School of Economic Sciences

Working Paper Series
WP 2008-4

Productivity Growth and Convergence in U.S. Agriculture: New Cointegration Panel Data Results

By

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2008

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Abstract

Dynamic effects of health and inter-state and inter-industry knowledge spillovers, total factor productivity (TFP) growth and convergence in U.S. agriculture are examined using recently developed procedures for panel data and a growth accounting model. Strong evidence is found to support the hypothesis that TFP converges to a steady-state. Health care supply in rural areas and research spillovers from other states and from nonagricultural sectors are found to have significant impacts on the productivity growth rate both in the short-run and long-run. These results suggest richer opportunities for policymakers to enhance productivity growth.

Key words: convergence, growth, pooled mean group estimator, total factor productivity

JEL codes: O30, D24

Productivity Convergence in U.S. Agriculture:

New Cointegration Panel Data Results

"Given limited resources, productivity growth is the only way to sustain and increase standards of living." (Acs, Morck, and Yeung 1999, p. 367) Yet, agricultural productivity and productivity growth varies greatly among countries and regions (Kawagoe, Hayami, and Ruttan 1988; Rao 1993; Gutierrez 2000). Even in the U.S., although every state has exhibited a positive growth rate in agricultural productivity for many decades, considerable variability of total factor productivity (TFP) growth has occurred among them. For example, during the period 1960-1999, the average annual TFP growth rate ranged from 0.73% for Oklahoma to 2.59% for Michigan (Ball, Hallahan, and Nehring 2004). The high variability of productivity and productivity growth among states has important public policy ramifications. Policy makers need answers to such diverse questions as: Does TFP converge or diverge for states in the U.S.? How should limited resources be allocated among the important drivers of productivity growth to best improve TFP? How do investments in health, education, research, and extension affect productivity growth both in the short-run and in the long-run? A systematic analysis of the impact of these major variables on productivity growth performance is central to answering these questions.

A major focus of empirical research on productivity growth has been to quantify the impact of important drivers such as research and development (R&D) (e.g., Huffman and Evenson 1992; Alston, Craig, and Pardey 1998; McCunn and Huffman 2000), human capital (e.g., Huffman and Evenson 1992; Makki, Tweeten, and Thraen 1999; McCunn and Huffman 2000; Yee *et al*. 2002; Yee, Ahearn, and Huffman 2004), and farm size (e.g. Berry and Cline 1979; Carter 1984; Weersink and Tauer 1991; Barrett 1996; Thirtle, Schimmelpfennig, and Townsend 2004). A stylized fact has emerged from both theoretical and empirical work that public agricultural research, public extension (outreach), and education have significantly positive impacts on productivity growth. In addition, a positive relationship has generally been found between farm size and agricultural productivity in developed countries (e.g., Weersink and Tauer 1991; Thirtle, Schimmelpfennig, and Townsend 2004) and a negative relationship in developing countries (Berry and Cline 1979; Carter 1984; Barrett 1996).

Despite the considerable amount of research that has focused on agricultural productivity, relatively little has attempted to determine whether regional differences tend to narrow or widen over time and what contributes to those changes (e.g., Ball, Hallahan, and Nehring 2004; McCunn and Huffman 2000; Gutierrez 2000). Yet, the issue of convergence or divergence of productivity has important policy ramifications for regional poverty reduction and increasing standards of living. For example, if productivity converges to a common level without intervention, there is little need for explicit policies in lagging states to promote catch up. If, on the other hand, convergence is conditional on institutions, then explicit policies would be needed to prevent further lagging of TFP and standard of living.

In addition, there are several modeling deficiencies in the *extant* literature on agricultural productivity. These include the narrow definition of human capital, failure to consider private innovation spillovers in productivity convergence tests, and inadequate estimation methods.

One example of this shortcoming is that, despite evidence that human capital is a central driver of productivity growth, nearly all previous literature has relied on schooling as the sole measure of human capital. Although health has been recognized as a major influence on the accumulation of human capital (Barro 1998), its role in agricultural productivity growth has been largely ignored. Yet, by increasing productivity of human resources, improved health can be expected to accelerate accumulations of both human and physical capital and thus advance sectoral productivity and standard of living (Bhargava *et al*. 2001).

