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Agricultural Productivity Convergence: Myth or Reality?

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We tested agricultural productivity convergence in the United States using the state level total factor productivity data and utilizing new estimation and cluster identification methods to identify convergence in the data. The empirical investigation did not indicate any evidence of agricultural total factor productivity (TFP) convergence at the state level. However, we found the evidence of TFP convergence at the regional level for some regions/clusters.

Key Words: agricultural total factor productivity, convergence, human capital, U.S. states

JEL Classifications: Q10, O47

Empirical tests of convergence hypothesis have found absolute convergence in productivity only for developed countries (e.g., Barro, 1991; Barro and Sala-i-Martin, 1995; Baumol, 1986; De Long, 1988; Islam, 1995; and Mankiw, Romer, and Weil, 1992). These studies were based on two common assumptions: developing countries are not fundamentally different from industrialized countries and that there is free, world-wide availability of technological knowledge. However, conditional convergence was found in some cases where samples consisted of both developed and developing countries (Cho and Graham, 1996; Mankiw, Romer, and Weil, 1992).

There is a general belief that productivity grows less rapidly in agriculture than in manufacturing sectors (Martin and Mitra, 2001). Economists such as Wichmann (2003) have found that transfer of improved agricultural techniques from the developed countries to developing countries is a lengthy process. It is this notion of slow productivity growth in agriculture that resulted in several theories and policies of economic development favoring the manufacturing sector. For example, Wichmann analyzed technology adoption in agriculture and convergence across economies and found the existence of an optimal technological gap between developed and developing countries. Thus, indicating full convergence never takes place between industrialized and developing countries. However, a study performed by Martin and Mitra (2001) on productivity growth and convergence in agriculture and manufacturing sectors favored the agriculture sector. The authors found that at all levels of development, technical progress was faster in the agriculture sector than in the manufacturing sector. Moreover, they found strong evidence of a rapid convergence in levels and growth rates of total factor productivity in agriculture, indicating relatively rapid transfer of technological

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innovations (knowledge) from one country to another. Others who have looked at agricultural productivity convergence issues are Rezitis (2005, 2010); Mukherjee and Kuroda (2003); and Ball, Hallahan, and Nehring (2004).

We offer continuity to the existing literature, but interject two new methods to test the convergences — a statistical method, which improves on the methods used by others, and a redefinition of "region" in beta convergence. The redefinition of "region" is not a mere technological quibble in our view. The theory of "beta" convergence indicates some sort of convergence among a subset of units (such as countries, regions), but it is not clear what those subsets contain. Previous authors have used exogenous criteria such as weather or altitude for region identification. However, it is well known in social sciences that categorization is possible in a large number of ways (the maximum number of such categorization is bounded only by the combination number, which can be very high even when number of states considered is low). Weather, politics, and nature of inhabitants are just a few of those criteria. It is unlikely that all those criteria will lead to formation of "region" which can be tested for convergence. A unique framework for such region identification is desirable to test the theory. By utilizing data based clustering to identify the regions, we believe we provide one answer in that direction. We use a v-fold cross-validation algorithm, normally used in pattern recognition literature for the purpose.

Literature Review

In the last decade, two different strands of literature have been prominent in identifying the convergence of total factor productivity or convergence in general. One, started by Kumar and Russell (2002), looks at the distribution of productivity by decomposing it into different components and identifying the components that are converging or diverging to something. The other strand, due to Philips and Sul (2007), provides a new method to test data-based clusters that are converging. One must be careful in applying Philips and Sul's method in convergence literature since it is related to sigma convergence. It should be noted that beta convergence doesn't imply sigma convergence (Furceri, 2005) and that one looks for beta convergence in testing whether poorer regions are catching up with the wealthier regions. In Table 1, we provide some major papers related to convergence test and how different tests have been applied to test for agricultural total factor productivity convergence in literature.

Additionally, literature in convergence initially suffered from clarity of definition, and it led to wrong tests and wrong conclusions (for example, look at the Lichtenberg's criticism of Barro and Sala-i-Martin (1995) results). Initial confusion also stemmed from the lack of robustness of the results. The structure of convergence literature in its initial phase therefore looks like an expedition, where researchers looked for convergence at any country group they could find, using whichever method seemed appropriate at the time. The literature has evolved from identifying convergence in a relatively global block (worldwide or Organisation for Economic Co-operation and Development (OECD) convergence) to the convergence in "regions" or a "country". Pioneering authors in this literature such as Baumol (1986); Barro (1991); Barro and Sala-i-Martin (1995); De Long (1998); Islam (1995); and Mankiw, Romer, and Weil (1992) found some form of convergence among OECD countries.

