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Estimating the impact of climate change on agricultural production: accounting for technology heterogeneity across countries*

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Abstract:
We estimate the impact of climate change on agricultural production in a panel of 127 countries from 1961 to 2002. In contrast to the existing literature we account for cross-sectional dependence and technology heterogeneity. We find no significant impact of climate change on agricultural production in high income countries, but significant adverse effects in middle and low income countries. These adverse effects include a moderate negative impact of increases in temperature on agricultural output and for low income countries also negative effects of reductions in precipitation and of increases in the frequency of droughts. The latter two effects are particularly strong in Sub-Sahara Africa where low-tech rain-fed agriculture with very limited climate change adjustment capacities dominates. Thus, our findings reinforce the importance of proper adaptation strategies to climate change considering heterogeneous production technologies across countries.

Keywords: agricultural production, climate change, panel data, cross-sectional dependence, parameter heterogeneity, common correlated effects estimator

JEL classification: C33, N50, O13, Q54

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1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC, 2013), average global surface temperature has increased by about 0.8 °C between 1880 and 2012. For the 21st century global warming exceeding 2 °C on average relative to the period 1850-1900 is projected by most scenario models. Even more pronounced increases in many regions are ‘very likely’ in the IPCC’s terminology. Trends for rainfall are more complex because there is considerable variation between and within countries. Overall, precipitation is on a downward trend at least since the 1950s. In particular in West Africa and the tropical rain-forest zones a strong decline in rainfall has been observed as well as more intense and widespread droughts (IPCC, 2013).

At the same time the importance of agricultural production increases to match growing global demand for food in times of continuing population and consumption growth. Agriculture also remains an important sector for many low-developed countries, contributing more than a fifth to their gross domestic product (GDP) and employing more than a quarter of their total labor force.[1]

Climate variables like temperature and precipitation can be viewed as agricultural production inputs and can have a potentially large impact on agricultural output. The impact is likely to be different across climatic regions. For example, a moderate increase in temperature and decrease in precipitation will probably have a smaller impact in temperate than in dry climate regions. Further, capacities to adjust agricultural production to climate change might be larger in countries with a large share of intensive farming than in low income countries where low-tech rain-fed agriculture dominates. Thus, it is important to understand the relationship between climate and agricultural production across countries with heterogeneous production technologies in order to design appropriate adaptation strategies.

Despite the potential importance of climate factors, most aggregate agricultural production function estimates have been restricted to relating agricultural output to traditional and modern production factors. Typically, traditional input factors include labor, land and livestock and modern factors are fertilizer and tractors, with livestock and tractors as proxies for traditional and modern capital formation (see e.g. Hayami and Ruttan, 1970; Craig et al., 1997; Fulginiti et al., 2004). None of these studies considers the influence of changes in climate on agriculture.[2]

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[1] In 2012, the World Development Indicators of the World Bank report a share of agriculture in GDP of more than 20 % for 30 countries (out of 136, for which data was available) with a maximum of 55.8 % (for Chad) and a population-weighted global average of 14.4 %. For the same year, the Food and Agricultural Organization reports a share of economically active population in agriculture of more than 25 % for 36 countries (out of 217) with a maximum of 44.1 % (for Bhutan) and a population-weighted global average of 18.7 %.

[2] Recently, there is a growing body of literature relating climate change to GDP. For example, Barrios et al. (2010) find that less rainfall leads to declining GDP growth rates in Sub-Saharan Africa countries, while they do not find any significant impact of increases in temperature. In contrast, Lanzafame (2012) finds supportive evidence between temperature and per-capita GDP growth in Sub-Saharan countries, while the evidence on rainfall is less clear-cut. On a global scale, Dell et al. (2012) find that higher temperatures reduce GDP growth rates in poor countries and have no discernable effects on GDP growth in rich countries, while changes in precipitation have no substantial effects on growth in either poor or rich countries. These different results show that there is no consensus in the literature. Further, the effects of climate change on GDP can give at most a rough indication of the more specific effects on agricultural production. The agricultural sector accounts only for a small fraction of GDP in some countries, is one of the sectors that are probably most directly influenced by climate change and focusing on GDP growth neglects substitution effects between the agricultural and other sectors.

To provide respective evidence, we analyze the influence of temperature, rainfall and droughts on agricultural production by applying a production function framework in a panel of 127 countries from various income classes over the period from 1961 to 2002. Different production technologies imply potentially very different adaptive capacities of the agricultural sector to climate change across countries. For example, O'Brien et al. (2004) find that irrigation contributes to higher adaptive capacity in intra-national comparison. In a study on India McKinsey and Evenson (1998) show that technology development affects the impact of climate change on agricultural production. Hence, in order to estimate a meaningful effect of climate factors on agriculture it is essential to consider heterogeneous production technologies to account for different adaptive capacities. We therefore allow for parameter heterogeneity in our global panel and also provide separate estimates for countries of different income groups.[3]

Closest to our work are Barrios et al. (2008) who consider climate factors in a production function and examine the impact of climate change on agriculture in Sub-Sahara Africa and other developing countries. They find a significant negative impact of temperature and a positive impact of rainfall on agricultural output in Sub-Saharan African countries. In contrast, they find no significant impact of temperature and rainfall for other developing countries, which they attribute mainly to technological adaptation. Their conclusion is that this difference in responses to climatic changes is responsible for a large part of the output gap in agriculture between Sub-Sahara Africa and the rest of the developing world in the last half-century.

An alternative to production functions estimates is the Ricardian approach (see Mendelsohn et al., 1994). It attempts to measure the effect of climate change via changes in land values. If land markets are operating properly, prices will reflect the present discounted value of land rents into the infinite future. Hence, this approach is able to account for the full range of compensatory responses to changes in climate made by farmers. However, the reliability of the Ricardian approach depends crucially on the ability to account fully for all factors correlated with climate change and influencing agricultural productivity. Omitted variables, such as unobservable farmer and soil quality, could lead to a bias of unknown sign and magnitude. Consequently, the Ricardian approach may confound climate with those other factors so that we chose to estimate production functions to control for various input factors directly. Further, the data necessary to apply a Ricardian approach, such as land values or agricultural profits, is not available for many countries (see e.g. Mendelshon et al., 1994; Deschenes and Greenstone, 2007; and Guiteras, 2009).[4]

Applying the production function approach in a global panel with 127 countries and a long sample raises the issue of cross-sectional dependence and non-stationarity. The presence of cross-sectionally and serially correlated errors violates the assumption that

[3] Earlier studies of agricultural production also stressed the importance of allowing production technology to differ across countries (see e.g., Hayami and Ruttan, 1985; Cermeño et al., 2003; Gutierrez and Gutierrez, 2003). However, none of them investigates this in a manner which allows for full heterogeneity of technology parameters as well as total-factor productivity (TFP), or includes climate factors.

[4] The main disadvantage of a production function approach is that it does not account for the full range of farmer adaptations. This property results in a tendency to bias the factor coefficients of the impact on agriculture downwards (Mendelsohn et al., 1994). While this bias may be rather small in low-developed regions, where adaptation to climatic changes was relatively low (like in Sub-Sahara Africa), there is a greater likelihood of a downward bias for other country groups. This bias has to be taken into account when interpreting the results, which are expected to be conservative estimates.

disturbances are independently distributed. Thus, estimations and inference based on models that do not account for common unobserved factors or shocks and non-stationarity of some data series can yield biased and misleading results, particularly in standard fixed effect panel estimators (see Phillips and Sul, 2003; Bai, 2009; Kapetanios et al., 2011). In the case of cross-sectional dependence, such common unobserved factors could for example be reflected in oil price shocks, a global financial crisis or local events that affect several countries via spillover effects. We test for cross-sectional independence of the different time series and reject it. To address these issues, we adopt the common correlated effects (CCE) estimator of Pesaran (2006), a sufficiently general and flexible econometric approach, which is applicable under both cross-sectional dependence and cross-country heterogeneity. Eberhardt and Teal (2012) use similar techniques in order to address the issue of parameter heterogeneity across countries, but they do not consider climate variables as agricultural production inputs.[5]

We find a moderate negative effect of warming and droughts and partially also a negative effect of reductions in rainfall in the global panel. Allowing for parameter heterogeneity and including common unobserved factors reduces the magnitude of the climate coefficients. Hence, traditional fixed effects and pooled OLS estimates overestimate the effects of climate change on agricultural output. When considering income groups, we find no effects in high-income countries, while there is a negative effect of warming in middle-income countries and additionally highly significant adverse effects of reductions in rainfall and of increases in the frequency of droughts in low-income countries. These effects of rainfall and droughts are especially pronounced in Sub-Sahara Africa. Together with our model diagnostics, these results underline the high relevance to consider technology heterogeneity when assessing the effects of climate change on agricultural production.