In addition, the impact of geographic and sectoral spillovers of private innovation on agricultural productivity convergence has not been explored. Because innovation is at least partly a public good, productivity growth is conditional not only on an entity's own innovation efforts but also on the innovation efforts of others (Griliches 1992; Coe and Helpman 1995; Fung 2005).[1] While the spillover effects of agricultural research on agricultural productivity growth has received some attention (e.g. Huffman and Evenson 1992; McCunn and Huffman 2000; Yee *et al.* 2002), spillovers from privately funded innovations have not been considered in any of the convergence tests. Failure to consider these spillovers could result in incorrect convergence test conclusions and biased estimates of the contributions of other drivers to productivity growth.

[1] Innovation is only partly a public good. It is largely non-rival in consumption, but because of patents, it may not satisfy the non-excludability condition for a public good. Innovation from public research is generally regarded as more of a public good, but changes in patent law over the last 25 years have permitted public entities to also patent their discoveries.

Further, the estimation methods previously used to examine agricultural productivity growth and productivity convergence have important weaknesses that could produce misleading results. Although panel data, with their important advantages over cross-sectional or time-series data, have been used to examine agricultural productivity growth and convergence hypotheses, no previous study, to our knowledge, has accounted for the dynamics of the adjustment process.

The objectives of this paper are to correct past weaknesses by testing three productivity convergence hypotheses and by examining the impacts of major drivers of productivity growth in U.S. agriculture. We pursue these objectives in ways that achieve greater reliability in the estimation and thus advance the literature in two ways. First, the paper measures the impact of health capital (proxied by health care supply in rural areas) and private R&D spillovers (both inter-state and inter-industry) on agricultural productivity growth in each of the contiguous 48 states. Second, improved panel estimation procedures are employed that permit more reliable examination of the dynamic effects of policy variables on productivity growth.[2]

The paper is organized as follows. Section I gives a brief overview of the theoretical concepts of productivity growth and introduces the panel testing and estimation techniques. Data are described in Section II. That is followed in Section III by the empirical results which include the time series properties of the data, tests of three convergence hypotheses, and findings about the importance of various determinants of productivity growth. Section IV summarizes our main findings and offers conclusions.

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[2] In addition to human capital and R&D spillovers, this paper also examines the impact on agricultural productivity growth of average farm size and selected policy variables, including investments within the state on public and private R&D and public extension.

I. Method of Analysis

Two primary concepts have been used to measure convergence of productivity across countries or regions. The first notion, σ-convergence, considers whether the dispersion of TFP among countries or regions diminishes over time. The second, β-convergence, considers whether a steady-state TFP level exists for each geographic unit, i.e., whether the correlation between a state's initial TFP level and its subsequent growth in TFP is negative. Although β-convergence is a necessary condition for σ-convergence, it is not a sufficient condition because β-convergence could occur by states with lower initial TFP growing at such rapid rates that they have higher TFP at a later period than states with higher initial TFP. In such a case, cross-sectional variance in TFP (or σ-convergence) may not occur (Quah 1993; Sala-i-Martin 1996; Bernard and Jones 1996). The existence of β-convergence implies a long-term catch-up mechanism which causes productivity differences to narrow across regions over time. However, this mechanism can be offset by temporary shocks which adversely (or favorably) impact short-run dispersion. As a result, β-convergence may not be fully reflected in changes of the dispersion of productivity levels (Barro, 1997).

Theoretical Models

To test for σ-convergence, we use changes in the variance across states to measure changes in TFP dispersion. Following Sala-i-Martin (1996), the basic model is defined as follows:

(1) $$\mathrm{var}_t(\ln \mathrm{G}) = \alpha_1 + \alpha_2 t + \varepsilon_t$$

where G is TFP, $\mathrm{var}_t(\ln \mathrm{G})$ is across-states variance of the logarithm of TFP in period t, α are parameters, and ε is a zero-mean random disturbance term. A significantly negative coefficient associated with the time variable t, i.e., $\alpha_2 < 0$, implies σ-convergence.

In the economic growth literature, two different tests of β-convergence have been developed. The first, known as absolute β-convergence, is implemented in this study to examine whether agriculture in the 48 contiguous U.S. states converge to the same steady-state TFP level in the long-run regardless of their initial TFP. A presumption of this type of convergence is that the only difference among the states is their initial TFP, which is eliminated over time regardless of their initial technologies, preferences and institutions (Sala-i-Martin 1996; Gutierrez 2000; Fung 2005).