Besides those classical studies, some other studies related to the agricultural productivities have been conducted. For example, Thirtle et al. (2003) calculated multifactor agricultural productivity indices for Botswana's agriculture. Results obtained using a unit root test indicated that there was no regional convergence in agricultural productivity. Gyawali et al. (2008) analyzed income convergence behavior of population in Alabama's black belt region and found it to have a conditional convergence among different census blocks. Garofalo and Yamarik (2001) estimated regional convergence by creating a state-by-state capital stock series. This study reconciled the growth empirics' technique of Mankiw, Romer, and Weil (1992) with the empirical results of Barro and Sala-i-Martin (1995) using the new database covering 1977–1996. The results indicated a convergence at the rate of 2% and suggested that the Solow's (1957) neoclassical growth model drives the empirical results of Barro and Sala-i-Martin (1995).

Table 1. Recent Literature in Convergence Test, Method Used, and Their Major Findings

Authors	Methods	Major Findings
Kumar and Russell (2002)	Nonparametric method, decomposition of productivity	Examined cross country distribution of labor productivity and concluded that technological change is decidedly nonneutral and that both growth and bipolar international divergence are driven primarily by capital deepening
Rezitis (2005)	Panel unit root method of testing convergence is used. Tests used were based on Levin, Lin, and Chu (2002); Breitung (2000); Im, Pesaran, and Shin (2003); Hadri (2000); and Harris and Tzavalis (1999).	Tests convergence of agricultural factor productivity in United States and nine European countries. Results indicated that the total factor productivity difference as measured by the distance of each country's productivity level from that of the United States is stationary.
Jerzmanowski (2007)	Decomposition	Decomposed total factor productivity into two factors: inefficiency and technology difference and found that inefficiency explains the income differences.
Phillips and Sul (2007)	Developed log t convergence test	Convergence in the relative cost of living in American cities is rejected; identifies different convergence clubs in the data.
Fousekis (2008)	Uses Phillips and Sul method	Tests convergence in poultry and egg market; finds convergence in poultry market, but clusters of convergence in egg market.
Panopoulou and Pantelidis (2009)	Uses Phillips and Sul method	Tests for convergence in CO_2 in 128 countries. Finds global convergence initially but identifies the clusters that converge to their own equilibrium later on.
Rezitis (2010)	Window Malmquist Index approach of total factor productivity in agriculture is calculated for nine European countries and the United States for 1973–1993. Convergence of TFP is tested using a panel unit root test.	Productivity convergence was found in a sub-set of study period (1983–1993) but not for the whole study period.
Liu et al. (2010)	Error correction method was used to test for σ convergence and β convergence in agricultural total factor productivity in the United States.	No σ convergence but β convergence was found.

In the empirical front, modeling and testing convergence hypothesis is also a subject far from being settled. Lichtenberg believes that the hypothesis of convergence and mean-reversion are not equivalent and asserts that the lowest initial productivity level followed by the highest subsequent productivity growth does not automatically imply convergence. He shows that under certain assumptions, degree of convergence (σ convergence) does not depend at all on mean-reversion (β convergence), but under other assumptions, it is a necessary condition but not a sufficient condition for convergence (σ convergence). He states that there is a convergence if

$$\frac{d[\mathrm{var}(y_t)]}{dt} < 0 \tag{1}$$

where $y_t = \ln(Y_t)$ Y_t being total factor productivity at time t and $\mathrm{var}(y_t)$ being the variance across economies. In the case of only two time periods, indexed by beginning period (1) and ending period (T), the hypothesis is expressed as

$$[\mathrm{var}(y_1)]/[\mathrm{var}(y_T)] > 1 \tag{2}$$

Mean-reversion as assumed by Lichtenberg (1994) is based on the following equation:

$$y_T - y_1 = \beta y_1 + u \tag{3}$$

We have suppressed the intercept for simplicity. The equation is rewritten as:

$$y_T = (1 + \beta)y_1 + u = \pi y_1 + u \tag{4}$$

where it is assumed that $-1 \leq \beta \leq 0$ and that $0 \leq \pi \leq 1$. According to Lichtenberg, most of the previous studies have estimated Equation (3) or (4) in order to test the hypothesis that $\beta < 0$ or that $\pi < 1$. This hypothesis is actually a mean-reversion hypothesis, which indicates that economies with the lowest initial productivity level tended to have the highest subsequent productivity growth. Mean reversion is just a necessary condition for convergence under certain assumptions but not a sufficient condition.

Lichtenberg's (1994) convergence hypothesis is as follows:

$$\begin{aligned}(\text{Test Statistic})\mathrm{T}_1 &= \frac{\mathrm{var}(A_1)}{\mathrm{var}(A_T)} = \frac{R^2}{(1+\beta)^2}\\ &= \frac{R^2}{\pi^2} \sim \mathrm{F(N\text{-}2,N\text{-}2)}\end{aligned} \tag{5}$$

where N is number of countries and R^2 is fit value obtained from regression analysis. He employed this convergence hypothesis to test per capita output convergence for 22 OECD countries from 1960–1985. The results indicated mean-reversion but no convergence. Among other researchers who analyzed the productivity issue using Lichtenberg's method, a study by McCunn and Huffman (2000) is prominent. McCunn and Huffman (2000) analyzed convergence in U.S. productivity growth for agriculture by using state level crop, livestock, and agricultural total factor productivity (TFP) data from 1950–82. They examined the question of convergence to a single TFP (σ convergence) or to a steady state rate of growth (β-convergence). The results indicated no σ convergence but found β-convergence, which is in accordance with Lichtenberg's study.

