPA* indicator over the whole sample period and all countries included in our subsequent estimations.[9]

An alternative to the *SPA* is the Weighted Anomaly of Standardized Precipitation (*WASP*) index, developed by Lyon and Barnston (2005). The construction of the *WASP* index implies that standardized anomalies are weighted according to the annual cycle of precipitation, thereby applying a higher weight to months with high rainfall values during a year.

More advanced rainfall indicators interpret precipitation as a realization of a probabil-

[9]We compute the long-term means as well as standard deviations over the whole available data range, i.e. over the period of 1901 to 2013.

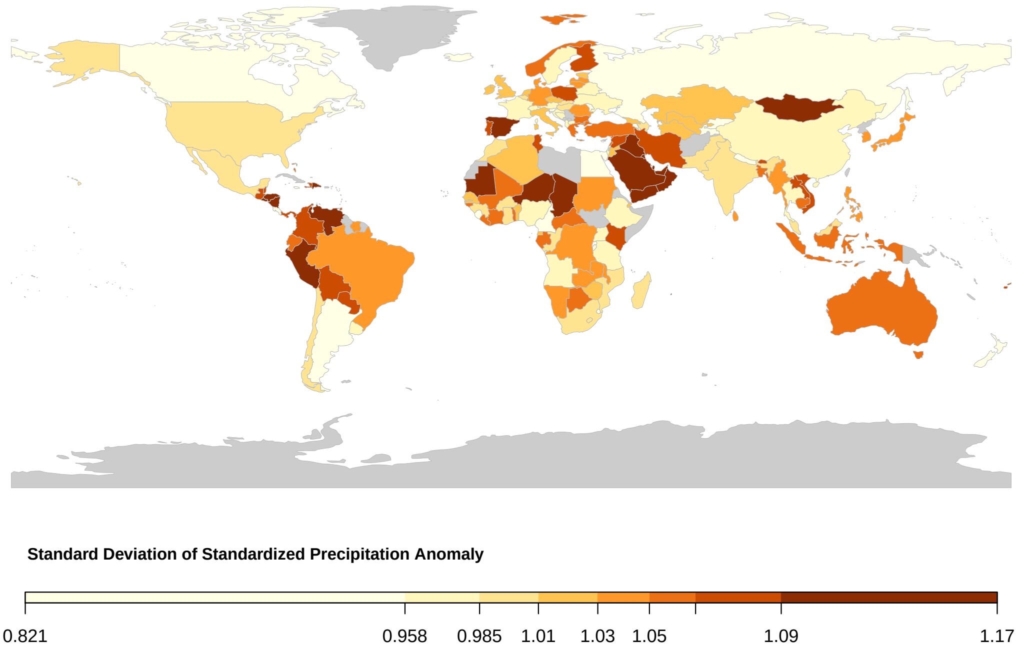

Figure 3: Standard Deviation of Standardized Precipitation Anomaly (1931-2014), 8 Quantiles, Source: CRU CY 3.22

ity function. It has been found that the distribution of rainfall can be well approximated by the gamma distribution. However, depending on the exact place, the parameters of the distributions differ considerably in their means (see e.g. Figure 1) and variances. Due to the differences in the distributional parameters it is problematic to directly compare rainfall events in different areas as one and the same deviation from mean rainfall might be judged as ordinary in one region whereas it is extraordinary in another one.

The standardized precipitation index (*SPI*), developed by McKee, Doesken and Kleist (1993), solves this problem by applying a three-step procedure. In the first step, the parameters of the regional gamma distribution are fitted using maximum likelihood estimation. In the second step the cumulative density function of the gamma distribution is used to calculate the cumulative probability of actual precipitation. In the third step the calculated cumulative probability is inserted into the cumulative probability function of the standardized normal distribution, thereby delivering a transformed, but standardized *SPI* value. The SPI value is to be interpreted as the number of standard deviations by which the observed anomaly deviates from the long-term mean. Altogether, the described procedure ensures that rainfall at very different locations can be directly compared. While the *SPI* was primarily developed for defining and monitoring drought events, the indicator can be used in a much broader sense to measure overly wet and dry periods. Figure 4 illustrates the interpretation of *SPI* values in the context of the normal curve.[10] Figure 5 shows the variability of *SPI* values for our sample countries over the period of 1931 to 2013.

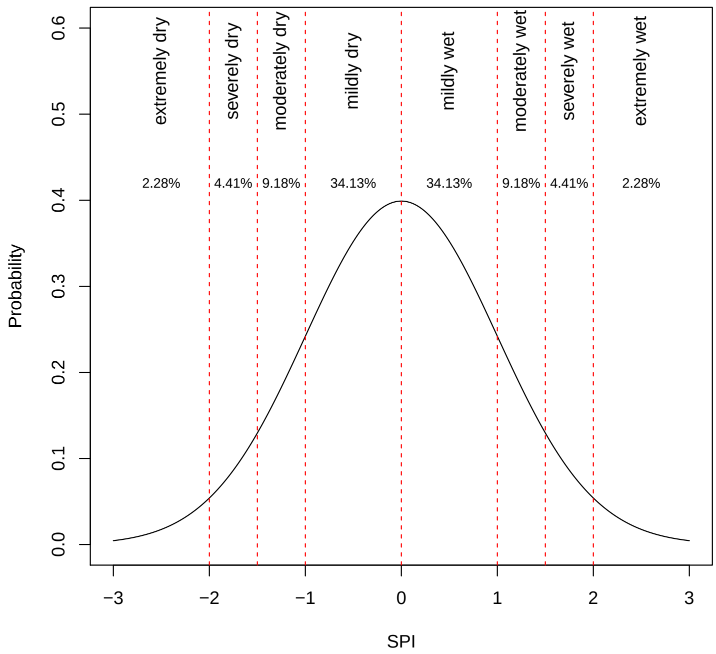

Figure 4: Illustration of Standardized Precipitation Index

All rainfall indicators discussed so far refer exclusively to precipitation. However, when the indicator shall be used to study the impact of rainfall on economic development, the water resources in a more general sense might be of interest. The available water resources in a location do not exclusively depend on rainfall but also on temperature, cloud cover, humidity, sunshine and winds, as all these factors affect evapotranspiration. Various indicators have been developed in the course of time to take these factors into account.

The Palmer Drought Severity Index (*PDSI*, see Palmer 1965) is an early version of this sort of indicators. It is based on the calculation of the moisture departure between actual precipitation and the expected precipitation under average climate conditions. In order to be able to calculate the index, it is necessary to construct a monthly water

[10]The classification of the quantiles follows the proposal in Guenang and Mkankam Kamga (2014).

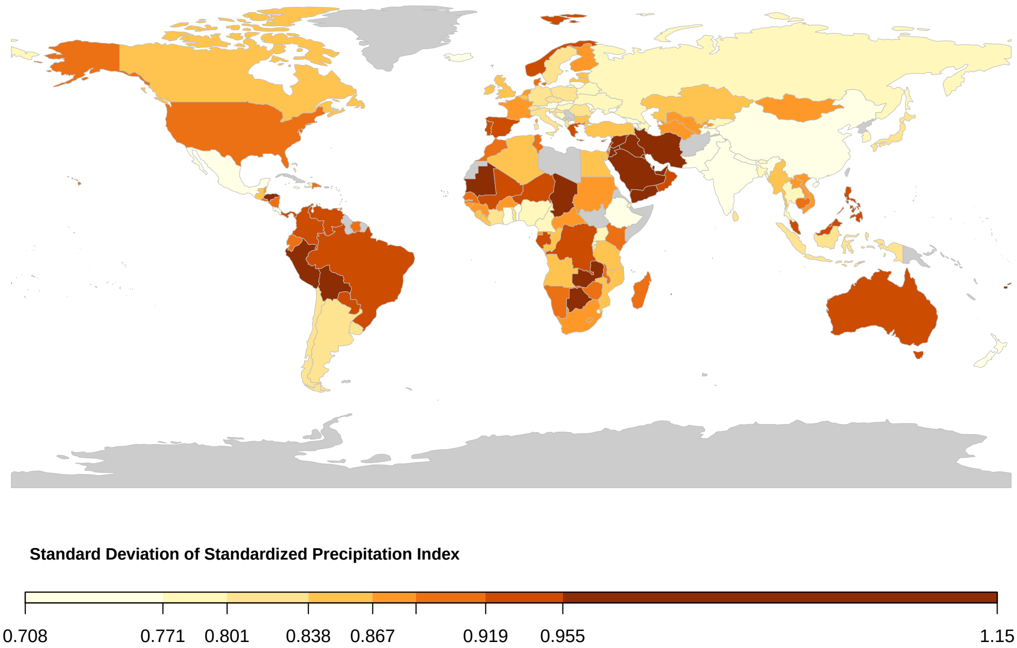

Figure 5: Standard Deviation of Standardized Precipitation Index (1931-2013), 8 Quantiles, Source: CRU CY 3.22

balance and to calibrate the local monthly coefficients for the various terms of the soil water balance. A common critique of the *PDSI* is that the index does not perform well in spatial comparisons. In order to solve this problem, Wells, Goddard and Hayes (2004) have proposed a self-calibrating variant of the *PDSI* which replaces empirical constants in the index computation with dynamically calculated values. While the index performs well in drought monitoring over longer time horizons of 9 to 18 months, it is less well suited for shorter-term periods of 1 to 9 months (Zhao et al. 2017). Vicente-Serrano, Beguira and Lopez-Moreno (2010) developed an alternative index, which is based on the earlier explained Standardized Precipitation Index (*SPI*). The Standardized Precipitation Evapotranspiration Index (*SPEI*) combines the Palmer Drought Severity Index's sensitivity to changes in evaporation demand, caused by temperature and fluctuations and trends, with the multitemporal nature and simple calculation of the SPI (Wang, Pan and Chen 2017). The *SPEI* has shown to perform well even for shorter time horizons (Zhao et al. 2017). Figure 6 shows the variability of *SPEI* values for our sample countries over the period of 1931 to 2013.

In our subsequent empirical analysis we concentrate on three of the discussed indica-

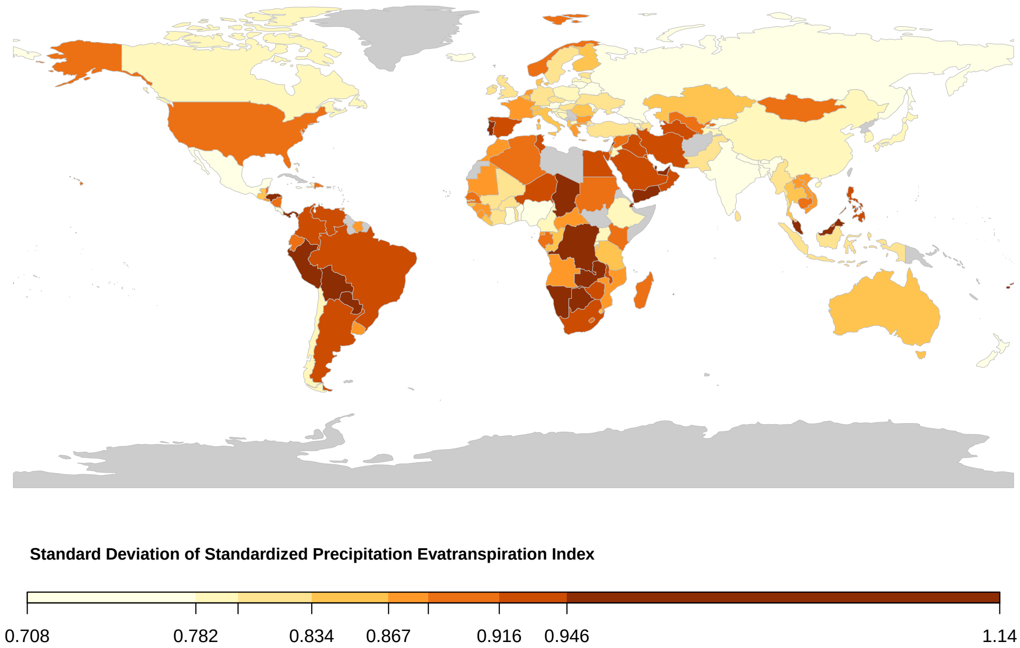

Figure 6: Standard Deviation of Standardized Precipitation Evapotranspiration Index (1931-2013), 8 Quantiles, Source: CRU CY 3.22

tors. As we employ data from more than 150 countries we refrain from using indicator variants which deliver incomparable results for differing climate zones. Out of the group of simple indicators we therefore rely on the standardized rainfall anomaly (*SPA*). As a more advanced alternative we additionally consider the standardized precipitation index (*SPI*), which was also adopted as mandatory indicator for defining meteorological droughts by the World Meteorological Organization (Hayes et al. 2011). Finally, as an indicator which also refers to potential evapotranspiration, we employ the standardized precipitation evapotranspiration index (*SPEI*). In order to show the differences between the three indicators, we calculate them for the whole sample period under the assumption that all sample countries would form a single country. The results, which are depicted in Figure 7, indicate that the *SPA*, the *SPI* and the *SPEI* are highly correlated, however, also differ to some extent. Especially over the last 15 years of our sample period the difference between the *SPA* and the *SPI* on the one hand and the *SPEI* on the other seems to increase systematically, which is a likely consequence of the observed ongoing rise of the average surface temperature.