The second, conditional β-convergence, tests whether each state converges to a unique steady-state TFP level when taking into account different technologies, preferences and/or institutions. The intuition behind conditional β-convergence is that TFP is driven by conditional variables (state-specific factors) that are at least partially under the control of local public and private decision makers and thus influence the growth endogenously. Absolute β-convergence does not imply conditional β-convergence, nor do tests of absolute β-convergence facilitate examination of the impact of productivity drivers that could lead to differences in state-specific steady-state TFPs. Consequently, a systematic analysis of the impact of major drivers on productivity growth require empirical testing of conditional β-convergence whether or not absolute β-convergence is rejected.

Following Fung (2005), we test absolute β-convergence based on the following model:

(2) $$g_i^A = \ln \tilde{G}_i - \ln G_i^0 = \beta_1 + \beta_2 \ln G_i^0 + \varepsilon_i^A ,$$

where g_i^A denotes TFP growth in state i between the initial and final periods; G_i^0 and $\tilde{G}_i$ are TFP in the initial and final periods, respectively, for state i, and the β_i are parameters. Testing for absolute β-convergence is equivalent to testing whether the growth rate of TFP is negatively related to the productivity level in the initial period. A significant negative coefficient associated with G_i^0, i.e., $\beta_2 < 0$, implies absolute β-convergence. If this hypothesis is not rejected, we conclude that all states converge to a common steady-state regardless of initial state-specific technologies, preferences, and institutions. To reduce random noise, we define t = 1 to $t = s$ as the initial time period, and $t = T- s + 1$ to $t = T$ as the final period; s is total length of both time periods. Thus, $G_i^0 = \sum_{t=1}^{s} G_{it} / s$ and $\tilde{G}_i = \sum_{t=T-s+1}^{T} G_{it} / s$.

Testing conditional β-convergence is based on the following dynamic growth model:[3]

(3) $\ln G_{i,t} = \mu_i + \phi_i \ln G_{i,t-1} + \delta_i' X_{i,t} + \varepsilon_{i,t}$

where $G_{i,t}$ denotes state i's TFP at time t; X is a vector of hypothesized determinants of TFP and includes farmer average education level (*Edu*), average health care supply level in rural areas (*Hs*), average farm size (*Fs*), public agricultural research investments (*Rpub*), private agricultural research investments (*Rpri*), public extension investments (*Ext*), public agricultural research spillovers (*PubSpill*), private agricultural research spillovers (*PriSpill*), and inter-sector private research spillovers (*InterSpill*); μ, ϕ, and δ are parameters. Since research and extension investments can affect productivity growth several years later, we use Akaike's Information Criterion (AIC) to determine the optimal number of lags on public and private agricultural

[3] A dummy variable is also included in the estimation equation to account for the impact of the 1983, one-year, U.S. Department of Agriculture payment-in kind (PIK) program.

research investment and public agricultural extension.

By subtracting ln $G_{i,t-1}$ from both sides of equation (4), we obtain the error correction model (ECM):[4]

$$(4) \quad \Delta \ln G_{i,t} = \mu_i + \lambda_i [\ln G_{i,t-1} + (\delta_i' / \lambda_i) X_{i,t}] + \varepsilon_{i,t}$$

where Δ represents first difference, $\lambda = \phi - 1$ which directly measures the speed of convergence toward a state-specific steady-state. A significant estimate of λ with a value less than 0 and greater than -2 implies conditional β-convergence.

Estimation and Testing Procedures

When testing for conditional β-convergence, we first examine the time series properties of each variable involved in the conditional growth model, equation (3). The low power of traditional tests for unit roots in small and moderate sized samples can lead to misleading results, but greater power can now be achieved using recent developments in panel unit root and cointegration test procedures (Hadri 2000; Pedroni 1999).

To test for stationarity, we apply the panel data procedure developed by Hadri (2000) which tests the null hypothesis that all the individual series are stationary around a deterministic level or around a deterministic trend against the alternative of a unit root. Hadri's unit root statistic is a residual-based Lagrange multiplier (LM) statistic. It can be developed by considering the following regression:

$$(5) \quad y_{it} = x_{it}'\beta + r_{it} + \varepsilon_{it}$$

where y_{it} is a time series, ε_{it} is a stationary process, x_{it} is the deterministic component, r_{it} is the

[4] Before estimating the ECM, we first conduct stationarity and cointegration tests for all variables in the equation.