The different findings for high- and low-income countries are also reaffirmed by analysis using the Ricardian approach. For example, in the case of the United States, Deschenes and Greenstone (2007) estimate the effect of the presumably random year-to-year variation in temperature and precipitation on agricultural profits and find that climate change will increase annual profits in US agriculture by 3.4 % and that changes in temperature and rainfall virtually have no effect on yields among the most important crops. Using a similar approach, but for the case of India, Guiteras (2009) estimate that major crop yields in India will be reduced by 4.5 % to 9 % in the medium term, and by 25 % in the long-run, respectively.

The remainder of the paper is structured as follows. Section 2 introduces the empirical model and describes the data. In section 3 we present and discuss the main results. This section is divided in sub-sections discussing cross-sectional dependence and time-series properties of the variables, pooled regressions, averaged country regressions, and alternative specifications to check robustness, respectively. Finally, section 4 concludes.

[5] Their results suggest that what they call the ‘agro-climatic environment’ drives similarities in TFP evolution across countries with heterogeneous production technology, which is also pointing to inter-regional climatic spill-over effects. They argue that this could be a possible explanation for the failure of technology transfer from advanced countries of the temperate ‘North’ to arid and equatorial developing countries of the ‘South’. Thus, it is essential to allow for parameter heterogeneity in order to account for heterogeneous production technology capacities to adapt to climate change.

2. Method and data

2.1 The econometric model and methodology

Following the literature (particularly Eberhardt and Teal, 2012), we apply a Cobb-Douglas production function to analyze agricultural production. Allowing for heterogeneous slope parameters, we consider the following linear panel regression model:

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it}, \quad i = 1, 2, \dots, N; t = 1,2, \dots, T, \qquad (1)$$

where y_{it} represents the agricultural net output in values in the i^{th} country at time t. $x_{it} = (L_{it}, n_{it}, live_{it}, f_{it}, tr_{it}, T_{it}, R_{it}, D_{it},)'$ includes (proxies for) labor (L), land under cultivation (*n*), livestock (*live*), fertilizer (*f*), agricultural capital stock (*tr*), and the climate variables, temperature (*T*), rainfall (*R*) and droughts (*D*). The country specific intercept is denoted by α_i and u_{it} is the error term. All variables in equation (1) are expressed in natural logarithms except of temperature, rainfall and the drought dummy. Further, the dependent variable and the agricultural input variables are expressed in per worker terms, such that the addition of the labor variable (L) in levels in the estimations indicates deviation from constant returns to scale (CRS).

The common unobserved factors as well as the spatial effects will be modelled through the error term. In particular, we shall assume that u_{it} has the following multi-factor structure:

$$u_{it} = \gamma_i' \mathbf{f}_t + \varepsilon_{it}, \qquad (2)$$

in which $\mathbf{f}_t$ is the *m* x 1 vector of unobserved common effects, which can be stationary or non-stationary (see Kapetanios et al., 2011) and are allowed to be serially correlated and possibly correlated with x_{it}. The individual-specific errors, ε_{it}, are assumed to be distributed independently of both, the regressors and the unobserved common factors.

To eliminate cross-sectional dependence (CD) asymptotically, arising from both, strong factors (like global oil price shocks or the like) and weak factors (such as local spillover effects, i.e. the lack of seasonal rainfall), we make use of the common correlated effects (CCE) type estimators developed by Pesaran (2006). Thus, the estimation and testing approach to equation (1) with multifactor errors (equation 2) has the following form:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \bar{\mathrm{g}}_i' \, \bar{\mathrm{z}}_t + \varepsilon_{it}, \quad i = 1, 2, \dots, N; t = 1,2, \dots, T, \qquad (3)$$

where $\bar{z}_t = (\bar{y}_t, \bar{x}_t')'$, with $\bar{y}_t$ and $\bar{x}_t$ being the cross-section averages of the dependent variable and regressors, respectively.

The CCE mean group estimator (CCEMG) allows coefficients of interest to vary across countries and is defined as a simple average of the individual country CCE estimators. In contrast, the CCE pooled estimator (CCEP) is computed by pooling observations over the cross-sectional units. If individual slope coefficients are assumed to be the same, then efficiency gains from pooling observations can be achieved (see Pesaran, 2006).

For comparison and robustness purposes, we will compute several regression models. In the pooled models we estimate OLS in levels (POLS), two-way fixed effects (2FE) and the Pesaran (2006) common correlated effects (CCE) pooled estimator. In the heterogeneous models we implement the Pesaran and Smith (1995) mean group (MG) and the heterogeneous version of the CCE estimator, the CCE mean group estimator (CCEMG). The aim of this exercise is to assess the size of bias of climate coefficients estimated by previous models (POLS, 2FE) with climate coefficients of the more appropriate CCE-approaches.

2.2 Data

The data used to estimate equation (3) is derived from three sources. All the agricultural data for our empirical analysis is taken from the Food and Agricultural Organization's FAOSTAT panel database. For a measure of agricultural output (y) we use real agricultural net output (in thousand International $) which covers practically all crops and livestock products originating in each country except for fodder crops. Intermediate primary inputs of agricultural origin are deducted, including fodder and seed. The quantities for each commodity are weighted by the respective 1999-2001 average international commodity prices and then summed for each year by country. The prices are in international dollars, which are derived using a Geary-Khamis formula for the agricultural sector.

The labor variable (L) represents the annual time series for total economically active population in agriculture, while the land variable (n) represents arable and permanent crop land (in 1,000 hectare). The latter consists of land under temporary agricultural crops (multiple-cropped areas are counted only once), temporary meadows for mowing or pasture, land under market and kitchen gardens and land temporarily fallow (less than five years). Livestock ($live$) is a proxy for capital formation in rural areas. To account for the economic relevance of different types of livestock, we follow the methodology of Eberhardt and Teal (2012) and construct the variable by applying specific weightings.[6] Fertilizer (f) is measured as the quantity, in metric tons, of plant nutrients consumed for domestic use in agriculture, which includes 'crude' and 'manufactured' fertilizers. For capital stock (tr) we follow the common convention and use the total number of agricultural tractors in use as a crude proxy.[7]

Temperature (T) and rainfall (R) data were constructed by Dell et al. (2012) relying on data from the Terrestrial and Air Temperature and Precipitation: 1900–2006 Gridded Monthly Time Series, Version 1.01 (Matsuura and Willmott 2009).[8] The latter provides worldwide (terrestrial) monthly mean precipitation and temperature data at 0.5 × 0.5 degree resolution (approximately 56 km × 56 km at equator), which Dell et al. (2012) aggregate to the country-year level weighted by population distribution, using geospatial software.[9]

Finally, data for drought events (D) is obtained from the International Disaster Databank of the Centre for Research on the Epidemiology of Disasters (CRED). CRED

[6] *live* = 1.1*camels + (buffalos + horses + mules) + 0.8*(cattle + asses) + 0.2*pigs + 0.1*(sheep + goats) + 0.01*(chicken + ducks + turkeys).
[7] Agricultural data available at: http://faostat.fao.org/.
[8] Data available at: http://www.aeaweb.org/articles.php?doi=10.1257/mac.4.3.66.
[9] For a detailed description of the dataset, see Appendix I in Dell et al. (2012).

defines a drought as an extended period of time characterized by a deficiency in a region's water supply that is the result of constantly below average precipitation.[10]

Table 1 provides summary statistics of the variables[11], while table 2 lists the total number of drought events per country and income classes of the whole sample period. The latter indicates that droughts occurred more frequently in countries of the lower middle and low income classes.