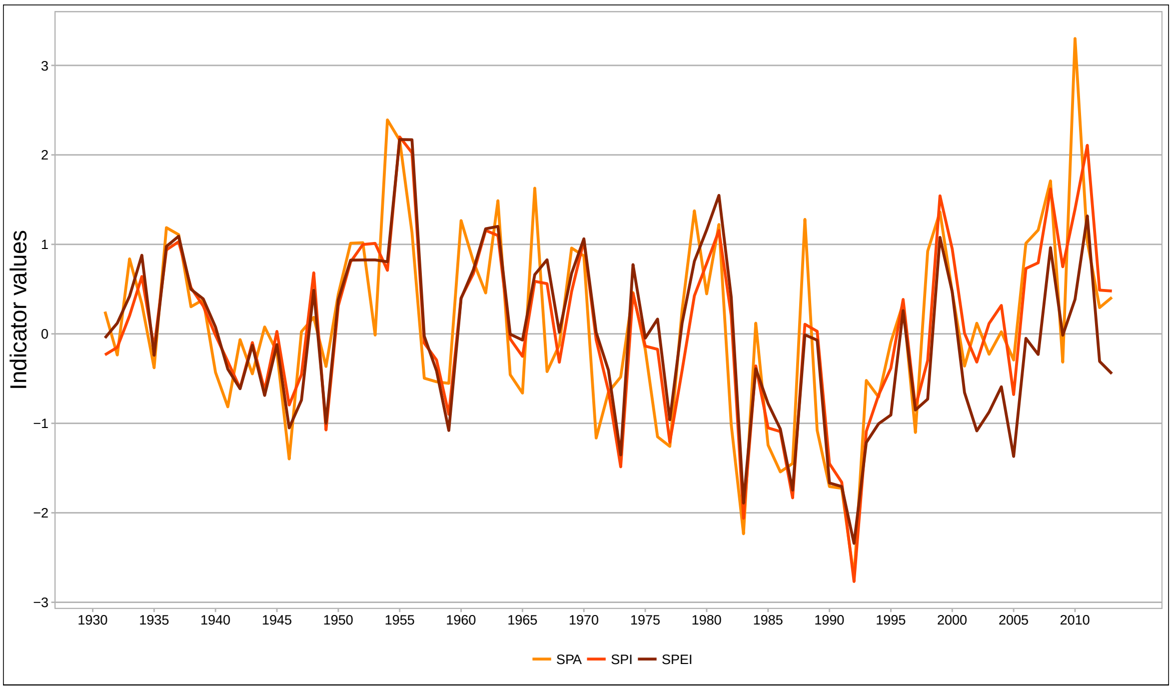

Figure 7: Comparison of *SPA*, *SPI* and *SPEI* Indicator (1931-2013), Source: CRU CY 3.22

3 Related Literature

The macroeconomic literature[11] on the impact of precipitation on economic growth started evolving roughly a decade ago. Most of the existing empirical literature aims at explaining annual per-capita growth of GDP by a measure of precipitation and a set of control variables. While the studies differ heavily in their sample periods, most studies cover at least 20 years. The existing studies also vary in their sample countries, however, most of them are concerned with developing countries with a comparatively large importance of the agricultural sector. Many studies focus on Africa and especially Sub-Saharan African countries. While the literature also differs to some extent in the concrete applied estimation approach and the employed data sources, a major source of variety is the employed precipitation measure. When reviewing the relevant literature in the following, we therefore organize this review around the employed

[11]It should be noted that a number of studies has investigated the impact of rainfall on income on the household level. This literature is typically based on survey data, collected in poor and vulnerable regions with high importance of the agricultural sector. An early study by Rosenzweig and Binswanger (1993) uses panel data on households from six villages in India over 10 years and finds rainfall variability to have a negative influence on farmers' investment decisions. Dercon (2002) uses household data from six villages in Ethiopia over the period in between 1989 and 1995 and reports strong negative household income effects of rainfall shortages. Molua (2002) comes to a very similar result based on farm household data from Cameroon. Alwang, Mills and Taruvinga (2002) show at the example of household data from Zimbabwe that droughts contributed significantly to increasing rural poverty.

rainfall measures.

Most existing empirical studies of the effect of precipitation on economic growth use annual mean rainfall as precipitation measure.[12] In a mostly descriptive analysis Richardson (2007) studies the relation between mean rainfall and economic growth in Zimbabwe in between 1960 and 2003. He finds a strong positive correlation between both measures which is lower only in times of exceptional political events. Brown et al. (2011) examine the effects of rainfall on economic growth in a sample of 42 Sub-Saharan countries over the period of 1975 to 2003. In their two-way fixed-effects approach the authors find a small but significantly positive effect of mean rainfall on the growth rate of per-capita GDP. However, no such effect could be found for agricultural value added. Akram (2012) studies the case of 8 Asian countries over the sample period of 1972 to 2009 within a fixed-effects panel estimation. He finds a positive contemporaneous effect of mean annual precipitation on economic growth, which primarily is caused by the agricultural sector. Lanzafame (2012) is concerned with economic growth in 36 African countries over the period of 1962 to 2000. However, in his reduced-from estimations he finds no effect of mean precipitation. The results remain unchanged when focusing exclusively on the 32 Sub-Sharan countries in the sample. Alagidede, Adu and Frimpong (2015) investigate the effect of mean precipitation on economic growth in 18 Sub-Saharan countries over the period of 1970 to 2009 using panel cointegration techniques. Again, the authors fail to find a systematic effect of mean annual precipitation on economic growth. Brenner and Lee (2014) construct a panel of 105 countries over the period of 1991 to 2009. Based on a GMM estimation approach with two-way fixed effects the authors fail to find a systematic effect in the full country sample. When restricting the sample to comparatively rich countries with low long-run average rainfall, mean precipitation turns out to have a positive impact on economic growth while rainfall is without impact in all other subsamples.

The study by Dell, Jones and Olken (2012) uses year-to-year fluctuations in precipitation as rainfall indicator. Their unbalanced panel consists of 125 countries and the

[12] The early study by Brown and Lall (2006) studies the effect of rainfall on the level of per-capita GDP rather than on economic growth. In order to do so the authors regress average per-capita GDP over the period of 1979 to 2004 on a number of rainfall indicators in a cross-section approach for 163 countries. The authors find a negative effect on per-capita GDP for both mean annual precipitation as well as for measures of rainfall variability.

sample period of 1950 to 2003. In their two-way fixed effects reduced form panel estimation approach the authors find that precipitation has a small but significant effect on economic growth. The effect of rainfall differs depending on a country's level of development. While rainfall turns out to increase economic growth in poor countries, the opposite holds true in rich countries.

Felbermayr and Gröschl (2014) study the effect of various types of natural disasters on economic growth in a large panel covering the period of 1979 to 2010 and more than 100 countries worldwide. The authors also study the case of floods and droughts, which they define by above-average rainfall (floods) and longer periods of less-than-average precipitation (droughts). Applying two-way fixed effects regressions the authors find a negative effect of floods and drought-events when adding the disaster-proxies separately. However, when including all disaster variables at the same time, floods become insignificant while droughts still reduce economic growth.

Three studies have yet employed standardized rainfall anomalies as rainfall indicators. The first study by Barrios, Ouattara and Strobl (2008) is concerned with the effect of rainfall (and temperature) on agricultural production in 107 developing countries over the period of 1961 to 1997. In their two-way fixed effects estimations the authors find that precipitation anomalies have a positive impact on agricultural production[13] only in the subsample of 40 Sub-Saharan African countries while no such effect exists in the rest of the developing countries. In their follow-up study Barrios, Bertinelli and Strobl (2010) find a similar result for economic growth as explanatory variable. Again, rainfall anomalies have a significantly positive effect on economic growth only in Sub-Saharan developing countries while no such effect could be detected for other developing countries. The authors conclude that the African Growth Tragedy is thus at least partly due to rainfall deficits in Sub-Saharan Africa. The already mentioned empirical study of Brown et al. (2010) for 42 Sub-Saharan countries not only studies the effects of mean rainfall but also employs the *WASP* index, a variant of the standardized precipitation anomaly (*SPA*). Here, the authors find dry periods to have a significantly negative effect on both, economic growth and agricultural value added. For overly

[13] Thus, overly wet periods go along with high agricultural production whereas dry periods depress agricultural production.

wet periods the authors fail to find a significant impact on economic growth or the agricultural sector.

Two studies have yet used the standardized precipitation index (*SPI*) to study the growth effects of rainfall. Boubacar (2015) is concerned with the effect of rainfall on agricultural productivity in 8 countries located in the Sahel region in Africa over the period of 1970 to 2000. Based on a panel probit analysis, the author finds that the probability of an increase in agricultural productivity depends negatively on the contemporaneous SPI. When the author includes one lag of the SPI, the cumulative effect becomes positive. For more lags the cumulative effect becomes insignificant. Berlemann and Wenzel (2016) use the standardized precipitation index to measure drought. In their panel study of 153 countries over the period of 1960 to 2002 they conclude that droughts have a significantly negative effect on economic growth over periods of up to ten years.

The standardized precipitation evapotranspiration index (*SPEI*) has yet only been used once in a recent study by Couharde and Generoso (2015). The authors study the case of 37 developing countries over the period of 1980 to 2011. Based on a panel smooth transition model the authors find systematic growth effects only in a subsample of 19 agricultural-dependent countries (with a share of agriculture in GDP of at least 18.6 percent), whereas no effect of rainfall could be detected for the remaining 18 countries.

Summing up, we might conclude that the existing literature fails to deliver a clear picture of the effects of precipitation on economic growth. While some studies find a positive effect on rainfall on economic growth, others find no effect at all. Even studies which are concerned with the same or at least similar sample countries deliver heterogeneous results. As an example, Barrios, Ouattara and Strobl (2008) and Barrios, Bertinelli and Strobl (2010) find a positive effect of rainfall on agricultural production and economic growth for the often studied Sub-Saharan countries. While Brown et al. (2010) find the same results when using mean precipitation as rainfall indicator, their result is more differentiated when using the *WASP* index. Here, only droughts have a negative growth effect while overly wet periods have no impact on economic growth. Lanzafame (2012) and Alagidede, Adu and Frimpong (2015) fail to find any effect for Sub-Saharan countries.

It is an intriguing question, which factors contribute to the comparatively heterogeneous findings. While the existing studies vary in many respects such as country samples and sample periods, especially the heterogeneity in the employed precipitation measures and the use of these measures in the empirical specification is likely a major source of the blurred picture. Most of the literature employs very simple rainfall indicators; the more advanced *SPA*, *SPI* and *SPEI* have yet rarely been used. Moreover, the vast majority of studies uses rainfall indicators in a linear manner, e.g. assume that the marginal effect of precipitation on economic growth is the same in periods of low and high rainfall. However, one might suspect that - at least in principle - both, overly wet and dry conditions might hinder economic growth, a finding which is consistent with the results reported in one of the few studies allowing for asymmetric effects by Felbermayr and Gröschl (2014). An additional factor which might significantly contribute to the heterogeneous findings is the "over-controlling problem" put forward by Dell, Jones and Olken (2014). As the vast majority of existing empirical studies uses a rich set of control variables and these control variables themselves might be influenced by climate variables, including these controls might lead to biased results. Finally, by far the most existing studies neglect that climate phenomena such as temperature and precipitation exhibit strong spatial dependencies, which might introduce additional biases.

4 Estimation Strategy and Data

In this section we explain our basic estimation strategy as well as the data, we employ in the following. We start out with describing the estimation approach. When doing so we concentrate on the baseline estimation results presented in Section 5. The various stability tests, we conduct in the two subsequent sections, will be explained later.

Our primary goal is to investigate whether precipitation has a systematic impact on economic growth. Most previous studies in the field rely on so-called "Barro regressions" (see e.g. Barro 1991, Mankiw, Romer and Weil 1992, and Islam 1995) to uncover the growth effects of climate (or natural disasters). This approach consists of estimating a baseline model of the determinants of economic growth and adding climate indicators to the regression equation

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \delta \cdot \ln X_{t-1,i} + \gamma \cdot C_{t,i} + \epsilon_{t,i} \tag{3}$$

where $lnGDP_{t,i}$ is the natural logarithm of the per capita gross domestic product in country i at time t, α_i are country fixed effects controlling for countries' time-invariant institutions, cultures and geographies, $X_{t-1,i}$ is a vector of one period lagged time-varying control variables, $C_{t,i}$ is a climate indicator[14] (here precipitation) and $\epsilon_{i,t}$ is the unexplained residual. The studies employing this approach then argue that only if the estimated coefficient of the precipitation indicator turns out to be significantly different from zero, rainfall has a systematic growth effect. However, this approach is problematic because of at least two reasons.

First, the included control variables themselves might be (and quite likely are) endogenous to rainfall. As Dell, Jones and Olken (2014) argue, including possibly endogenous control variables leads to an over-controlling problem. One might illustrate the over-controlling problem at the example of investments. Whenever precipitation has a direct or an indirect impact on investments, the estimated coefficient for the rainfall indicator in a Barro regression might be insignificant as the effect of precipitation is already captured by the investment coefficient. Whenever rainfall in fact has a medium- or long-term effect on economic growth, this effect must work through certain transmission channels with the traditional control variables in growth regressions being the most likely candidates. Thus, the Barro regression approach is at least not unproblematic.