stochastic component defined as $r_{it} = r_{it-1} + u_{it}$, and u_{it} is independently and identically distributed with variance σ_u^2. Using backward substitution, equation (5) can be rewritten as:

$$(6) \qquad y_{it} = x'_{it}\beta + e_{it}$$

where $e_{it} = \sum_{j=1}^{t} u_{ij} + \varepsilon_{it}$. From equation (6), the estimated variance of the error, denoted $\hat{\sigma}_e^2$, can be obtained as:

$$(7) \qquad \hat{\sigma}_e^2 = \frac{1}{NT}\sum_{i}^{N}\sum_{t=1}^{T}\hat{e}_{it}^2$$

where $\hat{e}_{it}$ is the estimated residual, T is the number of time periods, and N is the number of cross-sectional units. Hadri (2000) computes the LM statistic as:

$$(8) \qquad LM = \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T}S_{it}^2}{\hat{\sigma}_e^2}$$

where $S_{it} = \sum_{j=1}^{t}\hat{e}_{ij}$ is the partial sum of the residuals. With large T and N and adjusted by appropriate constants obtained from the moments of the underlying Brownian motion functions, the LM is distributed as standard normal under the hull hypothesis of stationarity. A large positive value of this statistic implies rejection of the null hypothesis of stationarity in the panel.

The second time-series step is to test panel cointegration for linear combinations of non-stationary variables. We test the hypothesis of cointegration by employing Pedroni's (1999) cointegration tests, which allow coefficients (cointegration vectors) to vary across units and includes individual fixed effects and time trends. This test is considerably more powerful than conventional methods. Pedroni calculates seven test statistics that are asymptotically normally distributed under the null hypothesis

$$(9) \qquad \frac{Z_{N,T} - \mu\sqrt{N}}{\sqrt{V}} \overset{a}{\sim} N(0,1)$$

where $Z_{N,T}$ is the statistic, and μ and V are the adjustment terms obtained from the moments of the underlying Brownian motion functions.[5]

Estimation issues have gained much attention in dynamic panel data growth models because heterogeneity in the intercepts or in slope coefficients can produce inconsistent estimates of convergence speed (Lee, Pesaran, and Smith 1997). This inconsistency can't be eliminated asymptotically (Lee, Pesaran, and Smith 1997). To address this inconsistency problem, we apply the pooled mean group estimator (PMGE) developed by Pesaran, Shin, and Smith (1999). This estimator presumes weak homogeneity by constraining the long-run slope coefficients to be identical across groups but it allows the short-run coefficients and error variances to vary across groups. The ability to estimate group-specific, short-run coefficients with long-run homogeneity restrictions across groups is the main advantage of using this newer methodology on models such as (3) and (4) with dynamic panels. The logic for expecting the long-run relationship among variables to be similar across all states is that they have access to similar financial markets and technology influences (Pesaran, Shin, and Smith 1999).

II. Data and Variables

[5] The critical values of these test statistics are tabulated in Pedroni (1999, table 2) for up to seven explanatory variables. Because we use nine explanatory variables, the adjustment terms for the panel cointegration tests were obtained as suggested by Pedroni (1999) using Monte Carlo simulation . Following his approach, we took 10,000 draws of nine independent random walks (i.e., the number of regressors) so T=10,000. Under the alternative hypothesis, all the statistics diverge to negative infinity (one to positive infinity). Therefore, each is a one-sided test for which a large positive value for the "panel v statistic" or a large negative value for the other tests results in rejection of the null hypothesis of no cointegrated relation among the variables.

The indexes of TFP for each of the contiguous 48 states for the period 1960-1999 were computed by Ball, Hallahan, and Nehring (2004) as the ratio of output to an index of land, capital, labor, and materials inputs. The comprehensive inventory of agricultural output and input quantities was compiled using theoretically and empirically sound procedures consistent with a gross output model of production and quality-adjusted input flows (see Ball *et al*. 1999 for details).

Deflated annual agricultural public research investment data for the period 1927-1995 for each state were compiled by Huffman (2005). Agricultural extension investments for the U.S. for the period 1951-1996 were from Huffman, Ahearn, and Yee (2005). They are total cooperative extension investments in current dollars deflated by the price index for agricultural research.

Average farm size for each state was measured as the average gross value of farm assets for each state. This measure of farm size is preferred since it captures not only the gross value of product but also the productive capacity of a farm.[6] It was computed for each year as the total gross value of farm assets reported for the state divided by the number of farms. Farm asset data for the years 1960-1999 were taken from the *Farm Balance Sheets* (USDA/ERS 1960-2003). Farm numbers for the same years were taken from *Farms, Land in Farms, & Livestock Operations* (and its predecessor publication) (USDA/NASS 1960-2005).