*** Table 1 about here ***
*** Table 2 about here ***

Figure 1 presents the population-weighted global means of the climate variables – temperature and rainfall – over the sample period. These variables show a clear trend: temperatures tend to rise, and increasingly so since about 1980, and rainfall experiences a downward trend.

Finally, figure 2 illustrates the sum of drought events in a given year. As a trend, the number of drought events increased over the sample period, with a considerable peak in the early 1980s and more pronounced year-to-year-volatility in the years since then.

*** Figure 1 about here ***
*** Figure 2 about here ***

Furthermore, the drought dummy is weakly but significantly positive correlated with temperature (0.12, $p<0.001$) and negative with rainfall (-0.07, $p<0.001$).

3. Empirical Results

3.1 Testing for cross-sectional dependence and unit roots

In this sub-section, we implement Pesaran's (2004) CD test for cross-sectional dependence in panel data. The test is robust to non-stationarity, parameter heterogeneity and structural breaks and has been shown to perform well even in small samples. The extend of cross-sectional dependence of the variables in levels and residuals from ADF(p) regressions of each variable across the 127 countries over the period from 1961 to 2002 are summarized in table 3 and table 4, respectively.

*** Table 3 about here ***

[10] Data is available at: http://www.emdat.be/, definitions from http://www.emdat.be/glossary/9.
[11] Note that we have an unbalanced dataset. In particular, 204 observations of the fertilizer variable are missing, resulting in 5108 observations that enter the panel regressions.

Table 3 indicates that average correlation varies considerable across variables, but is highly significant in all cases. With respect to climate, the correlation of temperature is of considerable size (0.352), while the correlation of rainfall is small, though significant on the 1 % level. This is plausible since rainfall variations and trends within a country are much more independent of common global or regional trends while this is not the case for temperature, for which interregional spill-overs play a much larger role.

*** Table 4 about here ***

The test on residuals from the ADF(*p*) regressions support the previous findings on cross-sectional dependence shown in table 3. For each lag p = 1, 2, and 3, the reported CD statistics in table 4 are highly significant, with the temperature variable displaying a very large test statistic. To investigate cross-sectional dependence of our regression models, formal CD test results and mean absolute correlation coefficients for residuals are also reported for each specification (see lower end of tables 6 to 9).

The presence of cross-sectional dependence in the variables and residuals from ADF(*p*) regressions implies that the use of standard panel unit root tests, such as the test proposed by Im, Pesaran, and Shin (2003), is not valid. To account for cross-sectional dependence when investigating stationarity, we therefore make use of the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007). This test follows the CCE approach and filters the cross-sectional dependency by augmenting the ADF regressions carried out separately for each country with cross-section averages. Furthermore, the CIPS test allows for heterogeneous unit root processes, while it assumes one unobserved factor. The corresponding test statistics for different lag orders are presented in table 5.

*** Table 5 about here ***

Overall, considering the present data dimensions and characteristics, and given all the problems and caveats of panel unit root tests, results in table 5 show that we can suggest most conservatively that non-stationarity for conventional agricultural input and output variables cannot be ruled out.[12] At the lower end of the following tables 6 to 9, which contain our main estimation results, we indicate residual stationarity for each empirical model by applying the CIPS test. If the presence of a unit root in the residuals cannot be rejected, t-statistics are invalid (Kao, 1999) and tend to vastly overstate the precision of the parameter estimates (Bond and Eberhardt, 2009).

[12] In contrast, temperature and precipitation are following a trend-stationary process with some certainty on the global level. However, we also implemented a Dickey-Fuller unit root test for each country separately and find that about a quarter (a third) of the countries have non-stationarity temperature (rainfall) series.

3.2 Pooled estimation results

The results of the pooled estimations are presented in table 6. The base model includes agricultural inputs only (columns 1, 4 and 7), the extended model includes temperature and precipitation (columns 2, 5 and 8) and the full model also includes the drought dummy (columns 3, 6 and 9). For all three models we provide OLS estimates in levels (POLS), two-way fixed effects (2FE) estimates and estimates computed with the pooled version of the CCE estimator (CCEP). In the lower panels of the table we report the implied returns to scale and labor coefficients as well as residual diagnostics with respect to stationarity and cross-sectional dependence.

*** Table 6 about here ***

The size and signs of the parameter coefficients of agricultural inputs are in line with previous findings. Interestingly, the parameter size of traditional inputs livestock ($live$) and land (n) are higher compared to the implied labor coefficient and modern inputs tractors (tr) and fertilizer (f). Furthermore, all specified global production functions in table 6 indicate decreasing returns to scale (DRS).[13] Including climate variables does not change the magnitude and signs of conventional inputs and the direction of returns to scale.

With respect to climate variables, we find that temperature has a negative impact which varies from -0.011 to -0.019, depending on the respective regression model. Thus, a 1 °C increase in temperature reduces agricultural output by about 1 % to 2 % on average. The rainfall coefficient is positive throughout, but significant and of considerable size in the POLS estimation only. However, the impact of climate is underpinned by the negative and significant coefficient of the drought dummy. Interestingly, the coefficient in the POLS estimation is about 7 times larger compared to the 2FE model and CCEP model. This indicates that without controlling for individual country fixed effects, the parameter coefficient of the drought dummy is vastly overestimated. Referring to the fixed effects models, agricultural output would drop by more than 2 % on average in a given year if one drought event occurs.

Turning to diagnostics, residuals in the CCEP model are stationary, in contrast to the standard panel estimators in levels (POLS, 2FE), for which non-stationary residuals cannot be rejected. Hence, standard panel estimators produce invalid t-statistics and tend to overemphasize the precision of the coefficients. Also the CD test provides mixed results. Although the mean absolute residual correlation has decreased in the CCEP model compared to the POLS estimation, the CD test nevertheless rejects the null hypothesis of cross-sectional independence. In contrast, residuals in the 2FE model are cross-sectional independent, but also reveal a higher mean absolute residual correlation. In conclusion, all these diagnostics indicate that parameters can be seriously biased using pooled regression models, especially OLS techniques. Our next step is therefore to allow for heterogeneity in the slope parameters.

[13] It is worth to mention here that Eberhard and Teal (2012) note that decreasing returns of scale could be due to empirical misspecification of the global production function.

3.3 Averaged country regression results

The averaged country regression results are presented in table 7. Again, there is the base (columns 1 and 4), the extended (columns 2 and 5) and the full model (columns 3 and 6) in two variants: as mean group (MG) estimator and as heterogeneous versions of the CCE estimator (CCEMG). Regarding average parameter estimates of the agricultural factor inputs, MG and CCEMG estimators yield qualitatively the same results compared to the pooled specifications. The only crucial exception is that the CCEMG models show insignificant coefficients of labor, indicating constant returns in the average country regressions. To account for that, we also estimated a restricted version of the model (in columns marked [b]).

*** Table 7 about here ***

Referring to the climate variables, coefficients have the same sign as in the pooled regressions, but the size of the coefficients has changed notably. The coefficients of temperature and droughts are again negative and in most cases significant while the coefficient of rainfall is again positive, but only significant in the MG model. Overall, allowing for parameter heterogeneity and including common unobserved factors reduces the magnitude of the climate coefficients (temperature, precipitation and drought) in the global agricultural production function.

With respect to diagnostics, results from the CIPS test reject non-stationarity of residuals in all models. Further, the mean absolute residual correlation is smaller compared to the pooled estimations but the CD test cannot reject cross-sectional independence only in the CCEMG models. Taking these test results into account, the CCEMG model with imposed CRS provides the best results from an econometric perspective. Overall, if stationarity and cross-sectional dependence are taken into account, robust estimation results are produced, which are smaller in size and less often significant.