Second, simply adding the contemporaneous or a lagged value of a rainfall indicator is not suitable to learn about the medium- and long-term effects of precipitation. Rainfall occurring at time t will likely affect economic growth in the contemporaneous period, but might have also an effect over various future periods. Thus, in order to learn about the full impact of precipitation, it is necessary to estimate the contemporaneous and the lagged effects of rainfall on economic growth and to cumulate it over the time horizon of interest.

[14] The indicator can also enter the estimation equation with a time lag.

In the light of these issues the most reliable approach is to estimate the growth model in a two-way fixed effects panel setting without possibly endogenous time-variant control variables, as proposed by Hsiang and Jina (2014). However, in line with the proposal by Auffhammer et al. (2013), we include a temperature indicator as control to isolate the pure effect of precipitation on economic growth. In our baseline specification we use the standardized temperature anomaly (STA) as control, which is calculated in the same way as the earlier described standardized precipitation anomaly. As the left-hand variable as well as the two climate indicators are available for much longer periods than additional economic or institutional control variables one might consider, this approach also has the advantage that the growth effects of precipitation are estimated from a comparatively large sample. As extreme weather conditions in general occur relatively rare, this advantage is likely large. Our preferred estimation approach is therefore

$$\ln GDP_{t,i} - \ln GDP_{t-1,i} = \alpha_i + \beta_t + \sum_{j=0}^{J} \left(\gamma_j \cdot P_{t-j,i}\right) + \sum_{j=0}^{J} \left(\eta_j \cdot STA_{t-j,i}\right) + \epsilon_{t,i} \tag{4}$$

with β_t being time fixed effects, P being a precipitation indicator and STA being the standardized temperature anomaly. J defines the maximal number of periods, rainfall (and temperature) is allowed to influence future economic growth. We then calculate the cumulative effect of precipitation on economic growth as

$$GCUM_J = \sum_{j=0}^{J} \gamma_j \tag{5}$$

In order to rule out heteroscedasticity problems as well as problems of autocorrelated residuals we base the calculation of confidence intervals on HAC standard errors (Newey and West 1987). Moreover, as precipitation is spatially correlated, we account for spatial correlation of the error terms by employing the procedure proposed in Conley (1999).[15] We thereby correct for spatial correlation up to a distance of 1,000 km.

In the first step of our analysis we estimate the model for three different rainfall indicators: the standardized precipitation anomaly (SPA), the standardized precipitation

[15]We implemented an adapted version of the Conley correction procedure proposed in Fetzer (2015).

index (*SPI*) and the standardized precipitation evapotranspiration index (*SPEI*). In the baseline specification we follow the overwhelming part of the literature and enter the precipitation indices as linear indicators. In the second step we then distinguish explicitly between positive and negative indicator values and estimate the effects of unusually low or high precipitation values separately, thereby allowing the effect of rainfall on economic growth to be non-linear. In the third step of our analysis we repeat the analysis for a number of subsamples separately to investigate whether the effects depend on the level of development and whether Sub-Saharan countries differ from other developing countries systematically, as it is often found in the literature.

In order to estimate the above described models we need appropriate data for the left hand variable, i.e. economic growth, as well as time series for the three precipitation indicators. We already introduced the source of the employed precipitation data and the calculation of the the three indicators in Section 2. The employed temperature data comes from the same source. Data on economic growth is available from different sources. We opted for extracting GDP per capita from the Penn World Tables (PWT 9.0, see Feenstra, Inklaar and Timmer 2015). Doing so allowed us to construct an (unbalanced) panel covering the period of 1951 to 2013 covering a total of 153 countries.

5 Estimation Results

In the following we present the estimation results for the earlier described baseline two-way fixed effects model. As the results of unit root tests indicate,[16] the left hand variable as well as the three precipitation indicators turn out to be stationary. As we have no ex-ante-information whether precipitation affects economic growth only contemporaneously or over numerous years we estimate the model from equation (4) for values of J ranging in between 0 and 20. Instead of reporting the full estimation results for every single model we show a graphical representation of the estimated cumulative coefficients for the three described precipitation indicators and the referring 90% confidence intervals (based on HAC standard errors). Whenever a coefficient is significantly different from zero on the 90% confidence level we mark the observation

[16]The results of the unit-root tests are reported in Table 1 in the Appendix.

in red color whereas it is shown in gray in the case of insignificance.

5.1 Full Country Sample

We start out with the results for the growth effects of precipitation in the full country sample. The estimation results are summarized in the upper part of Figure 8. We show the results for the *SPA*, the *SPI* and the *SPEI* indicator, respectively. For none of the three linear rainfall indicators we find a systematic effect on economic growth. Thus, at least in the full country sample, there is little evidence for a systematic effect of rainfall on economic growth.

However, as discussed earlier, one might suspect that the chosen estimation approach is inappropriate as the marginal effect of rainfall on economic growth might depend on the level of rainfall. While rainfall might have a positive marginal effect in overly dry years, the opposite might hold true in years with above-average precipitation. Whenever this pattern would in fact exist, the usage of a linear indicator for precipitation likely delivers an insignificant effect.

In order to study this issue in more depth, we generate two separate types of rainfall indicators, one for overly dry (we refer to this indicator as ”negative” indicator in the following) and one for overly wet periods (”positive” indicator). The negative indicator types preserve all negative indicator values; however, for positive values the indicator is set to zero. In order to make the negative indicators more easily to interpret, we use the absolute values of precipitation deficits. For the positive indicator types we preserve the positive indicator values and set the negative values to zero. The positive and negative indicator types can be constructed for all three employed precipitation measures.

The middle part of Figure 8 delivers the estimation results for the positive indicator types. In fact, almost all estimated cumulative coefficients for the positive rainfall indicators turn out to be negative, thereby indicating that rainfall tends to have a negative effect on economic growth in overly wet periods. However, in only a few cases the cumulative effects turn out to be significantly different from zero on conventional levels of significance.

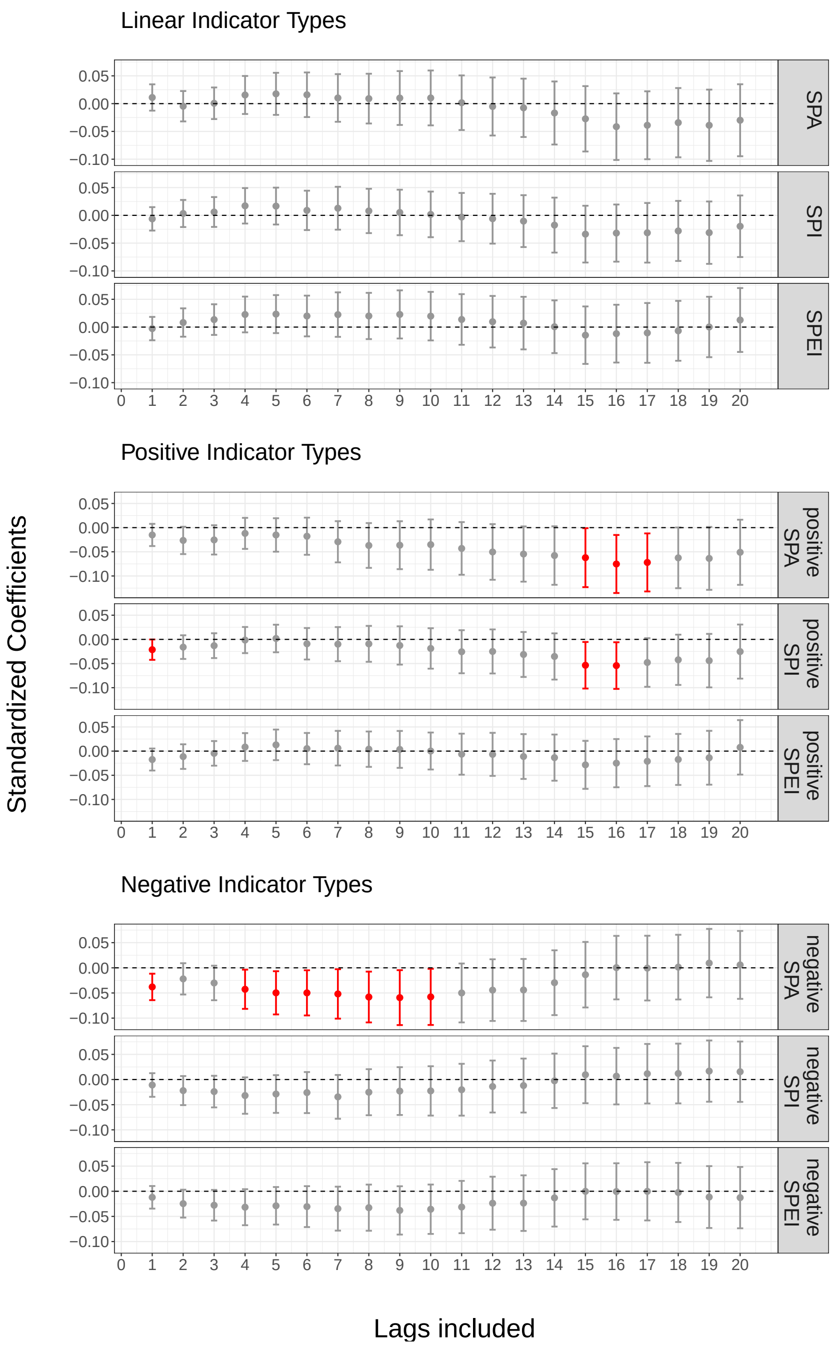

Figure 8: Cumulative Growth Effects of Precipitation, Full Country Sample, Various Precipitation Indicators (1951-2013)

The results for the negative rainfall indicators are shown in the lower part of Figure 8. As for the positive indicator types, most estimated cumulative coefficients turn out to be negative. However, only for the negative *SPA* indicator the cumulative coefficients are significantly different from zero for time horizons until 10 years.

5.2 Poor and Rich Subsamples

Previous studies have often focused on countries on low levels of development, mostly arguing that these countries are more vulnerable to climatic shocks as they can invest less resources in adaption strategies and are typically more dependent on agriculture. We therefore repeat our previous analysis for two subgroups of poor and rich countries. We divide our country sample into the two subgroups at the median per capita GDP. While the poor sample contains 87 countries, the rich country is slightly smaller (66 countries).[17]

The estimation results are displayed in Figure 9. The left part of the figure contains the results for the poor countries, the right one those for the rich countries. Again, we show the results for the linear precipitation indicators in the upper part of the figure. All three rainfall indicators deliver systematically positive cumulative coefficients for the group of poor countries, indicating that these countries tend to profit from additional rainfall. For the *SPEI* the cumulative effect is significant for time-horizons in between 2 and 11 years, for the *SPA* and the *SPI* only for considerably shorter cumulation periods. For the group of rich countries we find systematically negative cumulative coefficients. However, they never turn out to be significantly different from zero.

When concentrating on rainfall surpluses, i.e. when using positive rainfall indicators, the cumulative coefficients show no systematic sign and are never significantly different from zero in the sample of poor countries. However, in the rich country sample there is again a clear tendency for negative cumulative effects. Especially for the *SPA* indicator the negative effects are quite pronounced, however, turn out to be significant only in a few cases. Altogether, the evidence in favor of systematic growth effects of rainfall surpluses is thus very weak at best for both poor and rich countries.

However, a very clear picture evolves for rainfall deficits, i.e. when using negative rainfall indicators. For all three variants of this indicator we find strong, systematic and significantly negative cumulative effects of rainfall on economic growth over at least 13 years in the poor country group. Thus, rainfall deficits cause systematic negative growth effects not only in the short- but also in the medium- and long-run. These effects

[17] As our sample is unbalanced, we classify our countries on the basis of their per-capita GDP at the time when they enter the sample. As a consequence, the two subsamples have not an equal size.