In a critique of Lichtenberg's method, Carree and Klomp (1997) argue that Lichtenberg's assumption that the ratio of the variance in the first time period to that in the last period of the sample time series as F-distributed overlooks the dependency between the two variances. This causes a probability of committing a type-II error implying that one may incorrectly reject the convergence hypothesis. The authors propose two alternate tests for testing the convergence hypothesis. The authors derived the first test statistic (T_2) using the likelihood-ratio principle and second statistic (T_3) by correcting distribution of Lichtenberg's test statistic (T_1). The three tests are formulated as follows:

$$T_1 = \frac{\hat{\sigma}_1^2}{\hat{\sigma}_T^2} \tag{6}$$

$$T_2 = (N - 2.5)\ln\left[1 + \frac{1}{4}\frac{(\hat{\sigma}_1^2 - \hat{\sigma}_T^2)^2}{\hat{\sigma}_1^2\hat{\sigma}_T^2 - \hat{\sigma}_{1T}^2}\right] \tag{7}$$

$$T_3 = \frac{\sqrt{N}(\hat{\sigma}_1^2/\hat{\sigma}_T^2 - 1)}{2\sqrt{1-\hat{\pi}^2}} \tag{8}$$

where T_1 test statistic is F-distributed with N-2, N-2 degrees of freedom, T_2 test statistic has a χ^2 (1) distribution, and T_3 test statistic has a normal distribution with N-1 degrees of freedom, where N represents number of countries or regions in the sample. Carree and Klomp (1997) tested the convergence hypothesis employing these three tests for a data set of gross domestic per capita for 22 OECD countries for the 1950–1994 period. All three test statistics indicated a decrease in variance of productivities. However, when authors employed the test statistics for the 1960–1985, Lichtenberg's T_1 test statistic indicated no convergence of gross domestic product while the other two tests (T_2, T_3) indicated convergence. The authors also tested the convergence for short time periods by breaking the 1950–1994 periods into four sub-periods consisting of 12 years. The T_2 and T_3 test statistics for these sub-periods indicated convergence of gross domestic product while T_1 statistics found no convergence, indicating that Lichtenberg's test statistic for shorter time periods has a large probability of committing type-II error.

Method

This article employs three models of convergence for testing the U.S. state agricultural TFP growth rate convergence. The first model is similar to the one employed by Carree and Klomp (1997). The model is:

$$(9) \qquad y_{it} = \rho y_{i,t-1} + v_{it} \quad t = 2, \ldots, T,\ i = 1, \ldots, N$$

where $y_{it} = ln(Y_{it})$, where Y_{it} is the productivity in state i at time t, and

$$(10) \qquad \hat{\sigma}_t^2 = \frac{\Sigma_t (y_{it} - \bar{y}_t)^2}{N}$$

Equation (10) represents the variance of y_{it} across states. The intercept in the Equation (9) is suppressed. According to Carree and Klomp (1997), the null hypothesis of no convergence is equivalent to the parameter restriction $\rho^2 = 1 - \sigma_v^2/\sigma_1^2$. TFP converges overtime in case $\rho^2 < 1 - \sigma_v^2/\sigma_1^2$. Test static T_2 (Equation (7)) is used to test the null hypothesis of no convergence for the convergence model specified in Equation (9).

The second model employed is the one proposed by Lichtenberg (1994). This equation is derived from Equation (9).

$$(11) \qquad y_{iT} = \pi y_{i1} + u_t \quad i=1, \ldots, N$$

where $\pi = \rho^{T-1}$ and $u_i = \Sigma_{t=2}^{T} \rho^{T-1} v_{it}$. Lichtenberg (1994) proposed T_1 test statistic (Equation (6)) to test the null hypothesis of no convergence for the model in Equation (11), whereas Carree and Klomp (1997) argued that T_1 test statistic is not correct and proposed T_3 test statistic (Equation (8)) to test the convergence hypothesis for Equation (11).

Thirdly, McCunn and Huffman's (2000) approach is employed to test for unconditional convergence across geographic regions. The model is:

$$(12)^1 \qquad Var(\ln TFP_t) = \Phi_1 + \Phi_2 t + \varepsilon_t$$

The sufficient condition for convergence is that the cross-sectional dispersion in agricultural TFP decreases overtime, which means that negative φ_2 which is significantly different from zero indicates an unconditional convergence (McCunn and Huffman, 2000). We used the same approach used by McCunn and Huffman (2000) to test for unconditional convergence except for the fact that we used a cluster analysis method to identify convergence group. Additionally, we used human capital theory to describe the productivity difference among different states.

