The Effect of Climate Change over Agricultural Factor Productivity: Some Econometric Considerations

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It has been argued that climate change, especially recent global warming, has influenced the agricultural productivity. Its impact on average agricultural productivity and its variability has been documented in a large body of literature. Economists have also been interested in evaluating the returns to research in agriculture as a means of both understanding returns and as a backup for research advocacy processes. Recently the rate of return as measured through a total factor productivity approach has been falling. Pardey *et al*. (2007) have speculated this may be due to altered resources allocations and unfavorable weather conditions.

One explanation for the unfavorable weather component may be the early onset of climate change and if this persists is both another manifestation of societal sensitivity to climate change and an area where adaptation investments may be needed as climate change proceeds.

This article studies how climate change affects the impacts of public agricultural research investments on agricultural productivity. The proposed hypothesis is that current changing climatic variables are reducing the effect of public research investments on agricultural productivity. As a result, we should expect higher volumes of research investment, adapting to projected climatic conditions, in order to maintain the current rates of return of agricultural research.

The article is organized as follows: first we show a review of previous efforts in the determination of U.S. state agricultural productivity; second, we describe the data used in this study; then we discuss several estimation issues that arise because of the data structure, namely the non stationarity of the series, and the proposed methods to account for it; the next section discusses estimation results. We finalize this article with some concluding remarks.

Public investment in Ag. Research

Agricultural total factor productivity (TFP) can be defined as the ability or efficiency to produce agricultural outputs with a given amount of inputs such as labor, capital and materials. It is usually measured as the ratio of product per unit of equivalent input. One widely accepted assumption is that efficiency in production can be enhanced through more public and/or private investments in agricultural research. Besides, it is believed that some exogenous factors, such as climate, can alter in some ways (positively or negatively) the ability to produce more agricultural outcomes with a given amount of inputs and research investments.

Huffman and Evenson (2006a) found that both public agricultural research and agricultural extension have positive and significative impacts on state agricultural productivity. In their article, they describe the structure of public agricultural funding, noting that State Agricultural Experiment Stations (SAES) account for 60% of U.S. public agricultural research, with SAES funding being originated from different sources, making that funding relatively diversified. From a SAES viewpoint, funding comes in two ways: Formula funds, which are recurring and allocated among the states; and Grants, which are allocated after a reduced selected number of proposals have been accepted, with no guarantee of continuation after the initial grant period. Using a pooled cross-section time-series model of agricultural productivity, they showed that public agricultural research funds have a different impact depending on the source:

programmatic funding, including federal formula funds, has a larger impact on state agricultural productivity than federal grant and contract funding. They also found that reallocating funds from formula funding to grant funding lowers agricultural productivity.

Huffman and Evenson (2006a) obtained their results using an econometric model which related state agricultural total factor productivity (TFP) as a function of state public agricultural research capital, private agricultural research capital, and public agricultural extension capital. Since this article objective is to test for the effect of climate change over the return of public investment on agricultural TFP, we additionally included climatic variables into the aforementioned model, such as temperature, precipitation, and intensity of precipitation. All these variables are explained with more detail in the next section.

Data

We used annual observations for the 48 contiguous United States to form a cross-section time-series structure spanning from 1970 to 1999, obtaining 1,440 observations. Although climatic data is available for more periods, we used that time span in order to match with the agricultural TFP and research data used in Huffman and Evenson (2006a). They use state data on state agricultural TFP, public agricultural research capital (RPUB), share of SAES budget coming from federal formula funds (SFF), share of SAES budget from federal grants and contracts (GR), stock of public extension capital (EXT), public agricultural research spill-in stock[1] (RPUBSPILL), private agricultural research capital (RPRI), and regional dummies which group the states according to the Farm Production regions defined by the Economic Research Service (ERS) of the United States Department of Agriculture (USDA). All the monetary variables are expressed in constant dollars using the Huffman and Evenson (2006b) research price index.

One distinctive feature of agricultural research expenditure's impact is that it follows a trapezoidal pattern: first, there is a gestation period of two years, during which the effects of research are negligible; second, impacts are assumed to be positive and increasing, lasting about seven years; then, impacts reach a maturity constant level during six years; and finally, there is a constant decline of the impact which eventually reach zero value after twenty years. This feature was incorporated in the way Huffman and Evenson (2006a) constructed the agricultural research expenditures variable. For more details about how other agricultural research and TFP related variables were constructed or their original source, see Huffman and Evenson (2006a, table 3).

State-level climate data was obtained from the National Oceanic and Atmospheric Administration (NOAA) website. We took information on mean annual temperature (°F) and total yearly precipitation (inches), which are the most common climatic variables considered in these kinds of studies. We also constructed a measure of the intensity of yearly rain precipitation, defined as the ratio of total precipitations from the month with the highest amount of precipitation to the yearly total. This measure can range by construction from 1/12 (uniformly intense during the year) to 1 (one month gets all yearly rain).

We also tried to use more climatic variables in order to account for the effect of a more volatile climate or dryness severity over agricultural TFP. Those variables, such as standard deviation of temperature and precipitation, and the Palmer Drought Severity Index, resulted to be not significant in our model.

Finally, a linear trend was included in the model to incorporate the effect of exogenous or non observable technological progress. All the variables in the model are expressed in natural logarithms, so the coefficients can be interpreted as elasticities of TFP with respect to each explanatory variable.

Estimation methods

Baltagi (2008) affirms that the focus of panel data econometrics has shifted toward the study of macro panel with large N (number of individuals) and large T (number of periods. This type of model raises estimation issues such as non-stationarity, spurious regressions and cointegration.

The model we want to estimate relies heavily on the assumption that the related variables are stationary. Granger and Newbold (1974) showed that deterministic and stochastic trends in the series can induce spurious correlation between variables; as a result we can obtain correlations between variables that are increasing for different reasons and in increments that are uncorrelated (Banerjee et al., 1993).

A simple approach to correct this problem was to include a linear trend as a explanatory variable. However, spurious correlation can still be present after controlling for a linear time trend. Phillips (1986) stated that t-statistics for the time trend are generally inflated, when the other variables are not stationary, making us wrongly believe that a trend is significative when it is not.