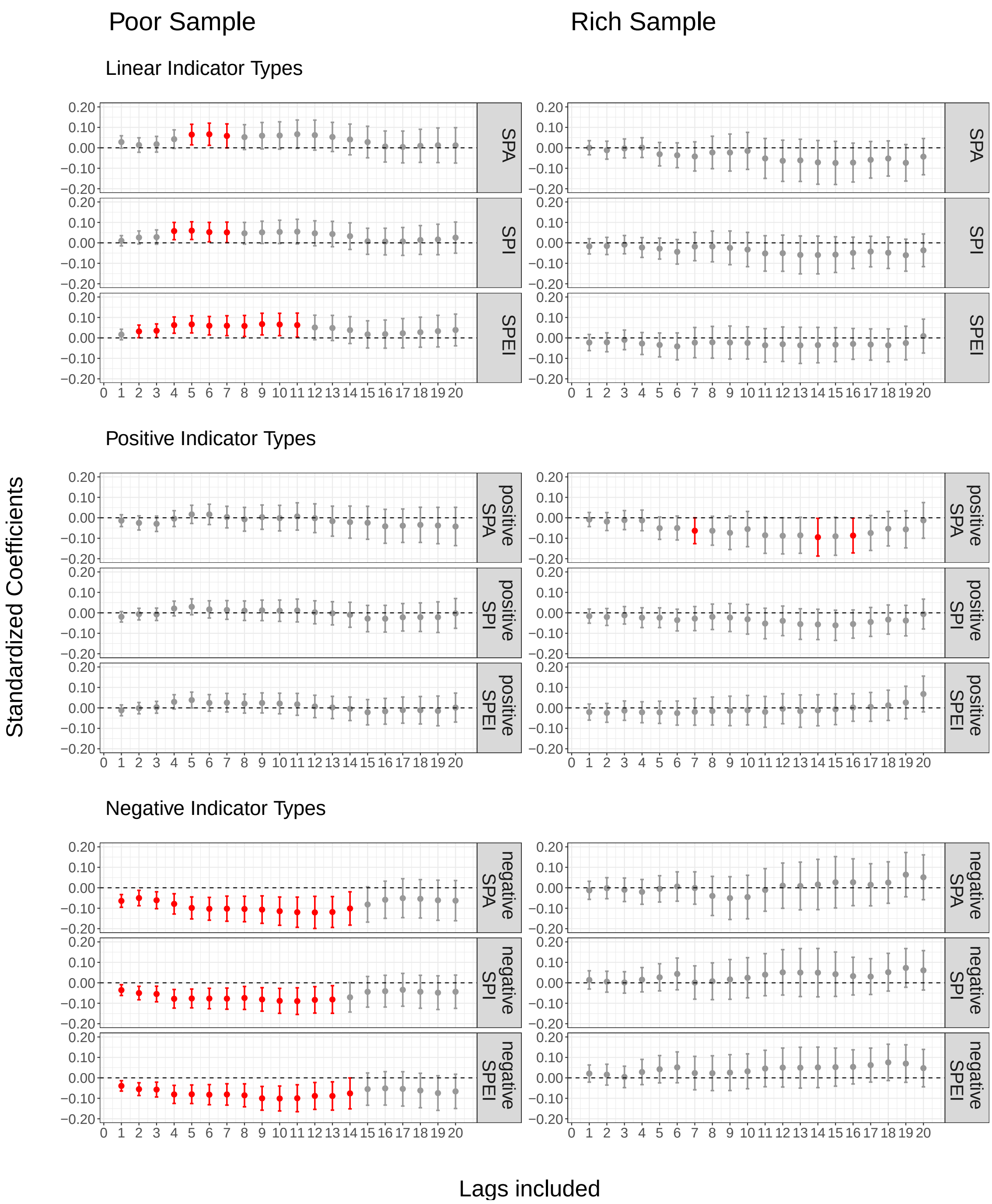

Figure 9: Cumulative Growth Effects of Precipitation, Poor versus Rich Country Sample, Various Precipitation Indicators (1951-2013)

are completely absent in the group of rich countries.

5.3 Sub-Saharan Africa

As already mentioned in the literature review, the group of Sub-Saharan African (SSA) countries has often been a focus in empirical studies of the growth effects of precipitation (deficiencies). As most SSA countries belong to the group of poor countries (exceptions are Angola, Djibouti, Gabon, Mauritius, Namibia and South Africa) it is well possible that the effect for the poor country group is driven by the Sub-Saharan African country group. In order to check this we repeated all estimations for the group of SSA countries.[18] The results are shown in the right part of Figure 10. To enhance comparability we show the estimation results for the sample of poor countries in the left part of the same figure.

Interestingly enough, the results for the SSA countries mostly turn out to be weaker than those for the group of poor countries. While we end up with a similar picture for the linear indicator types, the mostly positive cumulative coefficients turn out to be significantly different from zero much less often. For the positive indicators, the cumulative effects turn out to be more systematic for SSA countries than for the group of poor countries. While the cumulative coefficients are mostly insignificant for the *SPA* and the *SPI*, the *SPEI* delivers a number of significant effects in the short- and medium-term. Thus, especially in the SSA countries it seems to be important to control for evapotranspiration. For rainfall deficits we find much weaker results as for the group of poor countries. While the negative indicators still deliver mostly negative cumulative effects, they turn out to be significant only very rarely in the SSA group.

6 Stability Tests

While we already investigated the stability of our results from various perspectives by using three different rainfall indicators, studying different time perspectives in between 1 and 20 years and using various country subsamples, numerous additional stability tests might be of interest. In the following we describe the conducted stability tests and describe our major findings. In order to keep this section readable, we show only the most interesting and relevant parts of the stability tests graphically and report on the rest verbally. The omitted graphs can be found in the Appendix. As our previous results indicated that the growth effects of rainfall are likely differing between comparatively

[18]Our sample of SSA countries consists of the following 42 countries: Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Cote D'Ivoire, Democratic Republic of the Congo, Djibouti, Equatorial Guinea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Togo, Uganda, United Republic of Tanzania, Zambia and Zimbabwe.

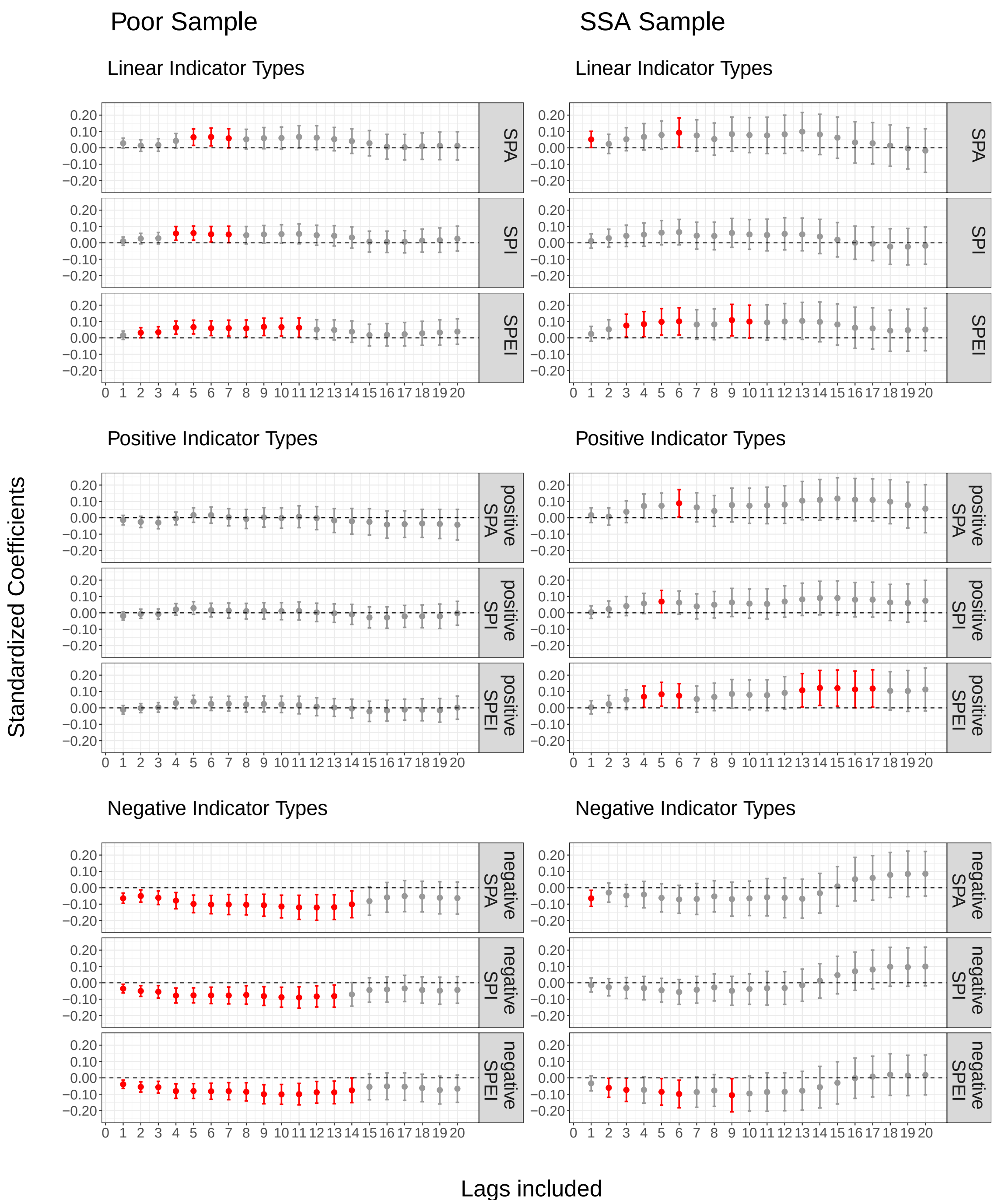

Figure 10: Cumulative Growth Effects of Precipitation, Sample of Sub-Saharan Countries, Various Precipitation Indicators (1951-2013)

dry and overly wet periods, we refrain from showing further results for the linear indicators. We also refrain from further studying the group of SSA countries as we have shown earlier that the effects in the group of low income countries are not driven by this subsample of countries.

6.1 Results for Alternative Precipitation Datasets

As Aufhammer et al. (2013) have recently argued, the choice of the weather dataset is a possible pitfall in empirical studies of the effects of climate and weather. Especially in less developed regions with limited monitoring networks the weather shock used to identify response coefficients in econometric estimations might vary strongly with the data source used. According to Aufhammer et al. (2013) this problem arises especially in the context of precipitation data. They therefore propose to conduct sensitivity tests by using more than one data source to determine whether the estimation results are robust. We follow this advice and repeat the analysis with some alternative rainfall datasets.

As explained earlier, our previous empirical analysis is based on one of the most often used source of precipitation data, the CRU dataset published by the Climate Research Unit of the University of East Anglia. The CRU data have previously been used by the earlier described studies of Barrios, Ouattara and Strobl (2008), Barrios, Bertinelli and Strobl (2010), Brown et al. (2011) and Couharde and Generoso (2015). However, precipitation data is available from numerous different sources. At least four different sorts of datasets can be distinguished: (i) data collected by gauge stations (as the CRU CY dataset, used in our preceding empirical analysis), (ii) data gathered by satellites, (iii) combined gauge-satellite data and (iv) global atmospheric retrospective analysis models. As worldwide satellite imagery is not available before the late 1970s, using this sort of data would leave us with a much smaller and thus incomparable sample. Thus, we refrain from employing datasets which partially or even completely rely on satellite data and, as an alternative, choose two precipitation datasets which are based on gauge station data and cover at least the same period and the same countries as the CRU CY dataset.

As a first alternative to the CRU CY dataset we use the UDEL dataset, published by the University of Delaware. The UDEL dataset is a monthly, globally gridded, high resolution station (land) data set for air temperature and precipitation (see Willmott and Matsuura 1995). The dataset is based on measurement of up to 22,000 gauge stations around the globe. Data from the UDEL database were e.g. used in Akram (2012), Dell, Jones and Olken (2012) and Lanzafame (2014).

As a second alternative we employ the GPCC dataset, hosted at the German Weather Service DWD. This database is also the official precipitation data center of the World Meteorological Organization (WMO). Data sources include synoptic weather observation data received via WMO's Global Telecommunications Systems and climatological monthly precipitation totals at the same stations extracted from GPCC's collection of global normals and thus more than 70,000 stations worldwide.

Both datasets allow to calculate *SPA* and *SPI* values. As explained earlier, the calculation of the *SPEI* requires evapotranspiration data. At least for the GPCC dataset, this sort of data is unavailable. In order to be able to calculate *SPEI* values nevertheless we rely on the evapotranspiration data from the CRU CY dataset to calculate *SPEI* values.

Interestingly enough, a comparison of the UDEL and the GPCC datasets with the CRU CY for the Mediterranean and the Middle East by Tanarhte, Hadjinicolaou and Lelieveld (2012) comes to the conclusion that the three data sources deliver highly correlated and thus comparable results, however, also differ to some extent. One thus might expect that our main results should apply also when using these alternative sources of rainfall data.