Cluster Analysis

We used a v-fold cross-validation algorithm for automatically determining the number of clusters in the data. This algorithm is immensely useful in all general "pattern-recognition" tasks. This cluster analysis method is later compared with other methods in the existing literature, in particular the one where clusters are determined exogenously. Our repudiation of existing methods where clusters are exogenously determined stems from the philosophy that the number and characteristics of the groups are to be derived from the data and shouldn't be assumed prior to the analysis (Afifi and Clark, 1999).

The general idea of v-fold cross-validation method is to divide the overall sample into a number of *v* folds. The same type of analysis is then successively applied to the observations belonging to the v-1 folds (training sample), and the results of the analyses are applied to sample *v* to compute some index of predictive validity. The results for the *v* replications are aggregated (averaged) to yield a single measure of the stability of the respective model, i.e., the validity of the model for predicting new observations (details on this method can be found in Smyth, 2000).

[1] Equation (12) can be transformed so that the convergence test can be based on panel unit root approaches. See papers by Rezitis (2005, 2010).

Data

Data samples used for this study were obtained from United States Department of Agriculture, Economic Research Service (USDA/ERS). The estimates of TFP for the 48 contiguous states for 1960–96 were obtained from the USDA/ERS website. The TFP values were calculated taking Alabama 1996, as the base period. Table 2 illustrates the ranking of the states in terms of TFP during the initial and last period of the data set. Human capital data sample used in the analysis were obtained from Mulligan and Sala-i-Martin (1995).

Results

To test the convergence of total factor productivity, the data samples were analyzed using all the three methodologies discussed earlier in the paper. The results using Lichtenberg's (1994) approach are presented in Table 3. The results show that the aggregate U.S agriculture sector does not show any evidence of convergence across the states based on the total factor productivity.

The results obtained by using Carree and Klomp's (1997) approach are also presented in Table 3. The results suggest that though the approach in testing the convergence hypothesis varies, the end result is the same for the data analyzed in this study. We fail to reject the null hypothesis of no convergence using this approach. Conclusion from this approach is similar to that of Lichtenberg (1994) approach indicating that there exists no convergence in the U.S agricultural sector at the aggregate state level.

Formation of Regions Using Cluster Analysis and Convergence

V-fold cross validation, as well as three other criteria (approximate expected overall R^2, cubic clustering criteria, pseudo F-test), indicated that in the case of 42 states (this excludes Hawaii, Alaska, and New England states), there are seven suitable clusters. In the case of 48 states, the ideal numbers of clusters were found to be six clusters (see Table 4). In the case of 42 states where we have found seven clusters, there are two clusters with only one state, West Virginia and Florida, therefore, leaving only five clusters to test for convergence. In the case of 48 states and six clusters, similarly, there are two clusters with only one state in them. In one cluster, we have Florida as the lone state, where as in the other, we had only West Virginia, resulting in a need to test for convergence in only four clusters.

We examined the convergence among state TFP based on the ideal number of clusters. As indicated earlier, these clusters were calculated based on the v-fold criteria as well as approximate expected overall R^2, cubic clustering criteria, pseudo F-test. For the case of 42 states, the result indicated a correct sign (i.e., convergence) associated with Φ_2 for three clusters and an incorrect sign (i.e., divergence) for the two clusters (see Table 5).

For the case of 48 states, the appropriate number of clusters was found to be six. Two of these clusters had only one state in them, thus only four clusters were tested for convergence. The results showed a correct sign associated with the coefficient Φ_2 for three clusters, but these coefficients were insignificant. One cluster, however, had a positive sign associated with f_2 indicating that there is a divergence in TFP among the states in that cluster.

If there is divergence, then one particular question of interest is what drives this overall divergence. One possible explanation might be path dependency of each region. Their divergence today is a result of historic events that probably occurred long ago. For example, some states had educational institutes that others didn't have. Some states were initially inhabited by educated migrants and skilled craftsman; others were inhabited by farmers who emphasized traditional methods of farming rather than innovations. Indeed, different papers in the past have indicated that divergence is complicated by the accumulation of human capital in each state and region. We will discuss this issue later when we discuss about the role of human capital.