Panel Unit Root Tests

To avoid this kind of problems we must test for stationarity of the variables. The way to test for non-stationarity is through a unit root test. Traditional unit root tests used to deal with testing one temporal series at a time. However, testing for unit roots in a panel structure as a whole is a relative new procedure with more complicated asymptotic properties that depend deeply on the assumed structure of the data to be tested. We have performed several tests to check the robustness of our results to different specifications and hypotheses.

Levin, Lin and Chu (2002) suggest a more powerful panel unit root test than performing individual unit root tests for each cross section. The null hypothesis is that each individual time series contains a unit root against the alternative that each time series is stationary. The structure to be tested has the following form, similar to an Augmented Dickey-Fuller (ADF) test but into a panel framework:

$$\Delta y_{it} = \rho_i y_{i,t-1} + \sum_{L=1}^{p_i} \theta_{iL} \Delta y_{i,t-L} + \alpha_{mi} d_{mt} + \varepsilon_{it}, \qquad m = 1, 2, 3 \tag{1}$$

where y is the variable to be tested[2] for unit root, Δ is the lag operator, p_i is the lag order, which is allowed to vary across cross sections and is determined into the test procedure, these terms are included to take into account heterogeneous serial correlation across cross sectional units; d_{mt} can take three values depending on the model specification: d_{1t} ={empty set}, d_{2t} ={1} including an individual constant and d_{3t} ={1, t} including an individual constant and an individual linear trend; ε is an error term, and ρ_i, θ_{iL}, α_{mi} are parameters to be estimated. The null hypothesis of unit root is $H_0 : \rho_i = \rho = 0$ for all i while the alternative is $H_1 : \rho_i = \rho < 0$ for all i. Levin, Lin and Chu (2002) showed that the estimator t^*_ρ is asymptotically distributed as $N(0,1)$.

As stated before, LLC test is restrictive in the sense that it requires ρ to be homogeneous across individuals. Im, Pesaran and Shin (2003) permit a heterogeneous coefficient on $y_{i,t-1}$, proposing an alternative testing procedure that averages the individual unit root test statistics. The estimated model is also the one given in equation (1). However, the null hypothesis is that each series in the panel has unit root, $H_0 : \rho_i = \rho = 0$ and the alternative hypothesis states that some individual series have unit roots while some are stationary, which can be expressed as $H_1 : \rho_i < 0$ for i = 1 , 2,…, N and $\rho_i = 0$ for $i = N + 1$,…,N.

The IPS $\bar{t}$ statistic, is defined as the average of all the N individual ADF statistics:

(2) $$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{\rho_i}$$

where t_{ρ_i} is the individual ADF t-statistic that tests $H_0 : \rho_i = 0$. Im *et al*. (2003) show that when the lag order is non zero for some cross sections, and after a proper standardization of $\bar{t}$, the resulting estimator, t_{IPS} is distributed as $N(0,1)$.[3] Using Monte

Carlo experiments, they show that if we select a large enough lag order for the ADF regressions, the small sample properties of IPS test outperform those from LLC test. However, Im, Pesaran and Shin (2003) found that both LLC and IPS tests present important size distortions when either *N* is small or *N* is relatively large with respect to *T*.

Besides the popular LLC and IPS tests, we performed three more sophisticated panel unit root test which try to correct some flaws that the former tests could present. They are: the Breitung (2000) test, which shows a higher power than LLC or IPS tests when they are compared in Monte Carlo experiments; the Maddala and Wu (1999) Fisher type test, which can be applied using ADF or Phillips-Perron (PP) versions of the unit root tests for each cross section, and is also found to be superior to the IPS test. Finally, we performed a residual-based Lagrange multiplier (LM) test developed by Hadri (2000), in which the null hypothesis is that all individual series do not have a unit root against the alternative of a unit root in the panel.

Panel Cointegration Tests

In the conventional time series case, cointegration refers to the idea that for a set of variables that are individually I(1), some linear combination of these variables can be described as stationary, say I(0). The vector of slope coefficients that gives this stationary combination is referred to as the cointegrating vector, which is generally not unique, and need to be normalize in some way. The following set of tests do not address issues of normalization or questions regarding the particular number of cointegrating relationships, but instead they are interested in the simple null hypothesis of no cointegration versus cointegration.

One obvious way to perform such kind of test is to take the residuals from a panel regression involving I(1) variables, and apply any of the aforementioned panel unit root test to those residuals. However, there are more sophisticated tests available which have more power, and deal with some particular structural issues that panels can exhibit.

Kao (1999) proposed DF and ADF tests of unit root for the residuals e_{it} as a test for the null of no cointegration. The DF test is applied to the fixed effect residuals using this specification:

$$\hat{e}_{it} = \rho \hat{e}_{i,t-1} + v_{it} . \tag{3}$$

We are going to use for this article two versions of the test which assume strong exogeneity of the regressors, those are:

$$DF_{\rho} = \frac{\sqrt{N}T(\hat{\rho}-1)+3\sqrt{N}}{\sqrt{10.2}} \tag{4}$$

and

$$DF_{t} = \sqrt{1.25}\,t_{\rho} + \sqrt{1.875N} \tag{5}$$

where $\hat{\rho}$ and t_{ρ} are the estimated parameter of equation (3) and its *t*-statistic, respectively. The asymptotic distribution of the tests converges to a standard normal distribution $N(0,1)$ by sequential limit theory.

Other tests we performed were: the Pedroni (1999) panel cointegration tests, which allow a considerable degree of heterogeneity and endogenous regressors. Indeed, an important feature of these tests is that they allow not only the dynamics and fixed effects to differ across members of the panel, but also that they allow the cointegrating vector to differ across members under the alternative hypothesis. These tests are applied over the regression residuals from the hypothesized cointegrating regression. In the most general case, this may take the form:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1it} + \ldots + \beta_{Mi} x_{Mit} + e_{it} \tag{6}$$

where M refers to the number of regression variables. Notice that this structure allows heterogeneity for the panel individuals at different levels: individual effects (α_i), individual linear trends (δ_i), and regressor coefficients (β_{mi}). Pedroni (1997) derives the asymptotic distributions and explores the small sample performances of seven different statistics that combine several model specifications.