[6] There are various other ways to measure farm size, e.g., acreage or gross value of sales or product. Although these traditional ways are easy to quantify, acreage does not account for differences in the productive capacity of the land input (Yee and Ahearn 2005), and gross value of sales is an output measure rather than an input capacity measure.

Farmers' education level was approximated by the weighted average of weekly working hours across various education levels and types of employment for each state. We constructed this index using demographically cross-classified weekly data on hours worked, where hours of work were classified by gender, age, education and employment types (including hired and self-employed workers). The data on hours worked, gender, age, education index, and employment types by employment category were from Ball (2005). Because education level was one of the variables used by Ball to account for quality differences in the labor series following the procedures of Jorgenson, Gollop, and Fraumeni (1987), inclusion of this variable as a separate regressor in the model is designed to pick up the residual effect of education not imbedded in the labor quality adjustment.

Without data on the health status of farm workers, we used a proxy of health care supply (*Hs*) measured by the total number of medical doctors (MDs) per 10,000 population in rural counties of each state. County-level data on the number of MDs and population for the years 1960, 1970, 1975, 1980-1983, 1985, 1986, 1988-1990, 1992-2004 were from the Bureau of Health Professions/National Center for Health Workforce Analysis. Rural counties in each state were identified using Urban Influence Codes developed by USDA/ERS (2003) which divide counties into metropolitan counties and non-metropolitan (rural) counties. A cubic interpolation algorithm was used to approximate missing values. This interpolation technique is generally more accurate than other methods such as linear interpolation (Maeland 1988). In this technique, all of the knots (known observations) are required to define all the polynomials that make up the entire curve rather than only using the neighboring knots to define piecewise interpolated curves as in the linear interpolation and double parabolic interpolation methods. Thus, using this technique allows us to fully use the information incorporated in the available observations.

Agricultural private research investments and inter-state and inter-industry knowledge spillovers for each state were proxied by the number of state-level patents. The data were from Johnson's (2005) inventory of patents by state and by industry for the period 1883-1996. His inventory included two industry partitions – one representing the innovation's industry of manufacture and the other the innovation's primary sector of use. Before 1976, the patents were classified using the Wellesley Technology Concordance. Since 1976, Johnson's patent classification followed the international protocol. The Yale Technology Concordance (Johnson and Evenson 1997) was used to calculate industries of manufacture and sectors of use. The panel data set on agricultural private research was prepared by multiplying the percent of patents granted by state each year by the number of patents granted for use in the agricultural sector.

The spillovers of private agricultural research in state *i* were computed by subtracting the number of patents granted for use in agriculture in the state from the total number of patents granted for use in agriculture in all states in the associated ERS region. The states were grouped into 10 ERS regions (McCunn and Huffman 2000): Northeast, Lake States, Corn Belt, Northern Plains, Appalachia, Southeast, Delta States, Southern Plains, Mountain States, and Pacific States.

The inter-industry spillovers of private agricultural research were computed by subtracting the number of patents granted for agriculture as the innovation's industry of manufacture from the number of patents granted for the innovation's use by the agricultural sector by state for each year. Because the effects of private research investments are partially reflected in the quality and prices of inputs used in the sector, inclusion of these private research variables are expected to pick up the residual effects of such investments.

The spillovers of public agricultural research in state *i* were computed by subtracting the state's public research investments from the sum of the public research investments for all states in the associated ERS region.

III. Empirical Results

In this section we present the results of the three convergence hypothesis tests and draw inferences about the primary productivity drivers for the contiguous 48 states. We start by testing for σ-convergence and absolute β-convergence. We then examine the time series properties of the variables included in the conditional TFP growth model, as well as their implications for estimation procedures. The time series properties are followed by estimates of the conditional TFP growth model, test of conditional β-convergence, and further investigation of the role of policies on productivity growth. A 5% significance level is used for all test conclusions.

The results for the σ-convergence test are presented in table 1. This hypothesis (that the dispersion of TFP across states diminishes over time) was rejected since the coefficient on the time variable *t* is not significantly different from zero. This finding is consistent with McCunn and Huffman (2000) and Gutierrez (2000). A common explanation for rejection of this hypothesis is that σ-convergence is sensitive to temporary shocks. In the agricultural sector, these could include fluctuation of such variables as demands, disease, or weather conditions.