Hence, idiosyncracies on the country level and in particular differences in technology play a relevant role. Consequently, we refine our results with respect to income groups (high, medium, and low income countries) to better reflect systematically different technologies in agricultural production and capacities in climate change adaptation. Table 8 shows the results. We applied the full version of the CCEMG model with imposed CRS as the qualitatively best model for high (column 1), middle (column 2) and low income countries (column 3),[14] as well as for the full sample without countries from Sub-Sahara Africa (column 4), and for countries from Sub-Sahara Africa only (column 5).

*** Table 8 about here ***

While the results show that agricultural production in high-income countries has hardly been affected by climate change at all, the other two income groups are affected.

[14] The high income group consists of high-income OECD and non-OECD countries, the middle income group includes upper as well as lower middle income countries; for details see table 2.

In both groups warming had a significant negative effect on output, particularly in the middle-income group. In the low-income group the coefficient for precipitation is highly significant and of considerable magnitude compared to global results. Droughts have only a significant effect on agricultural output in low income, but not in middle or high income countries. Looking at Sub-Saharan African countries only, the effects of precipitation and droughts are strongly intensified. In particular the coefficient on droughts doubles compared to all low income countries and becomes significant on the 1 % level.

These results underline the relevance of technology heterogeneity. They also seem plausible, because most high-income countries are located in temperate and cold climatic zones, dampening the adverse consequences of climate change, and their agricultural sector is industrialized, supporting capacity to adapt to negative effects from climate change. In contrast, low income countries are located predominantly in the arid and equatorial climatic zones, where low-tech rain-fed agriculture is dominating. These connections are also reaffirmed by the implied labor coefficient, which is large in the low-income group, but very low in the high-income group. Also in the case of Sub-Sahara Africa, the relevance of labor is considerable, especially compared to modern inputs (which do not yield significant results). In this case, also the effect of rainfall and especially of droughts turns out to be comparably large. For all models, diagnostics work perfectly well and non-stationarity as well as cross-sectional dependence can be rejected.

Overall, these results show that between-country differences in the effects of climate change are related to the character of agriculture. The role of technology is crucial and gaps between income groups are widening. While growth of output per worker is 3.5 % on average in the high-income group over the sample period, this growth is down to 2.2 % in the middle-income group and amounts to 0.5 % only in the low-income group, where agricultural land per worker is even constantly decreasing. These differences are to be taken seriously into account when deciding about necessary adaptation strategies, because our results show that climate change is already seriously affecting agricultural production, especially in poorer countries.

3.4 Alternative specifications

We use the full version of the CCEMG model with imposed CRS to show the robustness of the results from tables 7 and 8. Results of these robustness checks are shown in table 9 and can be compared with column 5b and 6b from table 7. We exchanged temperature and rainfall with their 5-years-moving-average (column 1), with their absolute (column 2) and relative (column 3) variation and with a drought and a flood dummy[15] without (column 4) and with (column 5) temperature and rainfall as additional regressors, checked for geometric effects in temperature and precipitation (column 6) and for various interactions of climate variables (columns 7 and 8).

*** Table 9 about here ***

[15] Also taken from http://www.emdat.be/, definitions from http://www.emdat.be/glossary/9.

Variations and averages of temperature and rainfall show similar but weaker results compared to their direct effect. To replace them with a drought and flood dummy performs well with respect to droughts, but the flood effect generally remains negligible. Also other robustness checks (not shown) do not challenge previous results. This includes an analysis of the lag structure of the full model, where a tendency of decreasing effects of rainfall and droughts but increasing effects of temperature can be observed (but with weak significance at best),[16] of the exclusion of certain countries,[17] and of experiments with climate zones.[18]

Two interesting findings nevertheless stand out. When considering geometric patterns, temperature as well as rainfall show counterbalancing effects. In both cases, first-order effects increase, while second-order effects partially offset these dynamics. However, both temperature coefficients also become insignificant. The second result is the interaction of temperature and rainfall, which produces a positive and highly significant coefficient. This indicates a generally decreasing (negative) effect of temperature when rainfall is increasing and hence a partial counterbalance of the two climate inputs. Again, diagnostics work perfectly well and non-stationarity as well as cross-sectional dependence can be rejected for all models.

4. Conclusion

In this paper, we estimate the relationship between agricultural production, conventional input factors and climate variables (temperature, rainfall, and droughts) for 127 countries over the period from 1961 to 2002. Both, previous agricultural production analyses in general and the analysis of climate factors in particular, reinforce the necessity to consider heterogeneous production technologies. Different from previous studies, we apply a production function approach allowing for parameter heterogeneity and CCE-type estimations in order to take into account cross-sectional dependence. Hence, we provide a qualitative improvement of the assessment and robust evidence for the influence of climate change on global agricultural production and for different income groups. In this context, we are able to show that model misspecification is a serious issue because of cross-sectional dependence and non-stationarity. Residual diagnostics especially indicate a bias of pooled regression models, but also of MG estimators.

Our results confirm earlier evidence of the relevance and magnitude of the effects of traditional and modern inputs in agricultural production, but climate factors add explanatory power to the model. Four major findings stand out: (1) we find evidence of significant negative effects of temperature and drought events on agricultural production in regressions with homogenous and heterogeneous slope parameters, while the effect of precipitation is positive but not regularly significant; (2) the effects generally diminish in size when allowing for parameter heterogeneity and controlling for cross-sectional dependence by applying the CCE-estimator; (3) while agricultural production in high income countries is hardly affected by climate change, middle and especially low income countries are affected by increases in temperature and the latter also by

[16] We analyzed up to three lags, results are available on request.

[17] Like China, India, or the Gulf states, results are available on request.

[18] We applied five climate zones and two different classifications, results are available on request. The only notable deviation from our main results is that the effect of temperature turns out to be positive and significant in countries with cold climates.

changes in precipitation and the frequency of droughts; (4) the adverse effects of climate change results are especially pronounced in Sub-Sahara Africa.

Overall, these results show that between-country differences of the effects of climate change are related to technological heterogeneity in agricultural production. Hence, further research is necessary to identify more details about connections and transmission channels. Particular challenges are the larger effects in middle and especially low income countries. This is – politically and economically – a crucial issue, because structural change in agriculture will take time, while local food security is an immediate issue. Hence, to dampen the negative consequences of already unavoidable climate change dynamics, it is necessary to apply adaptation measures which are sensitive to technological heterogeneity in the agricultural sector. This is also another direction of further research, especially with respect to econometric refinements of this field of analysis: while we control for parameter heterogeneity and find clear evidence of its relevance, explicit modelling of different production technologies and of the effects of TFP-levels on adaptation would certainly be desirable.

Overall, climate change is already negatively affecting global agriculture and thus endangering the livelihoods of large populations. In particular, low and middle income countries in the arid and equatorial climatic zones experience a negative impact. Given recent IPCC projections, this trend is very likely to continue and even aggravate in the future, especially in poor countries (see IPCC, 2014). Hence, our findings reinforce the importance of proper adaptation strategies considering the specific characteristics of agriculture as well as its specific vulnerabilities to climate change dynamics.

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Appendix:

Table 1: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Variables in levels					
y	5302	3.58	6.93	0.11	50.72
L (`000s)	5302	8,263.74	41,900.00	2.00	511,000.00
n	5297	4.74	12.72	0.11	140.47
live	5302	6.38	12.46	0.06	102.28
f	5108	0.41	0.92	0.00	7.05
tr	5302	0.12	0.28	0.00	1.97
T (C°)	5314	19.62	7.05	-3.00	29.58
R (100 mm)	5314	11.23	7.14	0.07	53.58
Variables in logs					
y	5302	0.18	1.39	-2.22	3.93
L	5302	13.95	1.89	7.60	20.05
n	5297	0.64	1.15	-2.20	4.95
live	5302	0.85	1.40	-2.77	4.63
f	5108	-3.22	2.66	-11.56	1.95
tr	5302	-5.13	3.01	-13.67	0.68

Notes: We report the descriptive statistics for output (in I$1,000), labor (headcount), tractors (number), livestock (cattle-equivalent numbers), fertilizer (in metric tons) and land (in hectare), temperature (°C) and precipitation (100 mm); small letters indicate per worker terms.