Finally, we performed a new family of tests by Westerlund (2007), which are based on structural rather than residual dynamics. These structural kind of test does not impose any common factor restriction,[4] which is a main reason associated to loss of power for residual-based cointegration tests. The tests are based on the estimation of the following error correction equation:

$$\Delta y_{it} = \delta_i' d_t + \alpha_i (y_{it-1} - \beta_i' x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{it-j} + \sum_{j=0}^{p_i} \gamma_{ij} \Delta x_{it-j} + e_{it} \tag{7}$$

where y is the dependent variable, x is a vector of independent variables, $d_t = (1,t)'$ is the set of deterministic components, and Δ is the first difference operator. Westerlund

(2007) states that if $\alpha_i < 0$, then there is error correction, which implies that y_{it} and x_{it} are cointegrated, whereas if $\alpha_i = 0$, there is no error correction and no cointegration.

Panel Error Correction Model

There is a tight connection between cointegration and error correction model (ECM) in the sense that ECM is consistent only if the implied variables are cointegrated. The same assumption that we make to produce cointegration implies (and is implied by) the existence of an ECM. This result is known as the Granger representation theorem, explained in Hamilton (1994).

Taking the more complicated framework of a multivariate and heterogeneous panel model, the error correction equation can be expressed as:

(8) $$\Delta y_{it} = \phi_i (y_{it-1} - \theta_i' X_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}' \Delta X_{it-j} + \mu_i + \varepsilon_{it}$$

where the parameter ϕ_i is the error-correcting speed of adjustment term. It is expected that $\phi_i < 0$, in which case there is evidence of cointegration. This means that the variables show a return to a long-run equilibrium. The vector θ_i' represent the long-run relationship between the variables, and the other estimated parameters $(\lambda_{ij}, \delta_{ij})$ characterize the short-run dynamics of the implied variables.

Pesaran, Shin and Smith (1999) proposed a Pooled Mean group (PMG) estimator that combines both pooling and averaging: the estimator allows the intercept, short-run coefficients, and error variances to differ across the individuals but constrains the long-run coefficients to be equal across individuals. Since equation (8) is non linear in the parameters, they developed a maximum likelihood method to estimate the parameters.

The estimators can be computed using the usual Newton-Rapson algorithm, which needs first and second derivatives of the likelihood function, or an iterative “back substitution” algorithm which requires only first derivative computations. See more details in Pesaran, Shin and Smith (1999).

Empirical Results

Huffman and Evenson (2006a) uses state level data on state agricultural TFP, public agricultural research capital (RPUB), share of SAES budget coming from federal formula funds (SFF), share of SAES budget from federal grants and contracts (GR), stock of public extension capital (EXT), public agricultural research spill-in[5] stock (RPUBSPILL), private agricultural research capital (RPRI), and regional dummies which group the states according to the Farm Production regions defined by the Economic Research Service (ERS) of the United States Department of Agriculture (USDA).

The Huffman and Evenson (2006a) version of the econometric model for agricultural TFP is

$$
\begin{aligned}
\ln TFP_{ilt} &= \beta_1 + \beta_2 \ln RPUB_{ilt} + \beta_3[\ln RPUB_{ilt}]SFF_{ilt} + \beta_4[\ln RPUB_{ilt}](SFF_{ilt})^2 \\
&\quad + \beta_5[\ln RPUB_{ilt}]GR_{ilt} + \beta_6[\ln RPUB_{ilt}](GR_{ilt})^2 + \beta_7 RPUBSPILL_{ilt} \\
&\quad + \beta_8 EXT_{ilt} + \beta_9 \ln RPRI_{ilt} + \beta_{10} trend + \delta_l + u_{ilt}
\end{aligned} \tag{9}
$$

where the sub-index *l* represent the Farm production regions mentioned before. Those regions are: *Northeast, Southeast, Central, North Plains, South Plains, Mountains*, and

Pacific. Huffman and Evenson (2006a) claim that since agricultural research capital is derived using thirty five years of data, SFF and GR were lagged twelve years, hence they are placed at the mid-point of the total lag length.

This model is expressed in a double-logarithmic functional form such that the estimated coefficient β_i represents the elasticity of TFP with respect to any variable of interest (RPUBSPILL, EXT, RPRI). According to Huffman and Evenson (2006a) the funding shares (SFF and GR) are multiplied with the public agricultural research capital (RPUB) with the intention of making the elasticity of TFP with respect to RPUB a variable that depends on the funding composition:

$$\partial \ln(TFP) / \partial \ln(RPUB) = \beta_2 + \beta_3 SFF + \beta_4 (SFF)^2 + \beta_5 GR + \beta_6 (GR)^2;$$

in the same way the effect on TFP of a one percentage change in SFF (or GR) is not constant and it can include nonlinear impacts of funding composition:

$$\partial \ln(TFP) / \partial \ln(SFF) = (\beta_3 + 2\beta_4 SFF) \ln RPUB$$

$$\partial \ln(TFP) / \partial \ln(GR) = (\beta_5 + 2\beta_6 GR) \ln RPUB.$$

The estimation method that Huffman and Evenson (2006a) used is the Prais-Winsten estimator defined in Beck and Katz (1995) and Greene (2003), which fits linear cross-sectional time-series models when the disturbances are not assumed to be independent and identically distributed (i.i.d.). Instead, in their estimations the errors are allowed to be heteroskedastic and contemporaneously correlated across panels. Additionally, that estimator may allow the disturbances to be autocorrelated within the panel. Their results are displayed in the columns 1 and 2 of Table 1 for comparison purposes with our findings.

One limitation to that estimation method is that it does not consider the case when the implied variables are not stationary. However, the first exercise we performed was to ignore any non stationarity issue, and use the same estimation methodology including our climatic variables into the model.