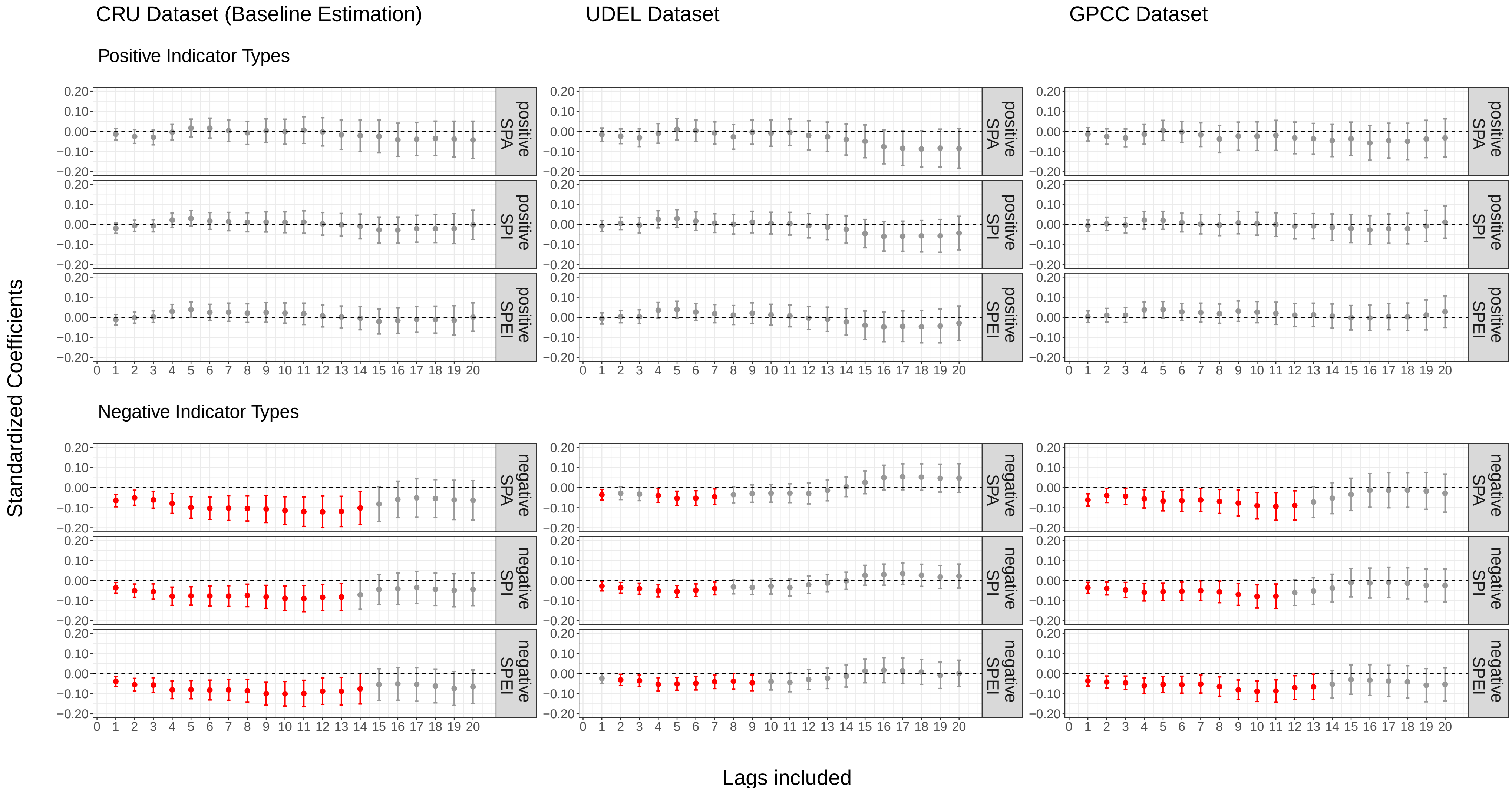

Figure 11: Cumulative Growth Effects Poor Country Sample, Different Precipitation Datasets (1951-2013)

The estimation results for the sample of poor countries are shown in Figure 11. In the upper part of the figure we display the results for the positive indicator types. Using the UDEL or the GPCC database instead of the CRU precipitation data leads to very similar results. For none of the three datasets we find any significant effect of overly wet periods on economic growth. The lower part of Figure 11 shows the results for the negative indicator types. When using the UDEL dataset, the results become weaker as in our baseline regressions. However, while the effects are somewhat smaller and less long-lasting, we still find negative growth effects over 7 up to 9 years depending on the applied indicator. When basing the analysis on GPCC data, the results are very similar to the baseline regressions.

Thus, while the choice of the rainfall dataset obviously has some influence on the results, our basic finding of negative growth effects of overly dry periods in the poor country sample turns out to be stable. However, when using the UDEL data the results are somewhat weaker as when using one of the other two sources of rainfall data. Moreover, we find consistently no systematic effect of overly wet periods on economic growth in the poor country sample.[19]

6.2 Effects of Droughts

Rainfall deficits are closely connected to droughts. As an additional stability test we study how the results are influenced by using a drought indicator rather than negative *SPI* values.

Empirical drought indicators are typically based on monthly data. Following McKee et al. (1993), drought can be defined as a period in which the *SPI* is continuously negative and reaches at least once the value of -1.0 or less. Thus, in a first step we use monthly data to identify which months belong to a drought event. To gain an annual drought indicator we then compute the sum of the *SPI* values, belonging to a drought

[19]While we found almost no systematic effects of rainfall on economic growth in the rich country sample when using the CRU data, the results for this subsample are more sensitive to the choice of precipitation data (see Figure 14 in the Appendix). For both the UDEL and the GPCC data we find systematic evidence of negative growth effects of overly wet periods when using the *SPA* or the *SPI*. For overly dry periods the UDEL dataset delivers similar results as the CRU dataset, while the results derived under the GPCC dataset point into the direction that in rich countries overly dry periods could be associated with positive growth effects. However, when using the *SPEI* we find no effects for neither the positive nor the negative indicators.

event on an annual basis. Analogously, we calculate a drought indicator based on the *SPEI*.[20]

In order to study the effect of droughts on economic growth we repeat the estimations for rainfall deficits, however, now use the described drought indicators derived from the *SPI* and the *SPEI* rather than the *SPI*- and the *SPEI*-values themselves. For the poor country sample the results become slightly more pronounced as most cumulative coefficients slightly increase in size.[21] Moreover, the cumulative effect of the drought indicator, derived from the *SPI*, is now significant for 14 years rather than for 13. For the full country sample and the sample of rich countries we observe almost no systematic effect, all cumulative coefficients remain insignificant. Thus, we conclude that our results are highly robust to an alternative classification of rainfall deficits.

6.3 Alternative Classification of Rich/Poor Sample

In our previous analysis we formed the two country groups of rich and poor countries based on real per-capita GDP. Countries with a below-median real per-capita GDP at the time when they first appear in the dataset were assigned to the poor country sample whereas countries with above-median real per-capita GDP were allocated to the group of rich countries. However, due to the considerable asymmetry of the worldwide distribution of real per-capita GDPs one might argue that a more reasonable cutoff-point between the two samples is the mean per-capita GDP. In order to check the stability of our results for this alternative group split we repeat all estimations for these groups.

Figure 12 shows the estimation results for poor countries defined by the median group split (left) and the mean group split (right) in comparison. For the positive indicator types the cumulative effects remain almost unaffected. Thus, regardless of the group split, we find no evidence in favor of the hypothesis that overly wet periods affect subsequent economic growth. Even for the negative indicator the results for the poor country groups are qualitatively similar. However, when splitting the groups at

[20] As there is no common definition of droughts based on the *SPA*, we refrain from constructing an additional drought indicator.
[21] The complete estimation results for droughts are shown in Figure 15 in the Appendix.

the mean income, the results become slightly weaker, as especially when employing the *SPI* indicator less cumulative coefficients remain significant.

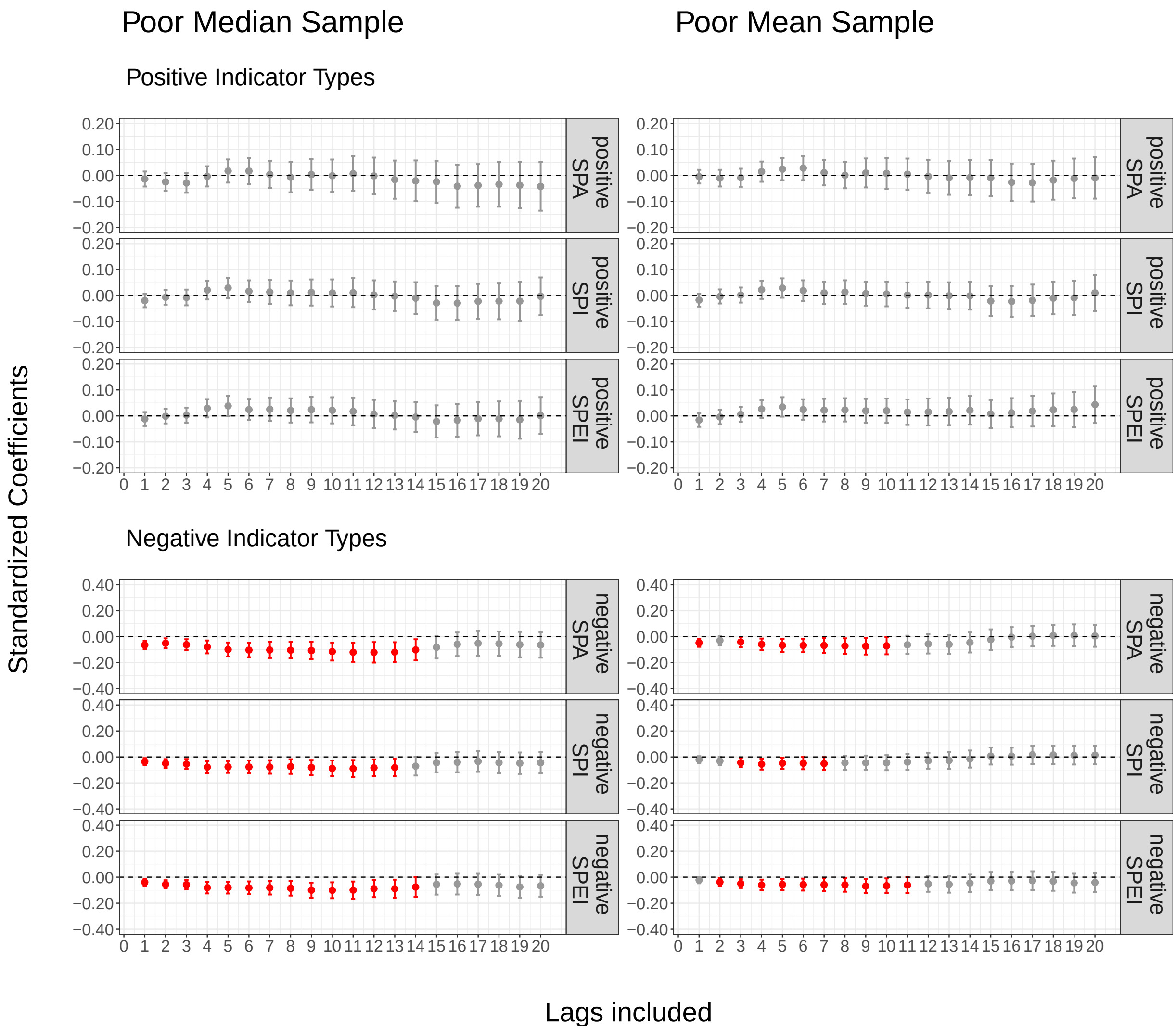

Figure 12: Cumulative Growth Effects Poor Countries, Alternative Sample Splits (1951-2013)

While the estimation results for the group of poor countries thus do at least qualitatively not differ systematically between the two different sample splits, this holds not true for the group of rich countries (see Figure 16 in the Appendix). While we found no systematic effects for the rich countries in our baseline estimations, dividing the sample at the mean rather than at the median leads to systematically negative growth effects for the positive indicator variant. For all three indicators and for almost all time horizons, the cumulative coefficients are now negative and at least when employing the *SPA* indicator, they also turn out to be significantly different from zero. Even for the *SPI* and the *SPEI* a number of cumulative coefficients are significantly different from zero, indicating that overly wet periods tend to have negative growth effects in comparatively rich countries. However, as we find this effect only when dividing the samples at the mean or use different precipitation datasets, we are be careful in interpreting this finding. For the negative indicator variants, the results remain mostly insignificant in the sample of rich countries.

6.4 Inclusion of Control Variables

In order to avoid the earlier discussed over-controlling problem, resulting from the inclusion of control variables which are likely themselves affected by rainfall events, we estimated two-way fixed effects models which use temperature as the only control variable. Although following this strategy seems to be the most reasonable estimation strategy, one might nevertheless be interested in the question whether the derived results carry over to the case of the inclusion of a richer set of control variables.

The empirical growth literature has considered numerous different potential growth determinants. The core set of control variables used in growth regressions (and especially in the earlier described Barro Regressions) consists of only a few variables which can directly be derived from theoretical models of economic growth such as the initial level of per-capita GDP, the saving rate and population growth. We follow this strategy and reestimate the models under the inclusion of these controls. For the initial level of GDP we use per capita output-side real GDP at current purchasing power parities from the Penn World Tables (Version 9.0). As measure for the saving rate we use the investment share in GDP at current purchasing power parities, extracted from the same source. Finally, we employ population growth from the from the Penn World Tables (Version 9.0) as control variable. Restricting our estimation model to this core set of controls comes at the advantage that we can estimate the models for exactly the same sample as our baseline models.[22] We thus can directly compare the results with and without additional controls.

In Figure 13 we show the estimation results for the poor country sample. In the left part of the figure we show the results from the baseline regression with only temperature as control variable. The right part of the figure displays the results we

[22]One might also consider to use institutional factors as controls. However, doing so would lead to a critical reduction of our sample period and sample countries. We therefore refrain from doing so.