Table 2: Country statistics

code	country	T	R	D	code	country	T	R	D
High-income OECD-countries									
AUS	*Australia*	15.96	8.34	15	IDN	*Indonesia*	25.55	21.97	9
AUT	*Austria*	7.60	9.33	0	IRN	*Iran, Islamic Rep.*	14.12	3.78	4
CAN	*Canada*	4.93	9.24	8	IRQ	*Iraq*	21.62	2.68	6
DNK	*Denmark*	7.86	5.66	1	JAM	*Jamaica*	24.65	18.87	5
FIN	*Finland*	3.26	5.97	0	JOR	*Jordan*	17.65	2.84	2
FRA	*France*	10.64	7.82	4	MAR	*Morocco*	16.92	4.29	7
DEU	*Germany*	8.74	7.50	0	PRY	*Paraguay*	22.18	14.78	6
GRC	*Greece*	14.62	6.34	1	PHL	*Philippines*	25.51	22.31	9
ISL	*Iceland*	2.49	8.54	0	ROM	*Romania*	8.88	5.36	2
IRL	*Ireland*	9.16	10.16	0	LKA	*Sri Lanka*	26.79	21.98	11
ITA	*Italy*	11.81	10.44	2	SUR	*Suriname*	26.64	20.97	0
JPN	*Japan*	13.14	16.12	1	SWZ	*Swaziland*	20.51	8.09	10
KOR	*Korea, Rep.*	11.24	12.60	3	SYR	*Syrian Arab Republic*	17.30	3.81	2
NLD	*Netherlands*	9.90	7.65	0	THA	*Thailand*	26.83	14.39	4
NZL	*New Zealand*	11.98	11.22	1	TUN	*Tunisia*	18.46	4.09	2
NOR	*Norway*	3.59	9.90	0	**Low income countries**				
PRT	*Portugal*	15.04	10.55	2	AFG	*Afghanistan*	11.16	3.51	7
ESP	*Spain*	13.88	6.60	11	BGD	*Bangladesh*	25.57	19.95	4
SWE	*Sweden*	5.44	5.97	0	BEN	*Benin*	27.00	10.93	7
CHE	*Switzerland*	5.28	12.25	0	BFA	*Burkina Faso*	27.68	8.01	22
GBR	*United Kingdom*	9.17	7.93	0	BDI	*Burundi*	20.14	11.44	3
USA	*United States*	12.96	8.96	6	KHM	*Cambodia*	27.54	14.14	6
High-income non-OECD-countries					CMR	*Cameroon*	24.23	18.22	4
CYP	*Cyprus*	19.26	3.83	2	CAF	*Central African Republic*	24.30	14.17	2
ISR	*Israel*	19.91	4.12	1	TCD	*Chad*	27.80	6.95	19
KWT	*Kuwait*	25.43	1.06	0	ZAR	*Congo, Dem. Rep.*	23.19	15.00	3
QAT	*Qatar*	26.53	0.78	0	COG	*Congo, Rep.*	24.09	14.80	1
SAU	*Saudi Arabia*	25.06	1.03	0	CIV	*Cote d'Ivoire*	26.12	13.32	1
ARE	*United Arab Emirates*	26.54	1.28	0	ETH	*Ethiopia*	19.69	10.82	21
Upper middle income countries					GMB	*Gambia, The*	26.12	10.00	13
ARG	*Argentina*	17.14	8.84	0	GHA	*Ghana*	26.54	13.39	5
BLZ	*Belize*	25.50	23.64	0	GIN	*Guinea*	25.18	19.86	4
BWA	*Botswana*	20.83	4.49	10	GNB	*Guinea-Bissau*	26.69	15.08	9
CHL	*Chile*	11.33	5.85	6	HTI	*Haiti*	24.21	10.97	9
CRI	*Costa Rica*	22.28	40.00	3	IND	*India*	25.20	12.09	15
GNQ	*Equatorial Guinea*	23.84	21.21	0	KEN	*Kenya*	20.01	12.34	14
GAB	*Gabon*	24.60	21.05	0	PRK	*Korea, Dem. Rep.*	7.68	9.69	1
HUN	*Hungary*	10.28	5.77	2	LAO	*Lao PDR*	23.66	18.29	7
LBN	*Lebanon*	16.82	9.55	0	LSO	*Lesotho*	12.20	6.91	7
LBY	*Libya*	20.39	2.33	0	LBR	*Liberia*	25.78	24.98	1
MYS	*Malaysia*	26.02	25.63	1	MDG	*Madagascar*	20.72	15.44	8
MEX	*Mexico*	18.61	8.96	7	MWI	*Malawi*	22.71	11.05	8
OMN	*Oman*	25.24	1.25	0	MLI	*Mali*	28.19	6.88	10
PAN	*Panama*	24.84	27.20	1	MRT	*Mauritania*	28.55	2.71	23
POL	*Poland*	7.86	5.95	0	MNG	*Mongolia*	-1.50	2.28	1
ZAF	*South Africa*	17.53	6.75	9	MOZ	*Mozambique*	24.14	9.83	14
TTO	*Trinidad and Tobago*	25.79	18.48	0	MMR	*Myanmar*	25.08	19.15	0
TUR	*Turkey*	12.15	6.03	0	NPL	*Nepal*	20.19	16.01	6
URY	*Uruguay*	17.21	11.03	2	NIC	*Nicaragua*	25.54	15.48	4
VEN	*Venezuela, RB*	25.33	11.58	0	NER	*Niger*	28.13	4.52	15
Lower middle income countries					NGA	*Nigeria*	26.72	13.11	3
ALB	*Albania*	13.01	12.47	3	PAK	*Pakistan*	22.54	4.12	4
DZA	*Algeria*	16.76	5.00	3	PNG	*Papua New Guinea*	21.93	27.58	4
AGO	*Angola*	22.17	10.81	9	RWA	*Rwanda*	19.75	11.18	8
BOL	*Bolivia*	18.80	10.61	6	SEN	*Senegal*	27.20	6.59	18
BRA	*Brazil*	21.90	13.88	13	SLE	*Sierra Leone*	26.05	25.69	0
BGR	*Bulgaria*	9.96	6.17	3	SOM	*Somalia*	26.81	4.05	11
CHN	*China*	13.65	9.84	20	SDN	*Sudan*	27.69	4.54	11
COL	*Colombia*	21.40	19.75	1	TZA	*Tanzania*	22.35	10.35	11
CUB	*Cuba*	25.33	12.05	8	TGO	*Togo*	26.16	12.14	3
DOM	*Dominican Republic*	25.25	16.05	1	UGA	*Uganda*	22.20	12.28	10
ECU	*Ecuador*	20.40	14.27	2	VNM	*Vietnam*	24.31	15.67	5
EGY	*Egypt, Arab Rep.*	21.14	0.46	0	YEM	*Yemen, Rep.*	22.95	2.70	5
SLV	*El Salvador*	23.27	16.31	4	ZWE	*Zimbabwe*	20.61	7.10	11
GTM	*Guatemala*	20.96	20.85	4					
GUY	*Guyana*	26.81	21.88	3					
HND	*Honduras*	24.01	14.31	7					

Notes: T = average temperature (°C), R = average precipitation (100 mm), D = total number of drought events; the sample period is from 1961 to 2002.

Table 3: CD test statistics and p-value of variables

Variable	**test statistics**	**p-value**	$\hat{\boldsymbol{\rho}}_{\boldsymbol{ij}}$	$\lvert\hat{\boldsymbol{\rho}}_{\boldsymbol{ij}}\rvert$
y	209.33	0.00	0.370	0.619
L	52.88	0.00	0.098	0.796
n	-3.33	0.00	-0.006	0.655
live	67.84	0.00	0.121	0.562
f	253.44	0.00	0.446	0.539
tr	261.78	0.00	0.467	0.682
T	203.29	0.00	0.352	0.377
R	41.13	0.00	0.071	0.175

Notes: $\hat{\rho}_{ij}$ where $i \neq j$ refers to the correlation coefficient for the variable in question between countries i and j; $|\hat{\rho}_{ij}|$ = is the absolute value of the same statistic; $CD = \sqrt{2T/N(N-1)}\ \sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$, which tends to $N(0,1)$ under the null hypothesis of cross-section independence. For more details see Pesaran (2004).