Before testing for absolute β-convergence (that all states converge to the same steady-state TFP level), we allowed for different time lags between the beginning and final time periods to reduce effects of random noise. We chose three cases with starting periods, $t = 1,\ldots,s$, with s set at 3, 5, and 10 respectively. The results are reported in table 2. The estimated coefficient associated with initial TFP ($\ln(G_i^0)$) was significantly negative for all three cases. These findings strongly support the hypothesis that agricultural TFP converges toward a common steady-state level for the 48 contiguous U.S. states regardless of their initial technologies, preferences, and institutions. Our support for absolute β-convergence is in line with the partial productivity results of Gutierrez (2000) who found that agricultural labor productivity converged to a common steady-state for all U.S. states during the period 1970-1992.

We next addressed the primary questions raised in this paper by testing the hypothesis of conditional β-convergence and by examining the impacts of crucial policies on productivity growth. To do so validly requires time series properties of the data to be tested and, depending on findings, estimating an error correction model to test for conditional β-convergence.

We first tested for stationarity in each time series involved in the conditional productivity growth model defined in equation (3). The Hadri panel stationarity test statistics are reported in table 3. The null hypothesis of stationarity was rejected in levels for each series. When tested in differenced data, six of the series are found to be stationary in 1st differences and four in 2nd differences. Consequently, we conclude that $\ln(G)$, $\ln(Edu)$, $\ln(Hs)$, $\ln(Rpub)$, ln(*InterSpill*), and ln(*RpubSpill*) are integrated of order 1, I(1), and ln(*Rpri*), ln(*Ext*), ln(*Fs*), and ln(*RpriSpill*) are integrated of order two, I(2). Intuitively, existence of a unit root or rejection of stationarity in the TFP variable indicates persistence of shocks, which provides further evidence why σ-convergence was not found in U.S. agriculture.

Before conducting the cointegration test, optimal lag lengths of innovation investments had to be determined since investments in innovation may not affect technology, or the nature of the production function, for at least seven years and perhaps as long as 30 years (Chavas and Cox 1992; Pardey and Craig 1989). Akaike's information criterion (AIC) was used to determine optimal lags on extension and on public and private research investments. The optimal lag on public research investments was chosen from lags of 7-30 years. The optimal lag on private research investments was chosen from lags of 3-23 years.[7] Because of the more limited length of the data series, the optimal lag on extension investments was chosen from lags of 3-9 years. The AIC was minimized at a lag length of 25 years for public research investments, 15 for private research investments, and 7 for extension investments.[8] The optimal lag lengths for public and private research were also applied to the corresponding spillovers.

Table 4 reports the cointegration test results. Based on consistency among six of the seven test statistics, the hypothesis of no cointegration was rejected. Existence of cointegration implies that a long-run relationship exists between TFP and its determinants.

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[7] Applying a nonparametric approach, Chavas and Cox (1992) found that the effects of private research on U.S. agricultural production increased slowly in the first 7 years, increased rapidly in the next 8 years, then decreased, with no effects beyond 23 years.

[8] These lag lengths are similar to those found by Liu and Shumway (forthcoming), Liu and Shumway (2006), Thirtle et al. (2002), and Makki et al. (1999).

Having found a cointegrated relationship among the series, we next estimated the error correction representation, equation (4), of the conditional growth model. To capture the long-run relationships in the data, the conditional growth model can be formulated using first-differenced data for I(2) variables and original data for I(1) variables. Thus, the dynamic model specified in (4) was modified by replacing ln(*Rpri*), ln(*Ext*), ln(*RpriSpill*), and ln(*Fs*) with their 1st differences. In addition to equation (4) (hereafter ECM I), another error correction model (hereafter ECM II) was estimated to capture the dynamic effects of exogenous shocks by including the 2nd differenced terms on $X_{i,t}$.[9]

The Pesaran PMG estimates for both models are reported in table 5.[10] The error correction coefficient (λ) (i.e., the coefficient on the variable $\ln(G_{i,t-1})$) was negative and significant in both models. The significantly negative error correction coefficient results in support for (nonrejection of) the hypothesis of conditional β-convergence. Even with shocks to the system, each state was found to adjust toward a state-specific steady-state.

The finding of β-convergence in U.S. agricultural productivity is consistent with some of the previous literature. For example, consistent with TFP β-convergence, Ball, Hallahan, and Nehring (2004) found evidence for technology catch up in the contiguous 48 states. McCunn and Huffman's (2000) supported the hypothesis of conditional β-convergence in 42 states for the period 1950-1982.