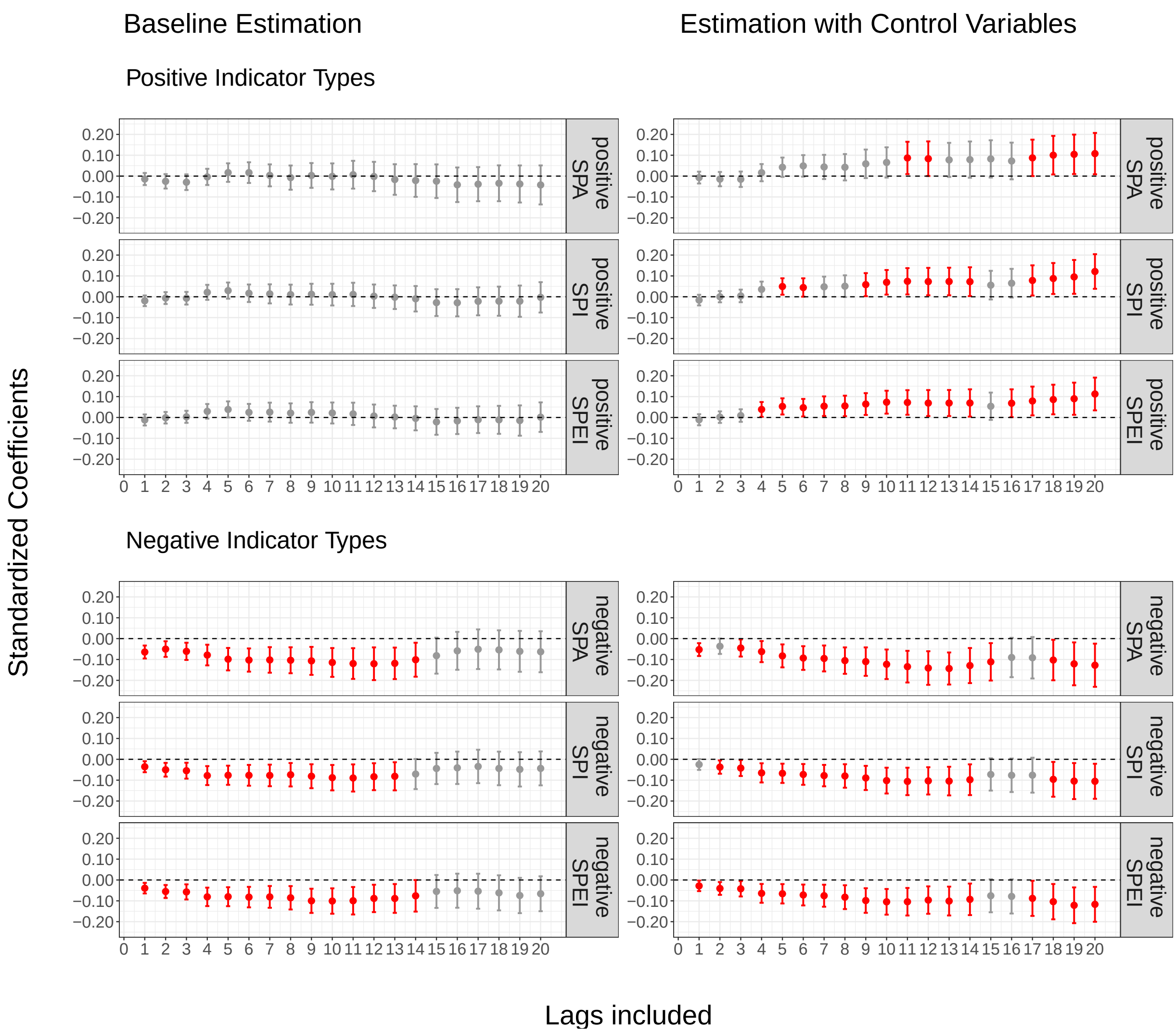

Figure 13: Cumulative Growth Effects Poor Country Sample with Controls (1951-2013)

derive under the inclusion of the full set of controls. When including additional controls, the effects of rainfall on long-run economic growth become more pronounced. While we already found systematically negative growth effects for rainfall shortages in the baseline regression for at least the following 13 years, these effects become even more long-lasting under the inclusion of controls. Moreover, the inclusion of controls also leads to significantly positive effects of rainfall surpluses in the poor country sample, an effect which was completely absent in the baseline regression. We find no systematic effects of including controls in the rich country sample.[23] Here, almost all cumulative coefficients remain insignificant.

[23]The referring results are shown in Figure 17 in the Appendix.

6.5 Additional Stability Tests

To further substantiate our findings we ran a number of additional stability tests. First, we use an alternative specification of the temperature variable in the estimations. Whereas we employ the temperature anomaly in our baseline regressions, we study the influence of using the absolute temperature as control. As temperature might be correlated to rainfall to some extent we also estimate the models without a temperature variable. The estimation results remain broadly unaffected by the way we control for temperature or exclude temperature completely from the estimation equations.[24]

We also studied whether and how the results are affected by our choice of the left hand variable. While we use real per-capita growth figures based on data from the Penn World Tables in our previous analyses, per-capita GDP is also available from the World Development Indicators Database. In an additional robustness check we repeated the analysis with growth figures from the Word Bank.[25] Even when using WDI data, we find no systematic growth effects of precipitation in the sample of rich countries. And even in the poor country sample the effects are similar to those derived in the baseline specification. Rainfall surpluses remain without systematic effect on growth figures whereas rainfall deficits go along with negative long-run growth effects. While the effects derived for the *SPA* indicator are very similar, the effects for the *SPI* and the *SPEI* are slightly weaker as in the baseline specification.

7 Conclusions

In this paper we deliver a systematic analysis of the short- and long-term growth effects of precipitation. Based on a rich panel dataset covering more than 150 countries and the period of 1951 to 2014 we find little evidence that rainfall has a systematic and statistically significant effect on economic growth in the full country sample. We detect no systematic effects of three alternative linear rainfall indicators (*SPA*,*SPI*,*SPEI*) over a time horizon of up to 20 years. When distinguishing between rainfall deficits and surpluses, the cumulative effects in the full country sample often become negative and

[24]The complete estimation results are shown in Figures 18 and 19 in the Appendix.
[25]The complete results are shown in Figures 20 and 21 in the Appendix.

thus show some more regularity. However, in by far the most cases the cumulative coefficients turn out to be not significantly different from zero. Thus, there is at best very weak empirical evidence in favor of the hypothesis of the existence of systematic growth effects of precipitation in the full country sample.

When focusing exclusively on rich countries, we end up with a very similar result. Regardless of which rainfall indicator we use and whether we use it in a linear fashion or rather distinguish between rainfall deficits and surpluses we mostly fail to detect systematic effects of rainfall on economic growth.

However, for the subsample of comparatively poor countries, the results are more differentiated. When using the linear indicator variants, we find some evidence in favor of the hypothesis that more precipitation goes along with higher growth at least in the medium-term. However, when distinguishing between rainfall surpluses and rainfall deficits, we find that this result is driven by the negative growth effects of rainfall deficits while rainfall surpluses show little systematic effects on economic growth. The negative growth effects of rainfall shortages in the poor country sample turn out to be significant for all three rainfall indicators for at least 13 years. Interestingly enough, this finding is not driven by the subsample of Sub-Saharan African countries. For this country group we find much weaker negative effects for rainfall shortages. However, there is some weak evidence pointing into the direction that rainfall surpluses tend to have a positive growth effect in SSA countries (at least when taking evapotranspiration into account).

Our central finding of systematically negative long-term growth effects of precipitation turns out to be robust across various sorts of stability tests, including the choice of alternative precipitation datasets, alternative definitions of the poor country sample and the inclusion of standard control variables (even if they likely are ”bad controls”). Altogether, we thus might conclude that at least precipitation shortages must be taken as a threat to economic prosperity in countries on low levels of development. The effects of overly dry periods seems to go well beyond the short-lived effects of crop-failure. To uncover through which channels rainfall shortages affect growth patterns is an interesting and important avenue of future research on the topic.

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Appendix

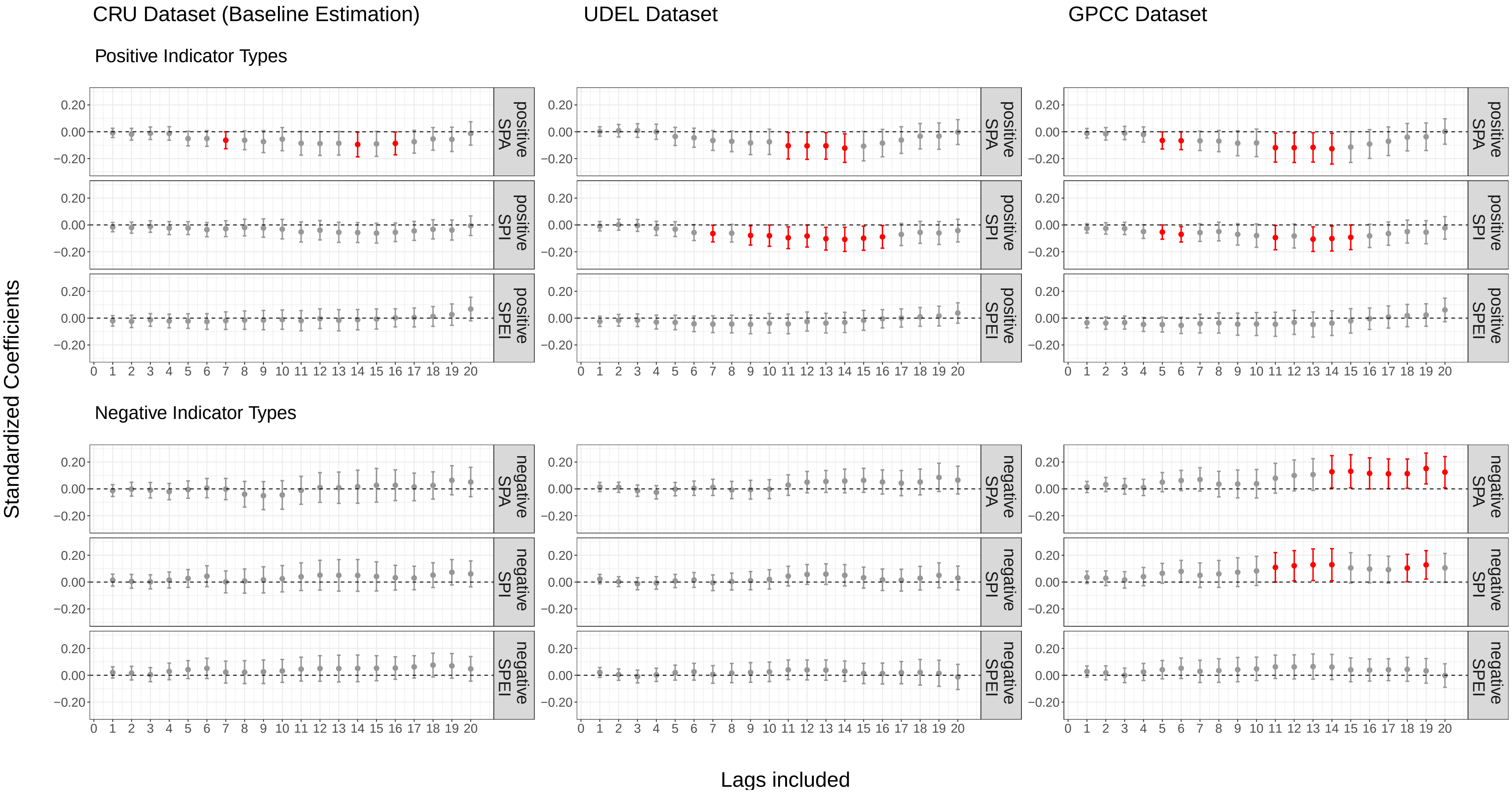

Figure 14: Cumulative Growth Effects Rich Country Sample, Different Precipitation Datasets (1951-2013)

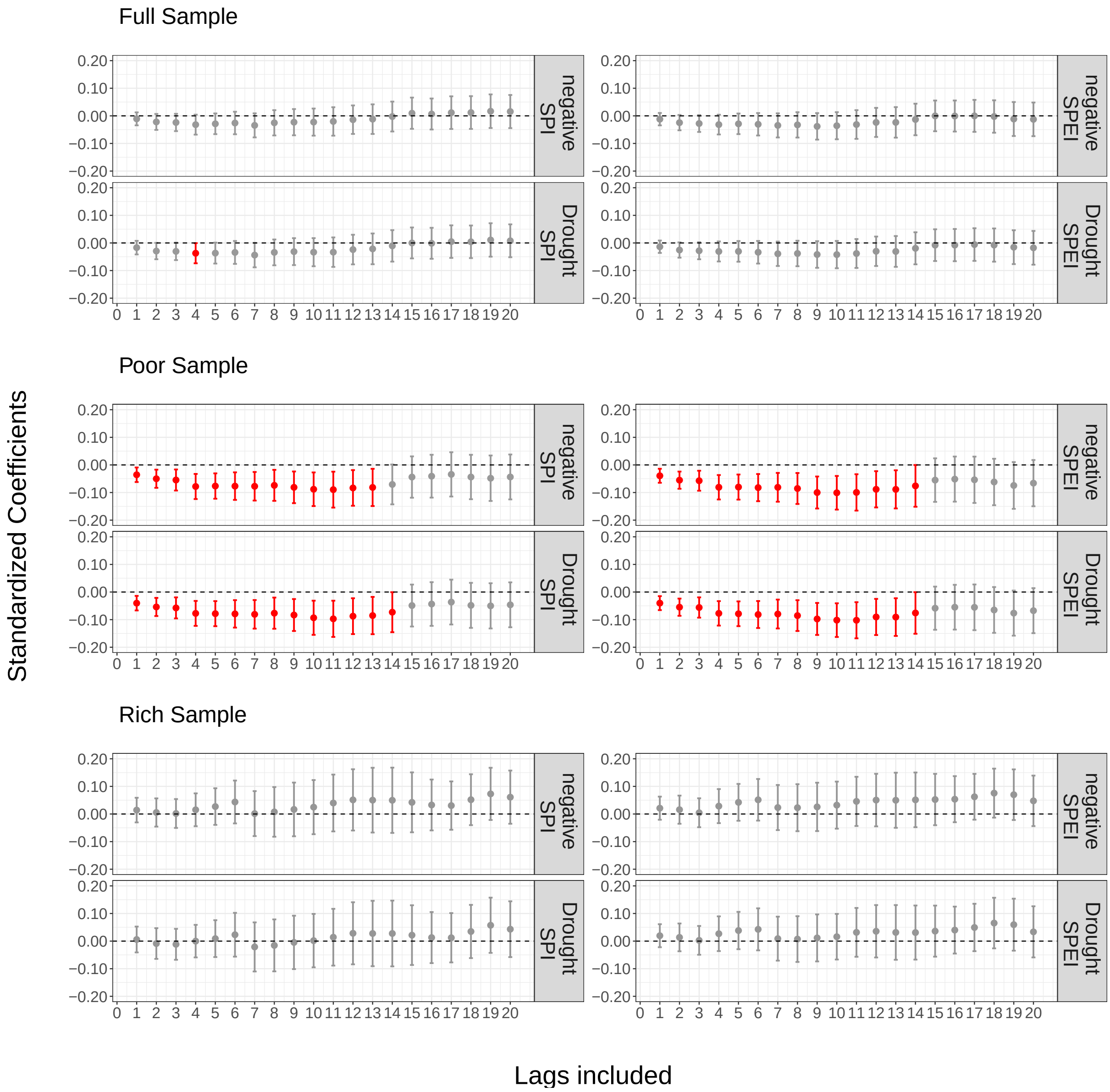

Figure 15: Cumulative Growth Effects of Droughts, Calculation based on *SPI* and *SPEI* (1951-2013)