Table 4: CD test statistics and p-value of ADF(p) regressions

Variable	**ADF(1)**	**p-value**	**ADF(2)**	**p-value**	**ADF(3)**	**p-value**
y	9.19	0.00	10.99	0.00	11.46	0.00
L	31.31	0.00	41.68	0.00	43.84	0.00
n	4.35	0.00	4.28	0.00	4.5	0.00
live	6.48	0.00	7.13	0.00	5.27	0.00
f	15.61	0.00	14.14	0.00	13.49	0.00
tr	7.00	0.00	6.64	0.00	7.24	0.00
T	123.42	0.00	118.27	0.00	111.68	0.00
R	19.5	0.00	19.13	0.00	18.2	0.00

Notes: *p*th-order Augmented Dickey-Fuller test statistics, ADF(p), for all variables are computed for each cross section unit separately. We include an intercept and a linear time trend in the ADF(p) regressions. $CD = \sqrt{2T/N(N-1)}\,\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$, which tends to $N(0,1)$ under the null hypothesis of cross-section independence. We use interpolated fertilizer data since CD tests are not possible with too much gaps. For more details see Pesaran (2004).

Table 5: CIPS unit root tests

	y		L		n		live		f		tr		T		R	
Variables in levels: ADF equation contains intercept																
lags	Ztbar	p	Ztbar	p	Ztbar	p	Ztbar	p	Ztbar	p	Ztbar	p	Ztbar	p	Ztbar	p
0	-7.66	0.00	12.79	1.00	6.34	1.00	2.81	1.00	-9.43	0.00	-1.20	0.12	-35.23	0.00	-40.23	0.00
1	-3.79	0.00	2.10	0.98	1.95	0.98	-1.68	0.05	-5.29	0.00	-2.29	0.01	-24.08	0.00	-21.77	0.00
2	-1.42	0.08	4.70	1.00	1.76	0.96	-1.21	0.11	-2.68	0.00	-0.96	0.17	-14.12	0.00	-14.29	0.00
3	-0.92	0.18	4.53	1.00	1.18	0.88	-0.92	0.18	0.61	0.73	-0.66	0.26	-11.17	0.00	-9.78	0.00
4	0.67	0.75	4.92	1.00	1.02	0.85	0.90	0.82	1.43	0.92	-0.21	0.42	-6.35	0.00	-5.49	0.00
Variables in levels: ADF equation contains intercept and trend																
0	-2.59	0.01	14.68	1.00	9.40	1.00	5.72	1.00	-9.08	0.00	1.58	0.94	-33.01	0.00	-36.72	0.00
1	2.01	0.98	-4.73	0.00	3.19	1.00	-0.38	0.35	-5.42	0.00	-1.18	0.12	-20.94	0.00	-16.67	0.00
2	5.11	1.00	2.14	0.98	3.33	1.00	0.62	0.73	-2.39	0.01	-0.37	0.36	-8.89	0.00	-8.85	0.00
3	5.57	1.00	2.62	1.00	2.24	0.99	0.90	0.82	0.78	0.78	1.21	0.89	-6.49	0.00	-4.46	0.00
4	8.67	1.00	2.35	0.99	2.11	0.98	2.36	0.99	1.97	0.98	0.21	0.58	-0.81	0.21	0.07	0.53
Variables in first differences: ADF equation contains intercept																
0	-49.61	0.00	-2.68	0.00	-29.21	0.00	-34.21	0.00	-48.31	0.00	-34.36	0.00	-52.69	0.00	-52.86	0.00
1	-35.97	0.00	-3.85	0.00	-16.38	0.00	-22.44	0.00	-35.45	0.00	-22.57	0.00	-50.20	0.00	-49.26	0.00
2	-21.45	0.00	-2.24	0.01	-8.40	0.00	-14.54	0.00	-25.11	0.00	-16.16	0.00	-36.05	0.00	-36.31	0.00
3	-15.68	0.00	0.94	0.83	-5.16	0.00	-10.67	0.00	-16.20	0.00	-9.88	0.00	-30.18	0.00	-27.73	0.00
4	-8.32	0.00	1.56	0.94	-2.54	0.01	-6.19	0.00	-10.38	0.00	-6.15	0.00	-20.38	0.00	-20.02	0.00

Notes: The reported values are CIPS(*p*) statistics, which are cross section averages of Cross-sectionally Augmented Dickey–Fuller (CADF(p)) test statistics, for more details see Pesaran (2007). The relevant lower 1, 5, and 10% critical values for the CIPS statistics are −2.23, −2.11, and −2.04 with an intercept case, and −2.73, −2.61, and −2.54 with an intercept and a linear trend case, respectively.

Table 6: Pooled regressions

	[1] POLS	[2] POLS	[3] POLS	[4] 2FE	[5] 2FE	[6] 2FE	[7] CCEP	[8] CCEP	[9] CCEP
L	-0.058***	-0.061***	-0.057***	-0.235***	-0.236***	-0.236***	-0.477***	-0.449***	-0.463***
	(-17.11)	(-16.60)	(-15.46)	(-3.63)	(-3.64)	(-3.64)	(-3.40)	(-3.24)	(-3.22)
n	0.258***	0.267***	0.267***	0.260***	0.261***	0.261***	0.183*	0.192*	0.150
	(30.58)	(29.99)	(30.26)	(3.32)	(3.35)	(3.35)	(1.68)	(1.76)	(1.48)
live	0.212***	0.234***	0.239***	0.350***	0.349***	0.347***	0.336***	0.339***	0.340***
	(27.44)	(30.58)	(31.19)	(8.37)	(8.33)	(8.29)	(8.13)	(8.07)	(7.77)
f	0.166***	0.157***	0.155***	0.072***	0.072***	0.072***	0.024***	0.024***	0.023***
	(27.66)	(27.38)	(27.37)	(6.45)	(6.49)	(6.49)	(4.13)	(4.13)	(3.85)
tr	0.132***	0.110***	0.108***	0.050***	0.050***	0.050***	0.071***	0.071***	0.069***
	(24.23)	(19.62)	(19.40)	(3.23)	(3.24)	(3.23)	(4.14)	(3.98)	(3.81)
T		-0.016***	-0.016***		-0.019**	-0.019*		-0.011*	-0.012*
		(-11.56)	(-11.09)		(-2.03)	(-1.97)		(-1.93)	(-1.94)
R		0.014***	0.013***		0.002	0.002		0.000	0.000
		(14.53)	(13.88)		(1.35)	(1.20)		(0.40)	(0.14)
D			-0.144***			-0.021*			-0.024***
			(-8.06)			(-1.75)			(-4.12)
Obs.	5103	5103	5103	5103	5103	5103	5103	5103	5103
Countries	-	-	-	127	127	127	127	127	127
Min. obs.	-	-	-	19.00	19.00	19.00	19.00	19.00	19.00
Avg. obs.	-	-	-	40.18	40.18	40.18	40.18	40.18	40.18
Max. obs.	-	-	-	42.00	42.00	42.00	42.00	42.00	42.00
Implied β_L	0.174	0.173	0.332	0.033	0.049	0.072	-0.091	-0.064	-0.009
Returns[b]	DRS	DRS	DRS	DRS	DRS	DRS	DRS	DRS	DRS
RMSE	0.432	0.419	0.417	0.148	0.147	0.147	0.077	0.077	0.076
Stationarity†	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)
Mean $\|\rho_{ij}\|$‡	0.415	0.392	0.379	0.400	0.397	0.397	0.196	0.199	0.199
CD (ρ)	-2.28 (0.02)	-2.74 (0.01)	-2.99 (0.00)	-0.24 (0.81)	-0.19 (0.85)	-0.26 (0.79)	-2.11 (0.04)	-2.05 (0.04)	-1.83 (0.07)

t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: [1]-[9] log output per worker; We include year dummies in equations [1] to [6].