Comparison with Existing Results

We compared our results with the existing result from McCunn and Huffman (2000), which tackles the question we explored in a different

Table 2. States Ranked by 1996 Level of Productivity

	1996		1960		Avg. Annual Growth of Productivity 1960–96	
State	Rank	Level	Rank	Level	Rank	Growth
CT	1	1.509	20	0.549	2	0.0284
FL	2	1.504	2	0.701	17	0.0212
GA	3	1.398	14	0.560	6	0.0254
NC	4	1.386	22	0.522	3	0.0271
IA	5	1.299	1	0.712	37	0.0167
WA	6	1.287	19	0.554	10	0.0234
ID	7	1.218	21	0.525	11	0.0234
SD	8	1.213	6	0.613	27	0.0190
ME	9	1.208	11	0.593	22	0.0198
DE	10	1.197	10	0.595	24	0.0194
AR	11	1.184	29	0.484	7	0.0249
KY	12	1.181	27	0.496	9	0.0241
CA	13	1.146	7	0.612	35	0.0174
WI	14	1.137	3	0.684	42	0.0141
MN	15	1.132	12	0.592	32	0.0180
NE	16	1.122	17	0.557	23	0.0195
PA	17	1.112	25	0.500	13	0.0222
VT	18	1.102	15	0.560	28	0.0188
SC	19	1.100	36	0.456	8	0.0244
IL	20	1.093	9	0.599	38	0.0167
CO	21	1.083	4	0.654	43	0.0140
NJ	22	1.080	13	0.581	36	0.0172
LA	23	1.074	46	0.386	1	0.0284
NY	24	1.042	8	0.603	39	0.0152
IN	25	1.040	24	0.510	21	0.0198
MS	26	1.034	44	0.398	4	0.0265
MA	27	1.033	33	0.477	15	0.0215
KS	28	1.032	5	0.636	45	0.0134
AL	29	1.000	23	0.511	29	0.0186
ND	30	1.000	40	0.437	12	0.0230
OR	31	0.990	31	0.479	19	0.0202
MI	32	0.981	47	0.384	5	0.0261
NM	33	0.969	37	0.450	16	0.0213
MD	34	0.954	34	0.468	20	0.0198
MO	35	0.933	26	0.498	34	0.0174
AZ	36	0.925	18	0.556	41	0.0142
NH	37	0.924	39	0.442	18	0.0205
VA	38	0.916	43	0.423	14	0.0215
UT	39	0.913	30	0.480	33	0.0179
OH	40	0.884	35	0.460	31	0.0181
NV	41	0.855	16	0.559	46	0.0118
RI	42	0.851	41	0.424	25	0.0193
TX	43	0.778	32	0.478	44	0.0135
TN	44	0.775	45	0.387	26	0.0193
MT	45	0.707	42	0.423	40	0.0143
OK	46	0.699	28	0.490	47	0.0098
WY	47	0.630	38	0.449	48	0.0094
WV	48	0.485	48	0.248	30	0.0186

Source: USDA/ERS 2003 State Productivity Data.

Table 3. Values Obtained From Three Test Statistics

Test Statistic	Test Value	Critical Value
T_1 (Lichtenberg, 1994)	0.78	2.12
T_2 (Carree and Klomp, 1997)	0.59	3.84
T_3 (Carree and Klomp, 1997)	1.04	1.64

way. Our research differs on methodology and clusters formation from their approach. Results from McCunn and Huffman's approach are presented in Table 6. When we look at regional data, there seems to be some evidence against the null hypothesis of no convergence in these particular regions. The results show Cornbelt and Lake States having a negative and statistically significant parameter estimate for time variable "t," suggesting convergence is taking place in these regions.

We also ran cluster analysis in which we attempted to find 10 clusters from the data following McCunn and Huffman's (2000) original selection of 10 groups. When we used data based clustering to find 10 clusters from data, the number of states and states within each cluster were quite different from McCunn and Huffman's original 10 groups and the states included in those groups (see Table 7). For example, in our analysis of 42 states, we found that there are three clusters containing only one state. A cluster identified by the cluster analysis contained 14 states. Compared with McCunn and Huffman (2000), the maximum number of states in a group was eight (Mountain Region). In our analysis of 48 states, we found three clusters containing only one state; however, only two clusters contained the same state. In the case of 42 states, we had North Dakota, Florida, and West Virginia in each cluster itself where as in the case of 48 states, we had Iowa, Florida, and West Virginia in a cluster itself. The convergence test is therefore conducted for only seven clusters in both cases. What we have consistently observed in all cases is that Florida and West Virginia are unique states that are unlike other states in TFP growth.

The results for regional convergence test based on 10 clusters and 42 states are presented in Table 8. The results indicate no regional convergence although three clusters had correct signs (negative coefficient) associated with the parameter Φ_2. In two clusters (Clusters 6 and 9), the sign was positive and significant, indicating that there is a divergence in TFP among states in these two clusters. One way to explain it is by using Bertola's (1993) logic: that in a situation in which technological advances are highly localized and its diffusion is slow, one may see persistent difference or divergence in regional or national productivity. The results for 10 clusters and 48 states are also presented in Table 8. We found that six clusters possessed a correct sign associated with parameter Φ_2, although none of those were found to be significant. Only one cluster (Cluster 2) had an opposite sign, which

Table 4. Appropriate Number of Clusters in Total Factor Productivity Data as Obtained from Cluster Analysis