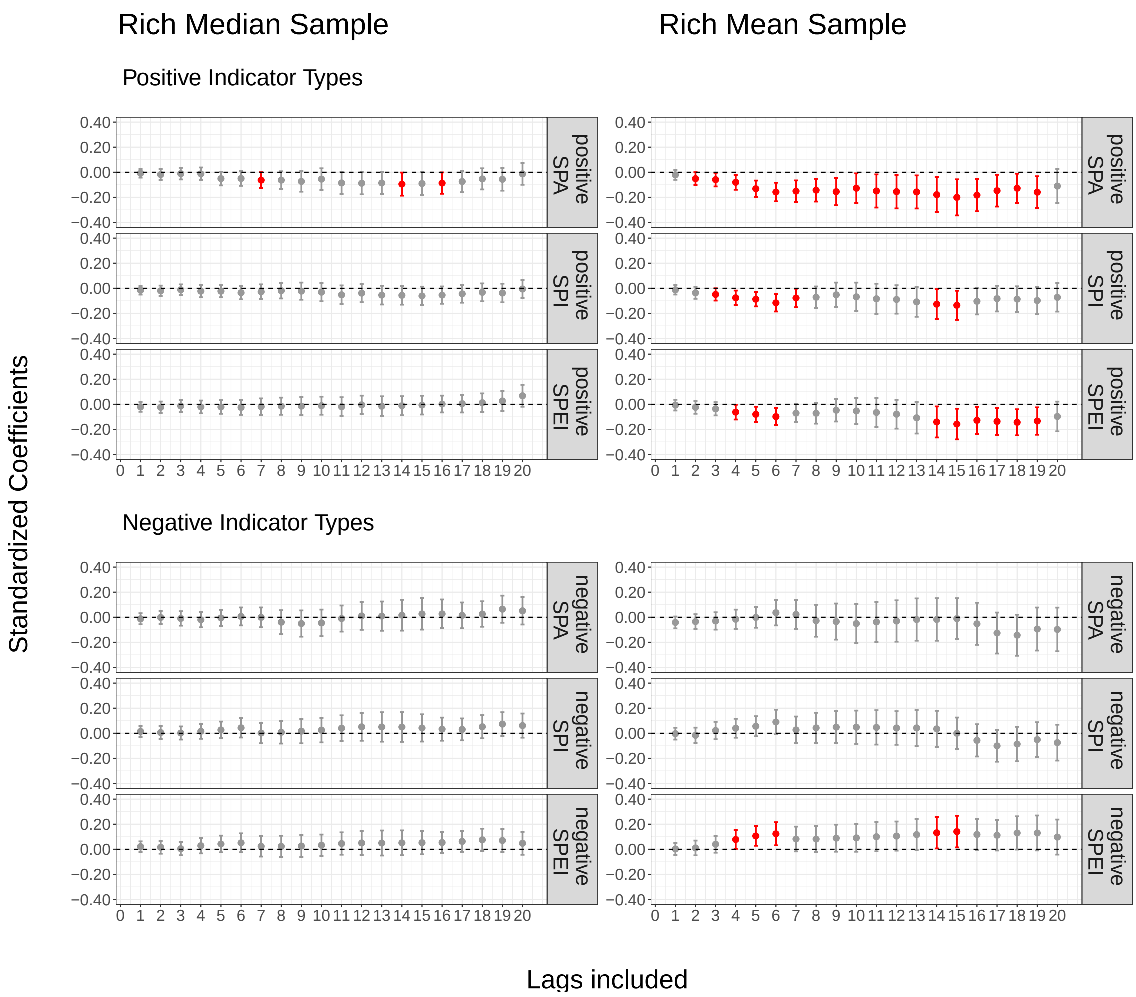

Figure 16: Cumulative Growth Effects Rich Countries, Alternative Sample Splits (1951-2013)

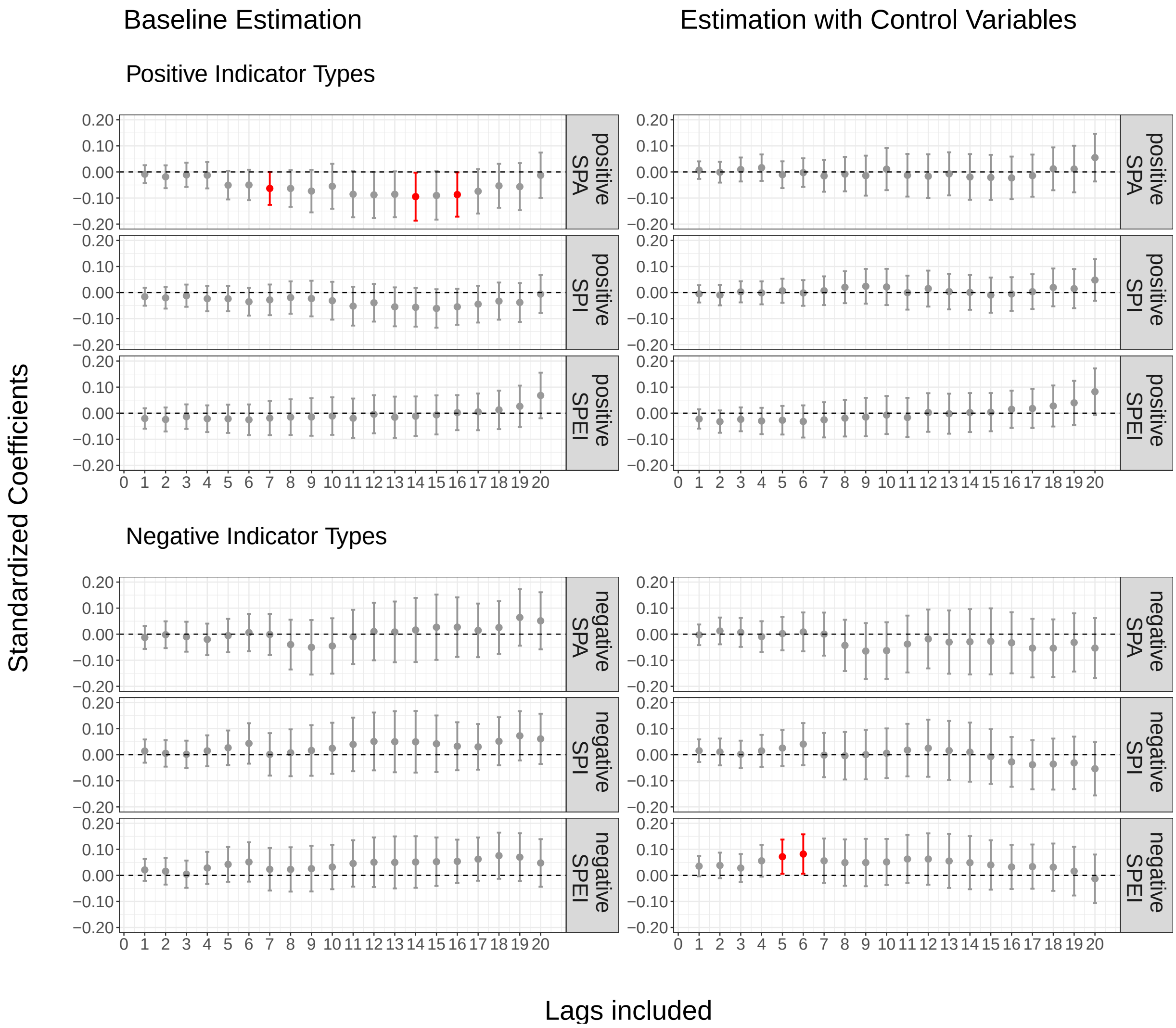

Figure 17: Cumulative Growth Effects Rich Country Sample with Controls (1951-2013)

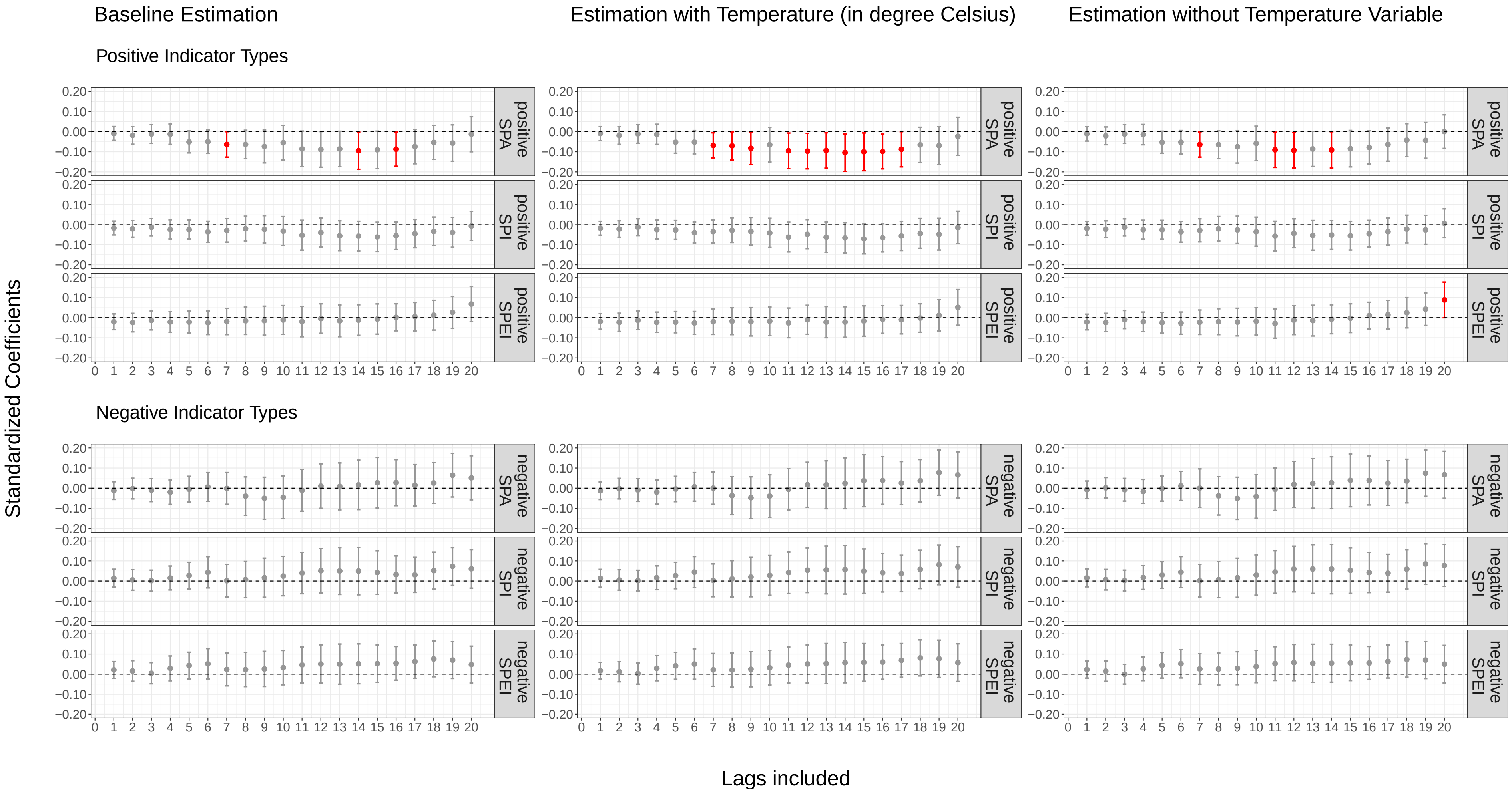

Figure 18: Cumulative Growth Effects Rich Country Sample under Alternative Temperature Controls (1951-2013)