[b] The implied returns to scale are labeled decreasing (DRS) if the coefficient on labor is negative significant, and constant (CRS) if this coefficient is insignificant. The implied labor coefficient is computed by adding up all the coefficients on the RHS variables (except for labor), subtracting them from unity and then adding the coefficient on labor (the result is the implied labor coefficient if constant returns were to hold). For more details see also Eberhardt and Teal (2012).

RMSE reports the root mean squared error.

Residual Diagnostics: † Pesaran (2007) CIPS test results: I(0) - stationary, I(1) - nonstationary. The series is considered to be I(0) if all tests (up to 3 lags) reject the H_0 of non-stationarity (results available upon request).

‡ Mean Absolute Correlation Coefficient and Pesaran (2004) CD test, H_0: cross-sectional independence.

Table 7: Mean group estimators

	[1] MG	[2] MG	[3] MG	[4] CCEMG		[5] CCEMG		[6] CCEMG	
				[a]	[b]	[a]	[b]	[a]	[b]
L	-0.360**	-0.340**	-0.319*	-0.086		-0.135		-0.047	
	(-2.21)	(-2.01)	(-1.93)	(-0.71)		(-1.12)		(-0.37)	
n	0.210***	0.192**	0.178**	0.211***	0.200***	0.142**	0.187***	0.139*	0.179***
	(2.76)	(2.38)	(2.14)	(2.93)	(3.64)	(1.96)	(3.16)	(1.70)	(2.96)
live	0.241***	0.259***	0.259***	0.305***	0.319***	0.304***	0.301***	0.305***	0.306***
	(7.89)	(8.09)	(8.21)	(9.03)	(9.16)	(8.54)	(8.92)	(8.52)	(8.70)
f	0.031***	0.028***	0.029***	0.032***	0.035***	0.023***	0.028***	0.022***	0.025***
	(5.03)	(5.10)	(5.36)	(5.14)	(5.65)	(4.12)	(4.61)	(4.05)	(4.62)
tr	0.074***	0.073***	0.075***	0.075***	0.105***	0.060***	0.111***	0.059***	0.110***
	(3.21)	(3.22)	(3.41)	(3.56)	(4.87)	(2.89)	(5.28)	(2.81)	(5.56)
T		-0.010***	-0.010***			-0.008**	-0.007*	-0.008**	-0.005
		(-3.32)	(-3.26)			(-2.18)	(-1.79)	(-1.99)	(-1.36)
R		0.002**	0.002*			0.002	0.002	0.001	0.002
		(2.28)	(1.78)			(1.55)	(1.57)	(1.09)	(1.54)
D			-0.011***					-0.012***	-0.010***
			(-3.87)					(-3.47)	(-3.64)
Obs.	5103	5103	5103	5103	5103	5103	5103	5103	5103
Countries	127	127	127	127	127	127	127	127	127
Min. obs.	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00	19.00
Avg. obs.	40.18	40.18	40.18	40.18	40.18	40.18	40.18	40.18	40.18
Max. obs.	42.00	42.00	42.00	42.00	42.00	42.00	42.00	42.00	42.00
Implied β_L	0.084	0.116	0.159	0.291	0.341	0.342	0.378	0.447	0.607
Returns[b]	DRS	DRS	DRS	CRS	-	CRS	-	CRS	-
RMSE	0.066	0.061	0.061	0.055	0.060	0.048	0.052	0.046	0.50
Stationarity†	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean $\lvert\rho_{ij}\rvert$‡	0.148	0.146	0.144	0.150	0.152	0.153	0.154	0.155	0.154
CD (ρ)	8.99 (0.00)	7.10 (0.00)	6.82 (0.00)	0.31 (0.76)	0.05 (0.96)	1.45 (0.15)	0.94 (0.34)	1.69 (0.09)	0.97 (0.33)

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Dependent variable: [1]-[6] log output per worker; We include linear trend in equations [1] to [3]; Outlier-robust mean of parameter coefficients across groups are presented.

[b] The implied returns to scale are labeled decreasing (DRS) if the coefficient on labor is negative significant, and constant (CRS) if this coefficient is insignificant. The implied labor coefficient is computed by adding up all the coefficients on the RHS variables (except for labor), subtracting them from unity and then adding the coefficient on labor (the result is the implied labor coefficient if constant returns were to hold). For more details see also Eberhard and Teal (2012).

RMSE reports the root mean squared error.

Residual Diagnostics: † Pesaran (2007) CIPS test results: I(0) - stationary, I(1) - nonstationary. The series is considered to be I(0) if all tests (up to 3 lags) reject the H_0 of non-stationarity (results available upon request).

‡ Mean Absolute Correlation Coefficient and Pesaran (2004) CD test, H_0: cross-sectional independence.

Table 8: Climate effects and income levels

	[1] **CCEMG** High income	[2] **CCEMG** Middle income	[3] **CCEMG** Low income	[4] **CCEMG** without SSA[a]	[5] **CCEMG** SSA[a] only
n	0.221^{**}	0.278^{***}	0.050	0.278^{***}	0.207^{**}
	(2.11)	(2.95)	(0.72)	(3.92)	(2.56)
live	0.386^{***}	0.288^{***}	0.309^{***}	0.298^{***}	0.296^{***}
	(4.64)	(5.79)	(5.18)	(6.79)	(5.17)
f	0.065^{***}	0.031^{***}	0.008	0.045^{***}	0.013
	(3.29)	(3.29)	(1.52)	(6.11)	(1.47)
tr	0.262^{***}	0.145^{***}	0.024	0.105^{***}	0.034
	(3.93)	(3.12)	(0.97)	(3.83)	(1.15)
T	-0.004	-0.014^{**}	-0.016^{*}	-0.009^{**}	-0.011
	(-0.58)	(-2.01)	(-1.86)	(-2.11)	(-0.85)
R	-0.003	-0.001	0.006^{***}	-0.000	0.008^{***}
	(-1.33)	(-0.38)	(3.04)	(-0.23)	(3.55)
D	0.000	-0.001	-0.010^{*}	-0.007^{**}	-0.019^{***}
	(0.93)	(-0.19)	(-1.70)	(-2.43)	(-3.13)
Obs.	1120	2094	1889	3580	1523
Countries	28	51	48	88	39
Min. obs.	24.00	19.00	26.00	24.00	19.00
Avg. obs.	40.00	41.06	39.35	40.68	39.05
Max. obs.	42.00	42.00	42.00	42.00	42.00
Implied β_L	0.073	0.274	0.629	0.290	0.472
Returns[b]	-	-	-	-	-
RMSE	0.043	0.52	0.48	0.050	0.050
Stationarity[†]	I(0)	I(0)	I(0)	I(0)	I(0)
Mean $\|\rho_{ij}\|$[‡]	0.154	0.151	0.161	0.149	0.161
CD (ρ)	0.59 (0.56)	-1.75 (0.08)	-0.93 (0.35)	0.43 (0.66)	-1.19 (0.24)