42 States		48 States	
Cluster	States in the Cluster	Cluster	States in the Cluster
1	3: GA, NC, WA	1	7: CA, DE, GA, IA, NC, WA, WI
2	14: PA, SC, AR, CO, MN, NE, NY, SD, ID, IL, IN, KS, KY, OR	2	18: AL, AZ, IN, LA, MA, MD, MI, MS, ND, NH, NJ, NV, OH, PA, RI, SC, UT, VA
3	1: WV	3	1: WV
4	6: MT, NM, OK, TN, TX, WY	4	1: FL
5	13: UT, AL, AZ, ND, NJ, NV, VA, OH, LA, MD, MI, MO, MS	5	7: MO, MT, NM, OK, TN, TX, WY
6	4: CA, DE, IA, WI	6	14: AR, CO, CT, ID, IL, KS, KY, ME, MN, NE, NY, OR, SD, VT
7	1: FL		

Table 5. Convergence Check Based on Appropriate Number of Clusters

42 States		48 States	
Cluster 1	Estimates (standard error)	Cluster 1	Estimates (standard error)
Φ_1	0.0063**	Φ_1	0.0094**
	(0.0013)		(0.0009)
Φ_2	−0.0000	Φ_2	−0.0000
	(0.0000)		(0.0000)
Cluster 2		Cluster 2	
Φ_1	0.0083**	Φ_1	0.0084**
	(0.0008)		(0.0015)
Φ_2	−0.0001	Φ_2	−0.0000
	(0.0000)		(0.0000)
Cluster 4			
Φ_1	0.0025*		
	(0.0014)		
Φ_2	0.0004**		
	(0.0001)		
Cluster 5			
Φ_1	0.0056**		
	(0.0008)		
Φ_2	0.0000		
	(0.0000)		
Cluster 6		Cluster 5	
Φ_1	0.0113**	Φ_1	0.0041**
	(0.0020)		(0.0014)
Φ_2	−0.0001	Φ_2	0.0003**
	(0.0000)		(0.0001)
Cluster 7		Cluster 6	
Φ_1		Φ_1	0.0065**
			(0.0007)
Φ_2		Φ_2	−0.0000
			(0.0000)

* and ** denote significant at 5% and 1% level, respectively.

Table 6. Regression of Cross-Sectional Variance of TFP on Trend by Regions, 1960–1996 (based on McCunn and Huffman (2000) clusters)

Reference Area/Coefficient	Estimates (standard error)
Appalachia (five states)	
Φ_1	0.1007** (0.0043)
Φ_2	0.0010** (0.0002)
Adj. R^2	0.28
Cornbelt (five states)	
Φ_1	0.0268** (0.0019)
Φ_2	−0.0003** (0.0001)
Adj. R^2	0.27
Delta states (three states)	
Φ_1	0.0079** (0.0016)
Φ_2	0.0000 (0.0000)
Adj. R^2	0.00
Lake states (three states)	
Φ_1	0.0707* (0.0042)
Φ_2	−0.0022** (0.0001)
Adj. R^2	0.79
Mountain states (eight states)	
Φ_1	0.0112** (0.0026)
Φ_2	0.0007** (0.0001)
Adj. R^2	0.40
Northeast (five states)	
Φ_1	0.0190** (0.0016)
Φ_2	−0.0001 (0.0007)
Adj. R^2	0.01
Northern plains (four states)	
Φ_1	0.0190** (0.0065)
Φ_2	−0.0003 (0.0003)
Adj. R^2	0.01
Pacific states (three states)	
Φ_1	0.0131 (0.0001)
Φ_2	−0.0000 (0.0000)
Adj. R^2	−0.02
Southern plains (two states)	
Φ_1	0.0001 (0.0007)
Φ_2	0.0001** (0.0000)
Adj. R^2	0.23
Southeast (four states)	
Φ_1	0.0356** (0.0039)
Φ_2	0.0001 (0.0001)
Adj. R^2	−0.01

* and ** denote significant at 5% and 1% level, respectively.

indicates divergence among the states within the cluster.

Human Capital

Human capital has been described as the contributor of growth in Mankiw, Romer, and Weil (1992), Lucas (1988), and Schultz (1961). Recent researches on total factor productivity convergence are emphasizing the needs for considering human capital as a factor of growth. For example, Miller and Upadhyay (2002) found that human capital has a significant impact on output when it is included as a factor of production. Human capital, when considered as an input, lowers the labor elasticity of output when compared with the production function without human capital. Similar findings were

Table 7. Cluster of States Used in the Convergence Check (10 clusters)