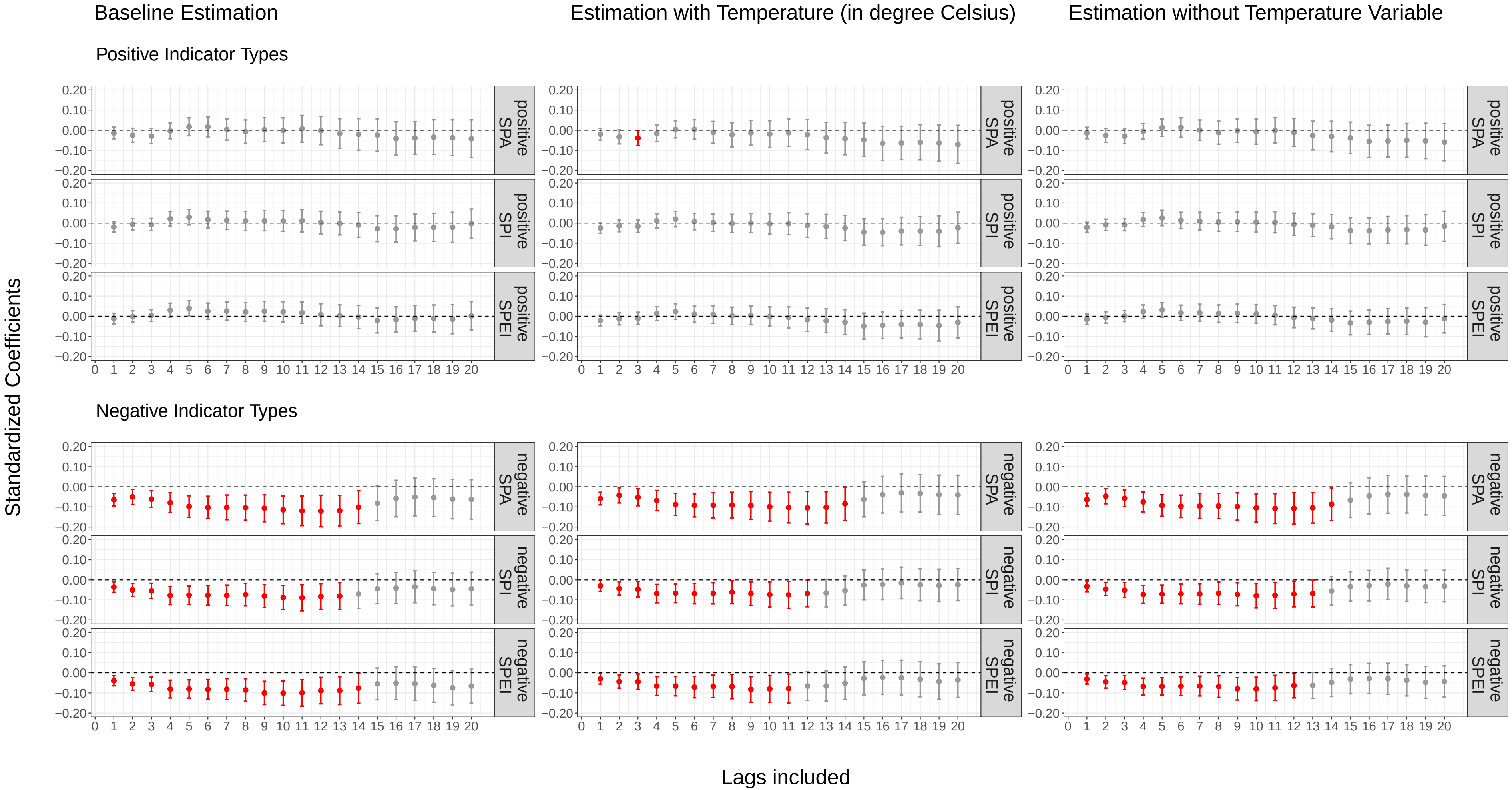

Figure 19: Cumulative Growth Effects Poor Country Sample under Alternative Temperature Controls (1951-2013)

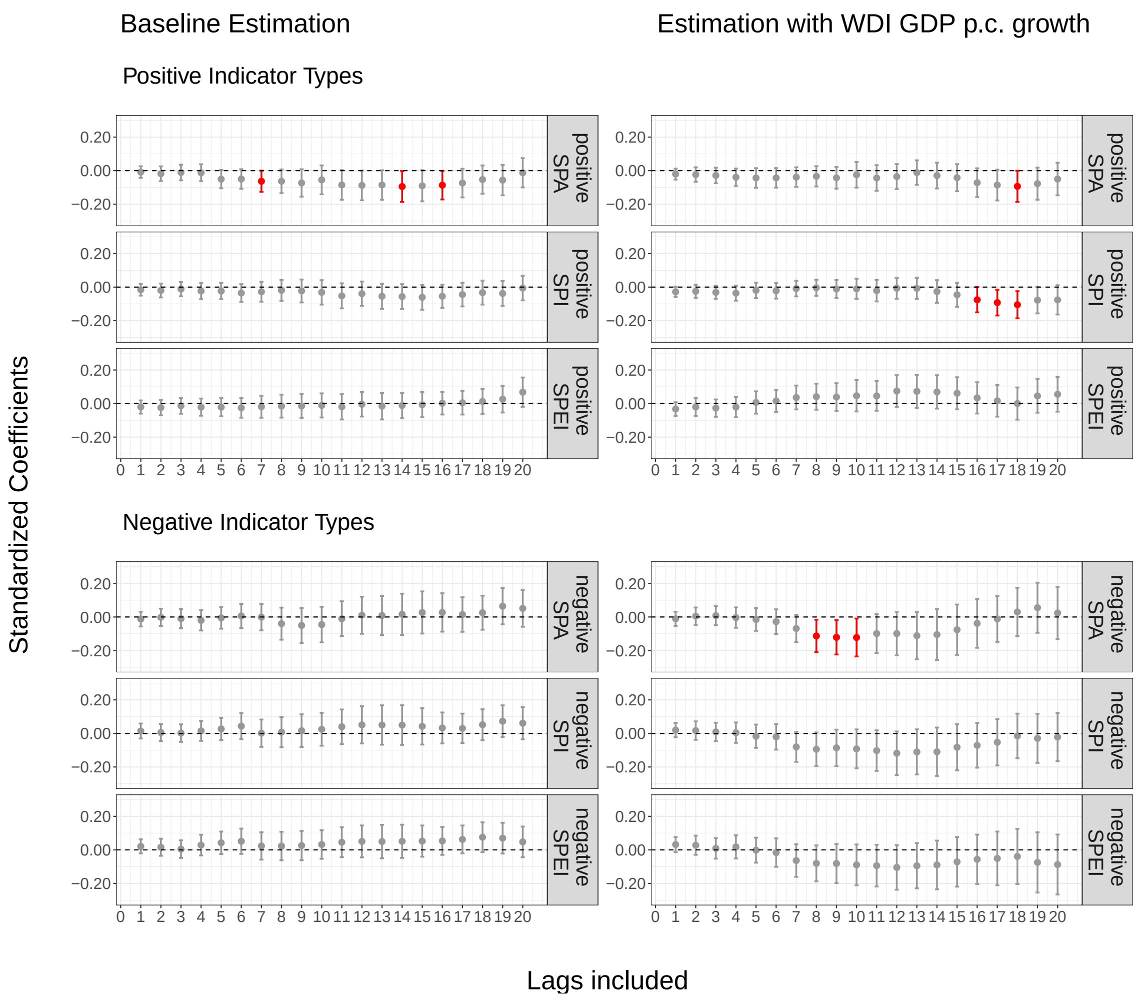

Figure 20: Cumulative Growth Effects Rich Country Sample, Based on WDI Growth Data (1951-2013)

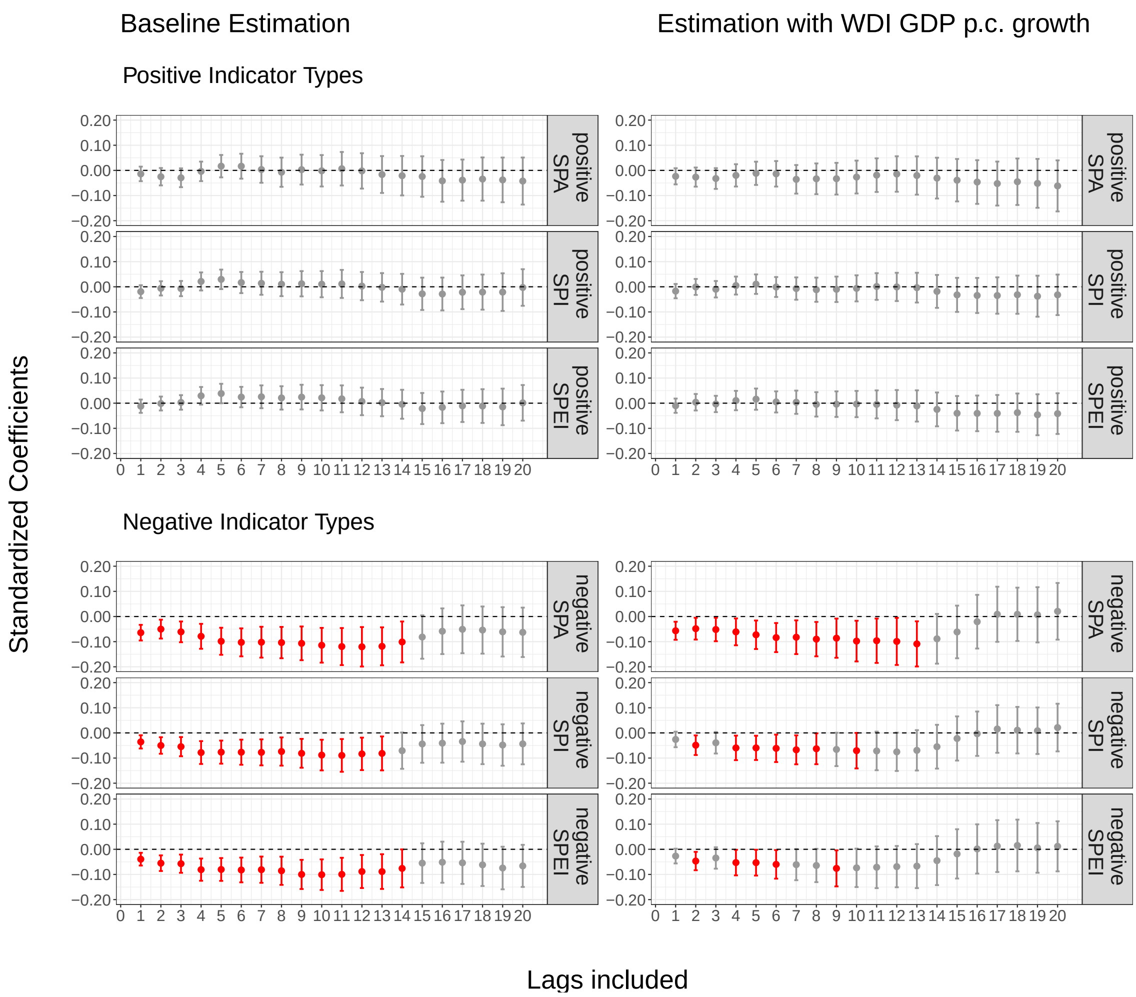

Figure 21: Cumulative Growth Effects Poor Country Sample, Based on WDI Growth Data (1951-2013)

Table 1: Augmented Dickey-Fuller Unit Root Test

Variable	lags (1)	lags (2)	lags (3)
Growth of real GDP per capita	-57.2384	-34.1049	-27.5300
	(0.0000)	(0.0000)	(0.0000)
Ln current GDP	-5.2827	-2.8909	-2.5759
	(0.0000)	(0.0020)	(0.0051)
Investment share in GDP	-7.4289	-3.9331	-2.0489
	(0.0000)	(0.0000)	(0.0204)
Government share in GDP	-1.5985	-1.9839	-1.4494
	(0.0552)	(0.0238)	(0.0738)
First difference of government share in GDP	-72.6695	-46.2342	-35.3322
	(0.0000)	(0.0000)	(0.0000)
Population growth rate	-33.6689	-7.7956	-7.1328
	(0.0000)	(0.0000)	(0.0000)
Std. rainfall anomaly (CRU)	-134.1425	-84.9801	-58.9692
	(0.0000)	(0.0000)	(0.0000)
Std. rainfall anomaly (UDEL)	-125.4172	-79.5070	-57.0822
	(0.0000)	(0.0000)	(0.0000)
Std. rainfall anomaly (GPCC)	-136.3721	-86.6706	-59.5888
	(0.0000)	(0.0000)	(0.0000)
SPI Indicator (CRU)	-118.6437	-71.5634	-54.2783
	(0.0000)	(0.0000)	(0.0000)
SPI Indicator (UDEL)	-109.4819	-67.8495	-51.3816
	(0.0000)	(0.0000)	(0.0000)
SPI Indicator (GPCC)	-120.7806	-73.4804	-53.9729
	(0.0000)	(0.0000)	(0.0000)
SPEI Indicator	-112.8024	-66.1138	-48.4967
	(0.0000)	(0.0000)	(0.0000)
Std. temperature anomaly	-93.2791	-65.8909	-50.1220
	(0.0000)	(0.0000)	(0.0000)
Mean annual temperature	-82.1855	-60.5367	-44.3865
	(0.0000)	(0.0000)	(0.0000)

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