The estimations of the Huffman and Evenson model with climatic variables are reported in columns 3 and 4 of Table 1. The natural logarithm of temperature was multiplied by the regional dummies to take into account differentiated effects of temperature in each region. We believe *a priori* that a higher temperature can be harmful in some regions located in the south, while it can be beneficial in more northern latitudes. Total Precipitation and Precipitation Intensity were reported with no region interactions because we believe that those variables do not have a behavior similar to temperature.[6]

One interesting result is the effect of the original research capital variables after controlling for climatic variables. Comparing our results with those from Huffman and Evenson (2006a), we find that the terms RPUB x SFF, RPUB x SFF^2, and RPUB x GR^2 are not significative anymore. The elasticity of TFP to Public research capital (RPUB) is reduced a 36% from 0.139 to 0.089,[7] the elasticity of TFP to Public Extension Capital (EXT) is reduced a 30% from 0.110 to 0.077, the effect of Public Research Capital Spill-in from near states (RPUBSPILL) becomes not significative after controlling for climatic variables, and the elasticity effect of Private Agricultural Research Capital (RPRI) which was negative but not significative before, now becomes significatively positive with a value of 0.044.

Regarding the regional dummies individual effects, we obtain that taking the Central region as benchmark, the Southeast and Pacific regions show a lower level, while the Southern Plains exhibit a higher level of Agricultural TFP, after controlling for all the other explanatory variables. This is evidence of the existence of unobservable effects that affect the agricultural productivity at different degrees in each region.

The main climatic variables effect are related to Total Yearly Precipitation, which has a positive effect over Agricultural TFP, with an associated elasticity of 0.069, while the effect of Precipitation Intensity, expressed as fewer but stronger storms is negative, showing an elasticity with a magnitude of -0.046. These results are consistent with our *a priori* conjectures. Meanwhile, we find statistical evidence that supports the idea of differentiated effects of temperature over regional TFP. In particular, we find that for the Southeast and Pacific regions the statistical effect of higher temperature over factor productivity is positive, while it is negative for the Southern Plains. There is no conclusive evidence with respect to the other regions. Finally, we find evidence of a positive linear trend in the Agricultural TFP.

Those results can be questionable if the included variables are non stationary. Table 2 shows the results of several panel unit root tests we performed. We used two different tests specifications to validate the robustness of our findings: only with individual effects, or with individual effects and individual trends for each cross-section. The tests were applied to all the variables of the econometric model from Table 1, in levels as well as to their first differences, to determine whether the tested variables are I(0) or I(1). Table 2 reports the test statistic, its significance level (*p*-value) and the number of observations implied by the test, which is a function of the number of lags chosen for the test.

One interested finding is that for some variables we can find contradictory results, one kind of test indicates that the variable is stationary while other test can suggest that it is not. For other variables, the tests are more conclusive, and almost all of them report the same qualitative result. Whenever we find inconsistent results for all the tests, we choose the result which is obtained in more cases, or with fewer contradictions.

The first evaluated variable is TFP[8]. For all the tests for which the null hypothesis is the existence of unit root, it is not rejected. For the variable in levels the significance values are very close to one. After differencing the variable, the null hypothesis of unit root is rejected for all the tests. Meanwhile, if we apply the Hadri test to that variable, the null hypothesis of no unit root is rejected when applied to the levels, but it is not rejected at 5% of significance when applied to the first difference. If those tests are applied using an specification that includes individual linear trends, the results are contradictory in the sense that some tests suggest the existence of unit root while at the same time other tests indicate that unit root is rejected. The final conclusion for this variable is to be in favor of the results supporting the existence of a panel unit root.

Using the specification with individual effects only, we can summarize our results in the following way. TFP is I(1), with no contradictory results for the tests in levels as wells as their first difference counterpart. RPUB is found to be I(1) with 4 contradictory results out of a total of 12 tests (2 in levels, 2 in differences). RPUB x SFF is I(0), with 3 contradictions in levels and no contradictions in first differences, RPUB x SFF^2 is I(0) with only one contradiction in levels, RPUB x GR is I(1) with 2 contradictions in levels, the case of RPUB x GR^2 gives us 3 contradictions in levels, but no contradictions in the first difference specification, we decide to consider this variables as I(1), EXT is considered as I(0) with 2 contradictions in levels and 1 in differences, RPUBSPILL is found to be I(1) with one contradictory result in levels and 2 in first differences. For RPRI the results show many contradictions, so it is difficult to determine a clear conclusion about this variable. It is apparently I(1) when the test is applied in levels (2 contradictions), but after differencing the variable, the test results suggest we need one more differentiation to make it stationary. The climatic variables Temperature, Precipitation and Intensity show a stationary pattern. We find that all of them are stationary, finding two contradictory results for Temperature, and only one in the other climatic variables.

The results abovementioned show us that some of the involved variables are in fact non stationary. One suggestion to deal with this problem would be to take first differences to the I(1) variables and estimate the econometric model in that manner. This is technically correct; however there is some statistical information that is lost in the differentiation process. We can still work with the non differenced variables if they hold the cointegration condition, and take advantage of a richer specification that incorporates both the long-run relation and the short-run dynamics, the Error Correction Model (ECM).

The panel cointegration test results are reported in Table 3. We first show the standard panel unit root tests applied to the estimated residuals of the pooled estimation including all the I(1) and I(0) variables from Table 1. Although those are not properly cointegration tests, several articles have used them to check for cointegration of I(1) variables.[9] We report those results for comparative purposes. Our results are very consistent regardless the method we used: the panel unit root tests suggest that the estimated residuals are I(0) using a model with trend or without trend, with the only exception of the Hadri test. All the test statistics are significative, rejecting the null hypothesis of unit root. For the more formal panel cointegration tests, the results are very similar, rejecting the null hypothesis of no cointegration. All the 14 variants of Pedroni test report that the variables are cointegrated, with the exception of two cases: the panel v-stat for a model with individual effects, and the group rho-stat for a model with individual constants and trends; Kao cointegration tests are fully consistent with those findings. Westerlund Error-correction-based test yields mixed results: one “group” statistic suggest cointegration, and the other one does not, while one “panel” statistic implies cointegration, and the other one rejects it. Our conclusion is that the statistical evidence supporting cointegration is very strong.