Cluster	Based on McCunn and Huffman (2000)	Based on Cluster Analysis		
		Cluster	42 States	48 States
1	NY, NJ, PA, DE, MD	1	9: AL, LA, MD, MI, MS, NM, OH, TN, VA	1: WV
2	MI, MN, WI	2	14: AR, CO, ID, IL, IN, KS, KY, MN, NE, NY, OR, PA, SC, SD	4: MA, NJ, RI, PA
3	OH, IN, IL, IA, MO	3	7: AZ, MO, NJ, NV, OK, TX, UT	12: TX, UT, VA, OK, TN, LA, NH, NM, NV, MD, MO, AZ
4	ND, SD, NE, KS	4	3: CA, DE, WA	2: WY, MT
5	VA, WV, KY, NC, TN	5	1: WV	13: AR, VT, WI, OR, SD, NE, NY, MN, ME, IL, KS, KY, CO
6	SC, GA, FL, AL	6	2: WY, MT	3: NC, ID, CT
7	MS, AR, LA	7	1: FL	7: AL, OH, SC, ND, MI, MS, IN
8	OK, TX	8	2: GA, NC	1: FL
9	MT, ID, WY, CO, NM, AZ, UT, NV	9	2: IA, WI	4: WA, GA, CA, DE
10	WA, OR, CA	10	1: ND	1: IA

shown in a study by Coulombe and Tremblay (2003). Their analysis indicated that in an open economy with perfect capital mobility, the dynamics of human capital accumulation is the driving force behind the economic growth. According to them, in the process of convergence, physical capital accumulation is driven by accumulation of human capital and per capita income disparities across economies are explained by disparities in human capital stock. Their results indicated that advance education indicator (human capital) explains roughly 70% of the relative evolution of per-capita income since 1951 across the Canadian provinces. Similarly, Maudos, Pastor, and Serrano (1999) had developed Malmquist indices of productivity including human capital as an additional input. Their results indicated the existence of a significant effect associated with human capital and its importance for an accurate measurement of TFP.

We take these results as our guide and explore if human capital can describe the disparities in agricultural total factor productivity differences over time across states as seen above in our result. The following panel data formulation is used to explore the relationship between human capital and total factor productivity in both parametric and nonparametric specifications

$$(13) \qquad TFP_{it} = f(H_{itk}) + u_{it}$$

Here, TFP is total agricultural factor productivity, H is human capital, u is error term. If the functional form $f(H)$ is specified, it is a parametric model. Our parametric model has linear specification between TFP and H. The number of states and time period for the data are appropriately recognized. We estimated fixed effects and random effects models in parametric specifications. In addition to parametric model, we also estimated Equation (13) using a nonparametric approach. Estimation results are compared with original data using a graphical approach.

The results from the panel data model are shown in Table 9. We estimated one-way fixed effects and two-ways fixed effects models. In the one-way fixed effects model, we assumed that agricultural productivity differences are caused by state heterogeneity in human capital. The result from the fixed effect model indicates that human capital does play a significant role in determining the total factor productivity. The coefficient associated with human capital in this model is significant at a level of 1%. R^2 from the

Table 8. Assessing Convergence among States Based on 10 Clusters

42 States		48 States	
Cluster 1	Estimates (standard error)	Cluster 2	Estimates (standard error)
Φ_1	0.0078** (0.0006)	Φ_1	0.0039** (0.0018)
Φ_2	−0.0000 (0.0000)	Φ_2	0.0001 (0.0018)
Adj. R^2	0.27	Adj. R^2	0.04
Cluster 2		Cluster 3	
Φ_1	0.0083** (0.0008)	Φ_1	0.0105** (0.0010)
Φ_2	−0.0001 (0.0000)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.27	Adj. R^2	0.27
Cluster 3		Cluster 4	
Φ_1	0.0063** (0.0001)	Φ_1	0.0105** (0.0010)
Φ_2	0.0000 (0.0000)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.27	Adj. R^2	0.27
Cluster 4		Cluster 5	
Φ_1	0.0034** (0.0008)	Φ_1	0.0105** (0.0010)
Φ_2	0.0000 (0.0000)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.27	Adj. R^2	0.27
Cluster 6		Cluster 6	
Φ_1	−0.0021 (2.2849)	Φ_1	0.0105** (0.0010)
Φ_2	0.0004** (0.0001)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.27	Adj. R^2	0.27
Cluster 8		Cluster 8	
Φ_1	0.0074** (0.0014)	Φ_1	0.0074** (0.0014)
Φ_2	−0.0001 (0.0000)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.10	Adj. R^2	0.10
Cluster 9		Cluster 9	
Φ_1	−0.0008 (0.0009)	Φ_1	0.0074** (0.0014)
Φ_2	0.0001** (0.0000)	Φ_2	−0.0001 (0.0000)
Adj. R^2	0.10	Adj. R^2	0.10

Note: For states within each cluster, refer to Table 2.
* and ** denote significant at 5% and 1% level, respectively.

model is 97% indicating that human capital is able to explain most of the difference in productivity difference. Hausman's test indicated that we failed to reject the state level homogeneity in agricultural total factor productivity. The coefficients associated with each state were found to be significant. The highest coefficient is associated with the state of Florida. The results from the two way fixed effects model indicated similar results, but the coefficient associated with human capital is found to be insignificant. Hausman's test statistics rejected the homogeneity of the state specific parameters in the model. Results from the random effects models (both one-way and two-way) also show the coefficient associated with human capital to be significant. The M-test indicates that we were unable to reject the presence of random effects in the models.