Results show that the convergence speed measured by λ was insensitive to the dynamic

[9] For I(2) variables, third differences were included.

[10] These estimates were computed using a GAUSS program by Pesaran, Shin, and Smith.

effects of exogenous shocks. In the ECM II model that considers dynamic short-run effects, the estimated value of λ (-0.44) was similar to that of the ECM I model (-0.41). This convergence coefficient measures the speed at which the system moves back to the steady-state growth path after an exogenous shock and the speed at which the productivity gap diminishes.[11] Our estimates of convergence speed are considerably higher than those estimated by McCunn and Huffman (2000) (2.8%) and Gutierrez (2000) (1.8%) for U.S. agriculture, perhaps due to our improved model specification.[12] They are closer to prior estimates in other countries than in the U.S. For example, Bernard and Jones (1996) estimated a 21% convergence speed for OECD agriculture, and Martin and Mitra (2001) estimated a 10% convergence speed for agriculture in a wide range of countries.

Table 5 also provides a number of important insights about sources of productivity growth. Of particular note, the results from both models show that rural health care supply and publicly funded research and extension have significantly positive impacts on TFP growth rates both in the short-run and long-run.[13]

Since improved health accelerates human capital accumulation and advances technical

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[11] Although the average convergence speed exceeds 40%, it exhibits high volatility across the 48 states. For example, the state-specific convergence speed (not reported here) estimated from ECM II ranges from a low of 10% for Connecticut to a high of 105% for South Carolina. Intuitively, Connecticut is the state relatively closest to its steady-state while South Carolina is furthest away from its steady-state.

[12] Our study advances previous studies in three ways. First, our model accounts for data nonstationarity and cointegration relationships using more reliable test procedures. Second, the effects of the policy variables are assessed within a dynamic panel data framework. Third, we consider the impacts of health care supply and inter-state and inter-industry innovation spillovers.

[13] However, the long-run impact of an increase in public extension investments is insignificant in the presence of dynamic impacts from exogenous shocks (ECM II).

progress, states with higher health levels would be expected to grow faster at each particular point of time and to end up with a higher steady-state agricultural TFP growth rate. We find that expectation strongly supported by the consistently positive estimated relationship in both the short- and long-run between health care supply (proxied by the number of medical doctors per 10,000 population in rural counties) and productivity.

The results imply that increased investments in public research by states with lagging productivity will facilitate their narrowing the gap with the productivity leaders in the long-run. Further, significantly positive short-run and long-run coefficients on public research spillovers indicate that assimilating public knowledge spillovers from other states also augments a state's TFP growth rate. Therefore, productivity-lagging states are able to grow faster both by investing more in public research and extension and by exploiting public innovation spillovers from other states in their region. As a result of both, their TFPs will tend to converge.

Because it takes into account short-run dynamic effects of exogenous shocks, the ECM II is the more realistic model and its results are particularly informative. In this model, all variables except farm size and public extension had a significant long-run impact on agricultural productivity. Of particular note, this finding applied even to private research investments and farmers' education, the effects of which were already partially embodied in the quality-adjusted data used in the analysis. In addition, their short-run dynamic effects amplified the residual effects of these variables. Other results of particular note include the significantly positive impact of private spillovers along with the significantly negative impact of private research investments on TFP growth both in the long-run and in the short-run. However, the payoffs from the former were larger than the latter in both cases and show an overall positive residual impact of private research investments on short-run and long-run TFP growth.[14]

Although a productivity-lagging state can grow more rapidly by efforts to capture the positive externality from publicly and privately funded research in other states, it is unlikely they can catch up by relying solely on these public good effects. As the productivity-lagging states approach that of the leader, significant amounts of their own research investments aimed at creating innovations are necessary for further growth. The absorptive capability of external research spillovers depends partly on own research efforts (Cameron 2005; Fung 2005).

Farm size, defined as average gross value of farm assets, played a significant role in enhancing farm productivity growth only in the short-run. This result is consistent with the findings of Weersink and Taur (1991), Yee, Ahearn, and Huffman (2004), and Thirtle, Schimmelpfennig, and Townsend (2004). The estimated short-run impact on productivity growth of the one-year PIK program in 1983 was significantly negative.