With the last results at hand, we estimated the TFP model using an ECM framework. As explained before, we assume homogeneous coefficients for the long-run equation and heterogeneous coefficients for the short-run dynamics coefficients. Table 1 only reports the long-run coefficients in order to compare these results with the previous ones. Notice that given the structure of the estimation method, the regional dummies cannot be identified for estimation.

Using the ECM framework, more variables become not significative which means that using a model without correcting for non stationarity can lead us to assign statistical effects to some variables, but those affects seems to be actually spurious. Using the same formulas aforementioned, the elasticity of Agricultural Total Factor Productivity (TFP) with respect to Public Agricultural research (RPUB) is now equal to 0.108, value that is in the midway between what we found with the previous two models (22% less than Model 1 result). Public Extension Capital (EXT) is now not significant, while Capital spill-in effects become positively significative, with a remarkable elasticity value of 0.596, several times higher than the values obtained before. The sign of the effect of Private Research Capital is negative, as in Model 1 but it is now significant and its elasticity value is -0.134.

Using this kind of model, the long-run relationship between temperature and TFP is statistically zero for all regions, with the exception of a negative effect for the Southeast. Concerning precipitation and its intensity, both variables are significant. Precipitation effect elasticity is 0.087, a value that is 25% greater than using Model 2. For precipitation intensity, we find that the associated elasticity is -0.053, which has the same sign as what is found on Model 2, but with a 15% higher magnitude than before. It is noticeable that when using an ECM there is no linear trend effect over Agricultural TFP.

Conclusions

This article examines the impact of climate change on agricultural total factor productivity at the state level, after controlling for public agricultural research and climate change. This paper takes the previous result of Huffman and Evenson (2006) in which they establish whether federal formula or competitive grant funding of agricultural research has a greater impact on state agricultural productivity. We estimated a pooled cross-section time-series model of agricultural productivity fitted to annual data for forty-eight contiguous states over 1970–1999, incorporating two new features: the inclusion of climatic variables such as temperature, amount and intensity of precipitation, and the evaluation and correction of problems due to non stationarity of some of the variables.

We found that some of the variables involved are I(1), which means that their inclusion into the econometric model can lead to undesired properties on the panel estimations. We correct the problem testing the existing of cointegration among the non stationary variables, and the estimation of a Panel Error Correction Model (ECM). Our findings suggest that after controlling for climatic variables and non stationarity, the effect of Public Agricultural Research Capital over Total Factor Productivity is reduced.

References

Baltagi, B. *Econometric Analysis of Panel Data.* 4th Edition. Chichester, West Sussex: John Wiley & Sons Ltd, 2008.

Banerjee, A., J.J. Dolado, J.W. Galbraith, and D.F. Hendry. *Co-integration, error-correction, and the econometric analysis of non-stationary data.* Oxford: Oxford University Press, 1993.

Beck, N., and J. Katz. "What to do (and not to do) with Time-Series Cross-Section Data." *The American Political Science Review* 89, no. 3 (September 1995): 634-647.

Breitung, J. *The Local Power of Some Unit Root Tests for Panel Data.* Vol. 15, in *Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Advances in Econometrics*, edited by B. Baltagi, 161-178. Amsterdam: JAI, 2000.

Dinda, S., and D. Condoo. "Income and emission: A panel data-based cointegration analysis." *Ecological Economics* 57 (2006): 167-181.

Evenson, R.E., and W.E. Huffman. *Science for agriculture: A long-term perspective.* 2nd Edition. Ames, IA: Blackwell Publishing, 2006b.

Granger, C.W.J., and P. Newbold. "Spurious regressions in economics." *Journal of Econometrics* 2 (1974): 111-120.

Greene, W. *Econometric Analysis.* 5th Edition. Upper Saddle River, NJ: Prentice Hall, 2003.

Hadri, K. "Testing for stationarity in heterogeneous panel data." *Econometrics Journal, Royal Economic Society* 3, no. 2 (2000): 148-161.

Hamilton, J.D. *Time Series Analysis.* Princeton, NJ: Princeton University Press, 1994.

Huffman, W.E., and R.E. Evenson. "Do Formula or Competitive Grant Funds Have Greater Impacts on State Agricultural Productivity?" *American Journal of Agricultural Economics* 88, no. 4 (November 2006a): 783-798.

Im, K. S., M. H. Pesaran, and Y. Shin. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115 (2003): 53-74.

Kao, C. "Spurious regression and residual-based tests for cointegration in panel data." *Journal of Econometrics* 90 (1999): 1-44.

Levin, A., C. F. Lin, and C. Chu. "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties." *Journal of Econometrics* 108 (2002): 1-24.

Maddala, G.S., and S. Wu. "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test." *Oxford Bulletin of Economics and Statistics* 61 (1999): 631-652.

National Oceanic and Atmospheric Administration (NOAA). *National Climatic Data Center.* http://www.ncdc.noaa.gov/oa/ncdc.html (accessed 2009).

Pardey P.G., James J., Alston J., Wood S., Koo B., Binenbaum E., Hurley T., Glewwe P. *Science, Technology and Skills. Background Paper for the World Bank's World Development Report 2008.* St. Paul, Rome and Washington D.C.: University of Minnesota, CGIAR Science Council and World Bank, 2007.

Pedroni, P. "Critical values for cointegration tests in heterogeneous panels with multiple regressors." *Oxford Bulletin of Economics and Statistics,* November Special Issue 1999: 653–669.

Pesaran, M.H., Y. Shin, and R.P. Smith. "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels." *Journal of the American Statistical Association* 94, no. 446 (June 1999): 621-634.

Phillips, P.C.B. "Understanding spurious regressions in econometrics." *Journal of Econometrics* 33, no. 3 (December 1986): 311-340.

Westerlund, J. "Testing for Error Correction in Panel Data." *Oxford Bulletin of Economics and Statistics* 69, no. 6 (2007): 709-748.