In the absence of any assumption related to functional form between total factor productivity and human capital, we should estimate the nonparametric model. The nonparametric model showed that a smoothing parameter value equaling to 0.809 should be used to study the relationship. Figure 1 shows the prediction using the nonparametric model. The figure also shows the 90% confidence interval of the predicted value. The nonparametric model has a better fit as indicated by the residual sum of square from the prediction model. Both parametric and nonparametric models thus show the correlation of human capital with the productivity.

Conclusions

The study tested the evidence of total factor productivity convergence in the United States' agriculture sector using a state level panel data. The empirical investigation carried out in this paper did not find any evidence of convergence while looking at the U.S. state-level agricultural TFP at aggregate level. However, we did find the support for convergence within some of the clusters or within some of the regions. The *ad hoc* groupings of states are modified using a cluster analysis approach. Cluster analysis resulted in entirely different sets of states than the grouping done by McCunn and Huffman (2000), although convergence in the regional level (cluster) did not

Table 9. Effect of Human Capital on Total Factor Productivity in U.S. Agriculture

Dependent Variable	One-Way Fixed Effects	Two-Way Fixed Effects	One-Way Random Effects	Two-Way Random Effects
Human Capital Index	3.02**	−0.21	0.78**	0.70**
	(0.23)	(0.22)	(0.02)	(0.06)
F-value or M-value	5.26*	25.94*	93.89**	11.65**
R-square	0.98	0.99	0.82	0.36

* and ** denote significant at 5% and 1%, respectively.

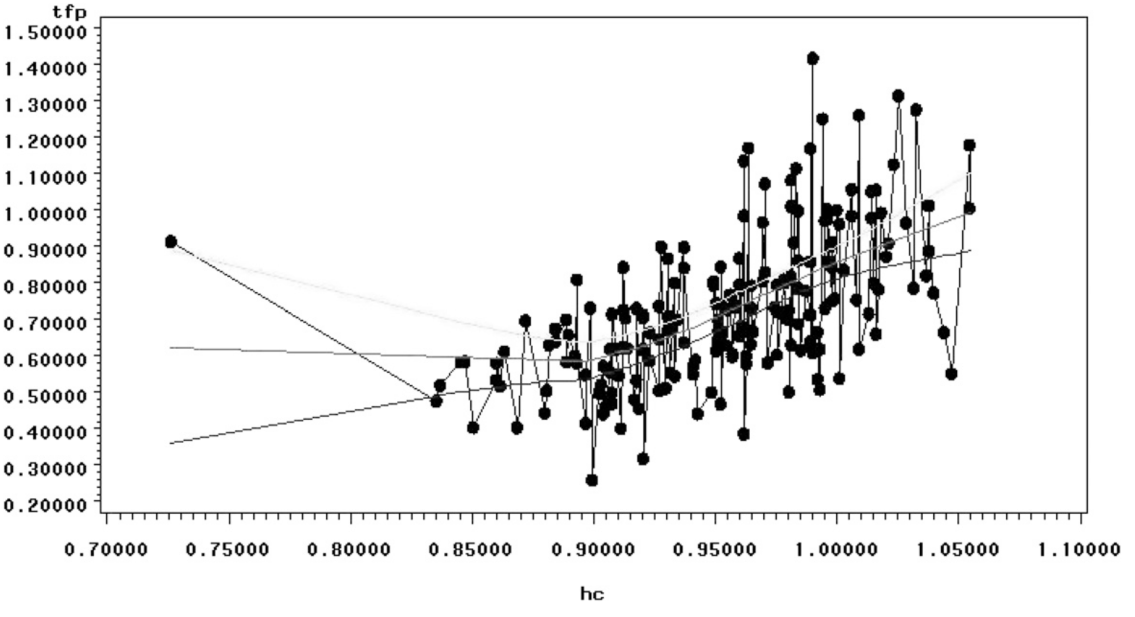

Figure 1. Prediction of Total Factor Productivity in Agriculture as a Function of Human Capital Index Using a Nonparametric Regression (Note: middle line is the predicted value, upper line is the upper confidence interval and lower line is the lower confidence interval)

improve significantly compared with the findings of McCunn and Huffman (2000).

An attempt to explain agricultural productivity differences across states with human capital in both parametric and nonparametric models support the idea that a higher human capital index means higher agricultural productivity. This finding is consistent with earlier findings in the human capital model describing it as a determining factor for regional differences in growth and economic development.

The implication for policymakers of this study is twofold: one is that there is indeed some degree of divergence in total factor productivity; and that the total factor productivity can be explained to some extent by human capital accumulation. If we are bothered by the implication of divergence, then we should invest in human capital accumulation in each state or region. These can be done directly, by investing in those institutions, or indirectly, by encouraging people from those regions to acquire more human capital. What is the better way — subsidizing training of individuals or investing directly in institutions within those states — can be the subject of further research.

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