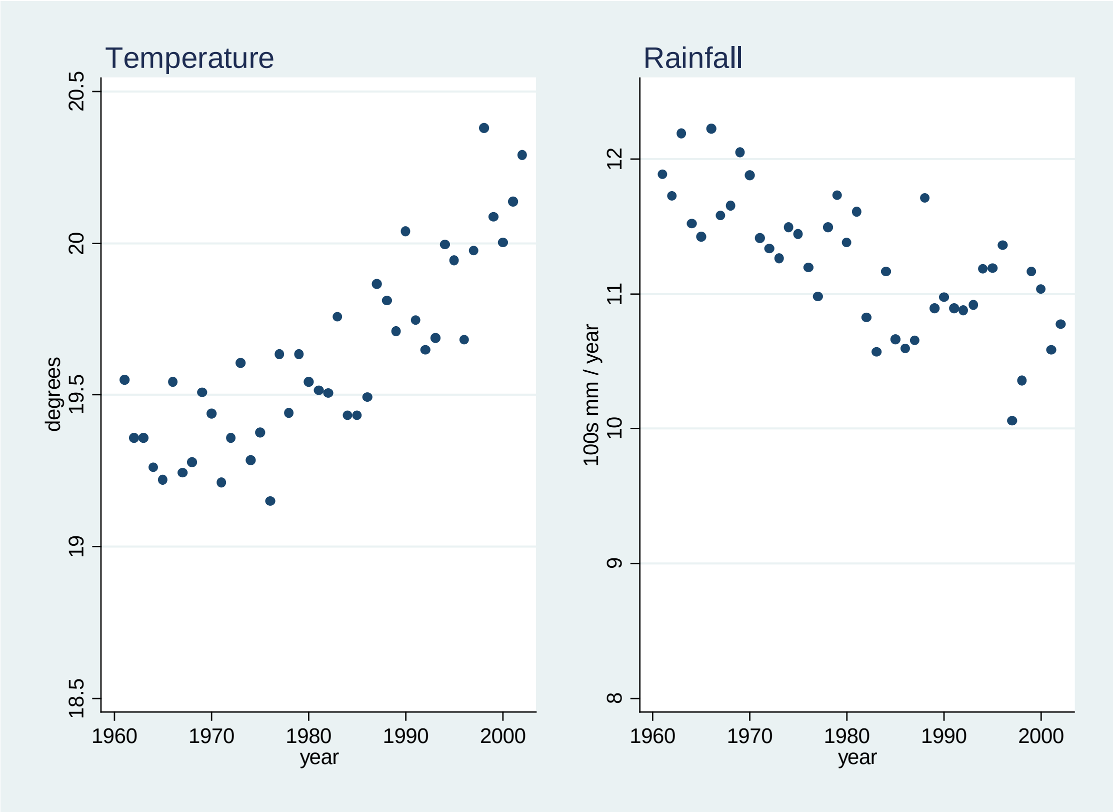
Method: Mean group type estimators, CRS imposed
t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: [1]-[5] log output per worker.
[a] SSA refers to Sub-Sahara Africa
[b] CRS imposed in equations [1] to [5].
For all other details see Table 7.

Table 9: Alternative specifications

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	CCEMG	**CCEMG**	**CCEMG**	**CCEMG**	**CCEMG**	**CCEMG**	**CCEMG**	**CCEMG**
	5-years-averages	Variation 1	Variation 2	Droughts and floods	Full model with floods	Full model with squares	Interaction 1	Interaction 2
n	0.144**	0.182***	0.175***	0.149**	0.173***	0.129**	0.149**	0.137**
	(2.37)	(3.02)	(2.95)	(2.57)	(2.86)	(1.99)	(2.36)	(2.12)
live	0.289***	0.299***	0.303***	0.304***	0.311***	0.322***	0.308***	0.317***
	(8.27)	(8.85)	(8.87)	(8.09)	(8.33)	(9.07)	(8.58)	(8.17)
f	0.018***	0.027***	0.026***	0.032***	0.026***	0.026***	0.030***	0.027***
	(2.96)	(4.67)	(4.65)	(4.70)	(4.34)	(4.61)	(4.26)	(4.30)
tr	0.129***	0.110***	0.112***	0.127***	0.113***	0.095***	0.111***	0.115***
	(5.17)	(5.51)	(5.55)	(5.71)	(5.33)	(4.54)	(4.34)	(4.42)
T					-0.006	-0.139	-0.051***	-0.007*
					(-1.56)	(-0.68)	(-2.71)	(-1.78)
R					0.002**	0.040***	-0.062	0.002
					(2.06)	(3.70)	(-1.63)	(1.51)
5-yr-T	-0.005							
	(-0.34)							
5-yr-R	0.002							
	(0.59)							
Abs. Var. T †		-0.007*						
		(-1.77)						
Abs. Var. R †		0.002						
		(1.59)						
Rel. Var. T ♯			-0.004*					
			(-1.79)					
Rel. Var. R ♯			0.000					
			(1.03)					
D				-0.012***	-0.010***	-0.009***		-0.073
				(-3.45)	(-3.57)	(-2.82)		(-1.40)
F				-0.001	-0.003			
				(-0.26)	(-0.94)			
T^2						0.003		
						(0.60)		
R^2						-0.002***		
						(-3.79)		
*T*R*							0.006***	
							(2.88)	
*T*D*								0.000
								(0.14)
*R*D*								0.001
								(0.85)
Obs.	4638	5103	5103	5103	5103	5103	5103	5103
Countries	127	127	127	127	127	127	127	127
Min. obs.	17	19.00	19	19.00	19.00	19.00	19.00	19.00
Avg. obs.	36.520	40.18	40.18	40.18	40.18	40.18	40.18	40.18
Max. obs.	38	42.00	42	42.00	42.00	42.00	42.00	42.00
Implied β_L	0.423	0.387	0.388	0.401	0.394	0.535	0.509	0.481
Returns[b]	-	-	-	-	-	-	-	-
RMSE	0.049	0.053	0.053	0.054	0.048	0.047	0.051	0.049
Stationarity	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
Mean $\lvert\rho_{ij}\rvert$	0.159	0.153	0.154	0.153	0.155	0.156	0.150	0.152
CD (ρ)	0.41 (0.68)	0.70 (0.48)	0.76 (0.45)	0.28 (0.78)	1.77 (0.08)	0.21 (0.83)	-1.51 (0.13)	-0.90 (0.37)

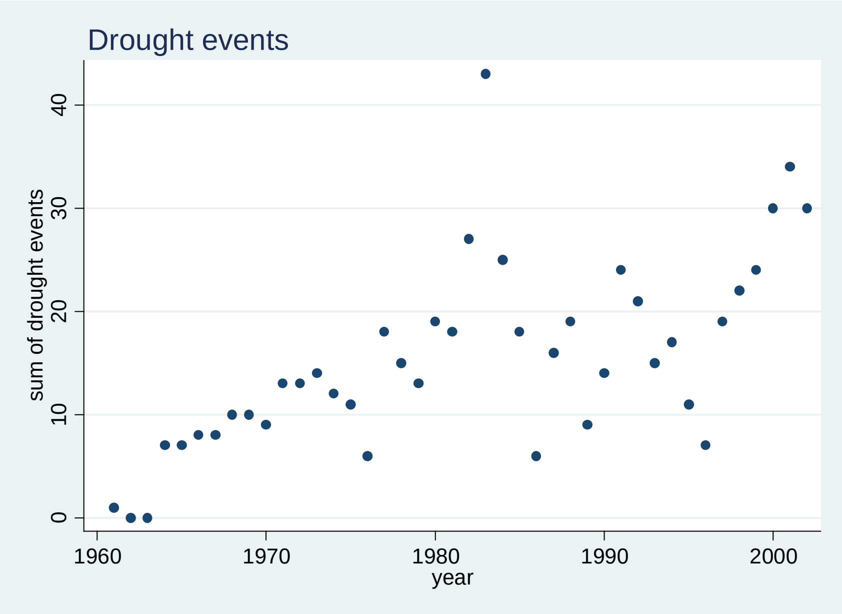
Method: Mean group type estimators, CRS imposed
t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Dependent variable: [1]-[8] log output per worker.
[b] CRS imposed in equations [1] to [8].
† Absolute variations of T and R were computed by subtracting from annual temperature/rainfall their 30 year averages of the period 1961 to 1991.
♯ Relative variations of T and R were computed by dividing absolute variations by the standard deviation of the respective time series.
For all other details see Table 7.

Figure 1: Temperature and rainfall trends, 1961-2002



Method: Global population-weighted average temperature and rainfall (127 countries).

Figure 2: Trends in global drought events



Method: Cumulated number of drought events per year (127 countries).