Table 1. Panel Estimates Model of Agricultural Productivity

Dependent variable: ln (Ag. Total Factor Productivity)	Model 1		Model 2		Model 3	
	Coefficient	p_value	Coefficient	p_value	Coefficient	p_value
ln (Public Ag. Research Capital)	0.1306	**0.000**	0.0919	**0.000**	0.1100	**0.000**
ln (Public Ag. Research Capital) × SFF_{t-12}	0.0354	**0.095**	0.0235	0.259	-0.0019	0.907
ln (Public Ag. Research Capital) × $(SFF_{t-12})^2$	-0.0277	**0.055**	-0.0199	0.150	-0.0078	0.490
ln (Public Ag. Research Capital) × GR_{t-12}	-0.0345	**0.003**	-0.0302	**0.007**	-0.0239	**0.010**
ln (Public Ag. Research Capital) × $(GR_{t-12})^2$	0.0403	**0.089**	0.0303	0.191	0.0254	0.373
ln (Public Extension Capital)	0.1104	**0.000**	0.0770	**0.000**	-0.0115	0.487
ln (Public Ag. Research Capital Spilling)	0.0348	**0.036**	0.0284	0.110	0.5959	**0.000**
ln (Private Ag. Research Capital)	-0.0010	0.986	0.1075	**0.044**	-0.1342	**0.004**
D1 (Northeast = 1)	0.0530	0.270	-0.4321	0.587		
D2 (Southeast = 1)	0.0045	0.900	-5.9156	**0.000**		
D3 (Central = 1)						
D4 (Northern Plains = 1)	0.1937	**0.000**	-0.4545	0.592		
D5 (Southern Plains = 1)	0.0621	0.132	3.8236	**0.012**		
D6 (Mountains = 1)	0.1147	**0.022**	-0.4957	0.590		
D7 (Pacific = 1)	0.0573	0.211	-5.9601	**0.000**		
Trend	0.0109	**0.000**	0.0125	**0.000**	-0.0006	0.845
ln (Temperature) × D1			0.1204	0.266	-0.3196	**0.005**
ln (Temperature) × D2			1.4404	**0.000**	-0.2313	0.198
ln (Temperature) × D3			-0.0063	0.975	-0.0606	0.611
ln (Temperature) × D4			0.1664	0.499	-0.0199	0.892
ln (Temperature) × D5			-0.9155	**0.019**	-0.4020	0.162
ln (Temperature) × D6			0.1661	0.171	0.1491	0.325
ln (Temperature) × D7			1.5448	**0.000**	-0.1189	0.728
Total Precipitation			0.0693	**0.003**	0.0868	**0.000**
Precipitation Intensity			-0.0459	**0.001**	-0.0530	**0.000**
Intercept	-3.4178	**0.000**	-3.5704	**0.000**		

Notes: Model 1 - Prais-Winsten regression, correlated panels corrected standard errors. See Huffman and Evenson 2006a for variable definitions.
Model 2 - Prais-Winsten regression, correlated panels corrected standard errors, with climatic variables.
Model 3: Long run equation using Pooled Mean Group Regression for non stationary heterogeneous panels, with climatic variables.
Significative variables in bold.

Table 2. Panel Unit Root Test: Summary

Sample: 1970 1999

Cross Sections: 48

	Individual effects						Individual effects & individual linear trends					
	Level			1st Difference			Level			1st Difference		
ltfp	Statistic	P-value	Obs.	Statistic	P-value	Obs.	Statistic	P-value	Obs.	Statistic	P-value	Obs.
Null: Unit root (assumes common unit root process)												
Levin, Lin & Chu t*	1.34	0.909	1329	-34.70	0.000	1307	-11.87	0.000	1367	-27.26	0.000	1297
Breitung t-stat	2.70	0.997	1281	-25.87	0.000	1259	-1.28	0.100	1319	-24.60	0.000	1249
Null: Unit root (assumes individual unit root process)												
Im, Pesaran and Shin W-stat	7.52	1.000	1329	-38.67	0.000	1307	-12.62	0.000	1367	-35.31	0.000	1297
ADF - Fisher Chi-square	33.01	1.000	1329	1116.74	0.000	1307	343.84	0.000	1367	1023.92	0.000	1297
PP - Fisher Chi-square	47.79	1.000	1392	1276.65	0.000	1344	619.49	0.000	1392	6263.40	0.000	1344
Null: No unit root (assumes common unit root process)												
Hadri Z-stat	23.07	0.000	1440	1.52	0.065	1392	10.22	0.000	1440	13.45	0.000	1392
lrpubs3												
Levin, Lin & Chu t*	-8.34	0.000	1257	-7.14	0.000	1254	0.94	0.827	1265	-7.11	0.000	1256
Breitung t-stat	1.57	0.941	1209	-1.59	0.056	1206	-8.01	0.000	1217	0.77	0.779	1208
Im, Pesaran and Shin W-stat	0.10	0.542	1257	-6.18	0.000	1254	-7.39	0.000	1265	-3.67	0.000	1256
ADF - Fisher Chi-square	162.77	0.000	1257	223.51	0.000	1254	331.37	0.000	1265	161.50	0.000	1256
PP - Fisher Chi-square	82.17	0.842	1392	59.13	0.999	1344	89.34	0.671	1392	26.69	1.000	1344
Hadri Z-stat	24.42	0.000	1440	12.65	0.000	1392	16.19	0.000	1440	16.50	0.000	1392
lrpubsf												
Levin, Lin & Chu t*	-1.40	0.080	1353	-30.05	0.000	1311	-3.94	0.000	1350	-19.26	0.000	1282
Breitung t-stat	-1.06	0.145	1305	-27.07	0.000	1263	-3.86	0.000	1302	-22.32	0.000	1234
Im, Pesaran and Shin W-stat	-2.45	0.007	1353	-31.51	0.000	1311	-5.43	0.000	1350	-25.93	0.000	1282
ADF - Fisher Chi-square	188.45	0.000	1353	899.42	0.000	1311	219.28	0.000	1350	710.57	0.000	1282
PP - Fisher Chi-square	167.99	0.000	1392	1058.25	0.000	1344	207.52	0.000	1392	2951.56	0.000	1344
Hadri Z-stat	17.07	0.000	1440	0.44	0.330	1392	9.38	0.000	1440	10.61	0.000	1392

lrpubsf2												
Levin, Lin & Chu t*	-1.45	0.073	1354	-30.45	0.000	1310	-4.57	0.000	1356	-20.49	0.000	1286
Breitung t-stat	-1.58	0.057	1306	-27.92	0.000	1262	-3.73	0.000	1308	-22.73	0.000	1238
Im, Pesaran and Shin W-stat	-2.85	0.002	1354	-32.11	0.000	1310	-5.89	0.000	1356	-26.64	0.000	1286
ADF - Fisher Chi-square	198.55	0.000	1354	916.12	0.000	1310	220.73	0.000	1356	732.74	0.000	1286
PP - Fisher Chi-square	188.98	0.000	1392	1065.98	0.000	1344	325.82	0.000	1392	3207.51	0.000	1344
Hadri Z-stat	17.18	0.000	1440	0.31	0.379	1392	9.09	0.000	1440	8.42	0.000	1392
lrpubgr												
Levin, Lin & Chu t*	-0.63	0.265	1371	-31.09	0.000	1311	-2.38	0.009	1361	-24.26	0.000	1291
Breitung t-stat	-2.25	0.012	1323	-27.97	0.000	1263	1.50	0.933	1313	-20.47	0.000	1243
Im, Pesaran and Shin W-stat	-0.45	0.326	1371	-31.48	0.000	1311	-2.38	0.009	1361	-27.85	0.000	1291
ADF - Fisher Chi-square	113.15	0.112	1371	892.05	0.000	1311	147.41	0.001	1361	815.96	0.000	1291
PP - Fisher Chi-square	129.06	0.014	1392	1012.61	0.000	1344	157.32	0.000	1392	2439.06	0.000	1344
Hadri Z-stat	16.94	0.000	1440	-0.98	0.837	1392	8.60	0.000	1440	9.03	0.000	1392
lrpubgr2												
Levin, Lin & Chu t*	-1.13	0.130	1357	-27.40	0.000	1290	-2.60	0.005	1352	-19.72	0.000	1279
Breitung t-stat	-1.97	0.025	1309	-25.58	0.000	1242	0.41	0.658	1304	-18.68	0.000	1231
Im, Pesaran and Shin W-stat	0.78	0.783	1357	-28.08	0.000	1290	-1.99	0.024	1352	-24.38	0.000	1279
ADF - Fisher Chi-square	130.28	0.011	1357	820.82	0.000	1290	184.66	0.000	1352	725.68	0.000	1279
PP - Fisher Chi-square	147.78	0.001	1392	1008.13	0.000	1344	189.45	0.000	1392	2870.66	0.000	1344
Hadri Z-stat	16.96	0.000	1440	-1.07	0.858	1392	9.21	0.000	1440	10.44	0.000	1392
lnextf												
Levin, Lin & Chu t*	-8.57	0.000	1369	-27.70	0.000	1329	-7.52	0.000	1365	-23.74	0.000	1322
Breitung t-stat	-2.17	0.015	1321	-10.67	0.000	1281	-0.55	0.292	1317	-9.79	0.000	1274
Im, Pesaran and Shin W-stat	-4.62	0.000	1369	-27.00	0.000	1329	-8.37	0.000	1365	-22.94	0.000	1322
ADF - Fisher Chi-square	177.55	0.000	1369	759.59	0.000	1329	233.68	0.000	1365	593.47	0.000	1322
PP - Fisher Chi-square	191.91	0.000	1392	848.49	0.000	1344	204.69	0.000	1392	1402.46	0.000	1344
Hadri Z-stat	22.67	0.000	1440	2.26	0.012	1392	10.29	0.000	1440	9.55	0.000	1392
lrspill3												
Levin, Lin & Chu t*	-6.87	0.000	1288	-9.79	0.000	1281	11.88	1.000	1281	-10.96	0.000	1251
Breitung t-stat	3.96	1.000	1240	-6.43	0.000	1233	-10.45	0.000	1233	-4.26	0.000	1203
Im, Pesaran and Shin W-stat	3.03	0.999	1288	-7.01	0.000	1281	0.26	0.601	1281	-5.23	0.000	1251

ADF - Fisher Chi-square	82.51	0.835	1288	227.70	0.000	1281	146.68	0.001	1281	167.88	0.000	1251
PP - Fisher Chi-square	78.04	0.910	1392	53.63	1.000	1344	65.76	0.992	1392	10.34	1.000	1344
Hadri Z-stat	24.95	0.000	1440	7.81	0.000	1392	12.86	0.000	1440	17.15	0.000	1392
lintst												
Levin, Lin & Chu t*	-27.50	0.000	1338	-0.56	0.288	1296	-24.92	0.000	1344	-1.47	0.070	1293
Breitung t-stat	-26.01	0.000	1290	-2.53	0.006	1248	0.45	0.675	1296	-3.60	0.000	1245
Im, Pesaran and Shin W-stat	-26.05	0.000	1338	0.75	0.774	1296	-25.92	0.000	1344	3.82	1.000	1293
ADF - Fisher Chi-square	773.77	0.000	1338	56.42	1.000	1296	687.66	0.000	1344	32.68	1.000	1293
PP - Fisher Chi-square	20.03	1.000	1392	33.92	1.000	1344	4.10	1.000	1392	15.56	1.000	1344
Hadri Z-stat	3.86	0.000	1440	3.81	0.000	1392	9.97	0.000	1440	14.64	0.000	1392
ltmp												
Levin, Lin & Chu t*	-24.45	0.000	1373	-37.46	0.000	1290	-23.78	0.000	1356	-26.78	0.000	1281
Breitung t-stat	-22.90	0.000	1325	-28.86	0.000	1242	2.65	0.996	1308	-21.59	0.000	1233
Im, Pesaran and Shin W-stat	-21.21	0.000	1373	-39.80	0.000	1290	-20.56	0.000	1356	-33.63	0.000	1281
ADF - Fisher Chi-square	588.70	0.000	1373	1148.30	0.000	1290	533.85	0.000	1356	923.85	0.000	1281
PP - Fisher Chi-square	589.13	0.000	1392	1371.55	0.000	1344	751.53	0.000	1392	11099.70	0.000	1344
Hadri Z-stat	9.24	0.000	1440	5.74	0.000	1392	4.22	0.000	1440	30.64	0.000	1392
lpcp												
Levin, Lin & Chu t*	-30.46	0.000	1372	-38.71	0.000	1278	-26.37	0.000	1366	-29.06	0.000	1263
Breitung t-stat	-18.68	0.000	1324	-29.56	0.000	1230	-3.56	0.000	1318	-28.92	0.000	1215
Im, Pesaran and Shin W-stat	-28.49	0.000	1372	-42.64	0.000	1278	-24.58	0.000	1366	-37.69	0.000	1263
ADF - Fisher Chi-square	819.33	0.000	1372	1199.32	0.000	1278	656.17	0.000	1366	1230.26	0.000	1263
PP - Fisher Chi-square	927.66	0.000	1392	1068.79	0.000	1344	1705.54	0.000	1392	11178.20	0.000	1344
Hadri Z-stat	1.16	0.123	1440	1.90	0.029	1392	7.35	0.000	1440	17.67	0.000	1392
lintens												
Levin, Lin & Chu t*	-28.00	0.000	1385	-36.97	0.000	1303	-24.51	0.000	1377	-29.46	0.000	1297
Breitung t-stat	-19.79	0.000	1337	-19.78	0.000	1255	-7.43	0.000	1329	-19.44	0.000	1249
Im, Pesaran and Shin W-stat	-28.65	0.000	1385	-45.08	0.000	1303	-26.71	0.000	1377	-40.49	0.000	1297
ADF - Fisher Chi-square	816.33	0.000	1385	1251.93	0.000	1303	708.93	0.000	1377	1310.62	0.000	1297
PP - Fisher Chi-square	849.33	0.000	1392	1251.86	0.000	1344	1007.49	0.000	1392	9078.77	0.000	1344
Hadri Z-stat	2.61	0.005	1440	-0.34	0.632	1392	7.19	0.000	1440	11.01	0.000	1392

** Probabilities for Fisher tests are computed using an asympotic Chi-square distribution. All other tests assume asymptotic normality.

Table 3. Cointegration Test: Summary

Sample: 1970 1999
Cross Sections: 48

Panel unit root tests:	Constant			Constant & Trend		
Residuals pooled estimation	Statistic	P-value	Obs.	Statistic	P-value	Obs.
Null: Unit root (assumes common unit root process)						
Levin, Lin & Chu t*	-11.69	0.000	1380	-11.65	0.000	1378
Breitung t-stat	-7.06	0.000	1332	-6.93	0.000	1330
Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	-13.34	0.000	1380	-12.24	0.000	1378
ADF - Fisher Chi-square	377.10	0.000	1380	324.39	0.000	1378
PP - Fisher Chi-square	406.35	0.000	1392	519.15	0.000	1392
Null: No unit root (assumes common unit root process)						
Hadri Z-stat	7.82	0.000	1440	9.55	0.000	1440

**Probabilities for Fisher tests are computed using an asympotic Chi-square distribution.
**All other tests assume asymptotic normality.

Pedroni cointegration tests	Constant		Constant & Trend	
	Statistic	P-value	Statistic	P-value
panel v-stat	-0.82	0.205	-3.76	0.000
panel rho-stat	-4.60	0.000	-2.45	0.007
panel pp-stat	-20.10	0.000	-23.80	0.000
panel adf-stat	-9.88	0.000	-9.69	0.000
group rho-stat	-2.22	0.013	-0.03	0.489
group pp-stat	-22.28	0.000	-26.89	0.000
group adf-stat	-8.24	0.000	-9.12	0.000

**All reported values are distributed N(0,1) under null of unit root or no cointegration.
**Panel stats are unweighted by long run variances.

Kao cointegration tests	Constant		Constant & Trend	
	Statistic	P-value	Statistic	P-value
DFrho	-31.88	0.000	-33.94	0.000
DFt	-17.59	0.000	-18.64	0.000

**Stats are distributed N(0,1) under null of no cointegration.

Westerlund cointegration tests

Lags: 1 - 2 Average AIC selected lag length: 1.98
Leads: 0 - 1 Average AIC selected lead length: .96

	Constant			Constant & Trend		
Statistic	Value	Z-value	P-value	Value	Z-value	P-value
Gt	-4.06	-11.71	0.000	-4.23	-10.39	0.000
Ga	-0.24	11.50	1.000	-0.13	13.81	1.000
Pt	-22.25	-6.80	0.000	-25.95	-7.75	0.000
Pa	-2.56	6.16	1.000	-1.99	9.57	1.000

**Z-values are distributed N(0,1) under null of no cointegration.

Endnotes

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[1] The impact on a given state of direct public agricultural research undertaken by other states in an area.

[2] According to the usual panel model nomenclature, for all this article the sub-index $i = 1,\ldots,N$ represents each cross section (state) and the sub-index $t = 1,\ldots,T$ represents each time period (year).

[3] For details on the construction and the asymptotic properties of the test, see Im, Pesaran and Shin (2003).

[4] Common factor restriction is the fact that residual-based tests require the long-run cointegrating vector for the variables in their levels being equal to the short-run adjustment process for the variables in their differences.

[5] The impact on a given state of direct public agricultural research undertaken by other states in an area.

[6] Not reported estimations with regional interaction for Precipitation and Intensity were performed with no satisfactory result, which supports our original idea.

[7] Calculated using the elasticities equations evaluated at the sample means for SFF and GR.

[8] All the variables evaluated are expressed in natural logarithms.

[9] For example, Dinda and Coondoo (2006).