The most startling result from this analysis is the estimated magnitude of the impact of increased health care supply in rural areas and productivity growth in U.S. agriculture both in the short-run and long-run. The results from ECM I imply that a 1% increase in health care supply in rural areas would enhance the TFP growth rate by 24% in the short run and raise the steady-state TFP growth rate by 58%. ECM II also indicates significant and similarly substantial response but with somewhat lower payoffs (17% in the short-run and 38% in the

[14] It is also possible that the procedure used to allocate private patents may be driving some of these unexpected results with regard to private research.

long-run).

Considerable caution must be exercised in interpreting the large magnitudes of these estimated impacts of health care supply on TFP growth. First, the number of medical doctors in rural areas may be positively correlated with wealth which in turn could be partially generated by high productivity growth. To examine this possibility, we used a mixed fixed and random coefficients estimation algorithm (Nair-Reichert and Weinhold 2001) to test for causality.[15] We failed to find evidence of causality running from Hs to TFP. Second, the high positive correlation (0.87) between farmer's education levels and health care supply in rural areas might cause the estimated effect of Hs to be biased upward. To examine this possibility, we re-estimated the model without the education variable. The estimated results showed an even larger positive effect of Hs. Third, another explanation, but one beyond the scope of this analysis to test, is that investments in support facilities and other health care workers in rural areas may increase more rapidly than the number of doctors. Since it is the bundle of health care resources that are being proxied in this study by number of doctors per 10,000 population in rural areas, it is possible that the estimated impact of health care supply is inflated.

In addition to testing for reverse causality between TFP and Hs, we also conducted a test for direct causality between Hs and TFP and rejected that hypothesis. Thus, while our empirical estimates of extremely high impact of changes in Hs on TFP are robust to all the alternative specifications considered, there is no significant empirical evidence of causality running from

[15] This procedure was used since it results in least bias among the estimators (Nair-Reichert and Weinhold (2001). In the mixed fixed and random coefficients model, the coefficient on the lagged dependent variable is specific to the group and the coefficients on the exogenous explanatory variables are treated as being randomly distributed.

Hs to TFP. Thus, the evidence is only correlative, not causal.

IV. Summary and Conclusions

In this paper we have tested three convergence hypotheses about total factor productivity in U.S. agriculture and examined the role of key dynamic drivers. It is the first paper to examine the impact of health care supply on agricultural productivity growth or the impact of health care supply or inter-state or inter-industry private research spillovers on agricultural productivity convergence. It has also employed improved panel estimation procedures that permit examination of the dynamic effects of policy variables on productivity growth.

Cross-sectional tests were conducted for σ-convergence and absolute β-convergence. A pooled cross-section, time-series test was conducted for conditional β-convergence. We found strong evidence in favor of both absolute and conditional β-convergence but no support for σ-convergence. Finding evidence supporting absolute β-convergence results in the conclusion that the gap in agricultural TFP among the 48 states tends to narrow over time regardless of initial technologies, preferences, and institutions. That is, states with lower initial TFP levels tend to grow more rapidly than states with higher initial TFP levels.

Two error correction models, with and without considering the short-run dynamic effects of exogenous shocks, were developed and employed to test conditional β-convergence and to examine the impacts of policy variables. In addition to failing to reject conditional β-convergence, the econometric results highlight several important drivers of productivity growth. Most important is the consistent finding of significantly positive short-run and long-run impacts of health care supply in rural areas. While health has been identified as a theoretically important variable in measures of human capital, it has not previously been included in agricultural productivity growth models. Data limitations have prevented inclusion of any direct measures of actual health levels, but data on health care supply were used as a proxy for health status in this model with highly informative results. Accounting for the short-run effects of exogenous shocks, our results imply that increases in rural health care supply has very large impacts on the long-run (steady-state) agricultural TFP growth rate. Significant short-run effects indicate that states with higher rural health care supply also catch up faster in agricultural TFP.

We also examined the roles played by R&D and associated spillovers in TFP growth. Public research and extension investments generally had a significant influence both on the short-run and steady-state TFP growth rate. This finding supports the expectation that an increase in public research investments will lead to an increase in TFP not only in the short-run but also in the long-run. Additionally, knowledge spillovers from agricultural public research investments, agricultural private research investments, and nonagricultural sectors' research efforts advance TFP growth both in the short-run and long-run. As a result, an increase in assimilation of research efforts from other states and from other industries raises the ability for productivity lagging states to catch up with the leaders. Farmers' education levels are also quantitatively important as well as statistically significant in advancing the productivity growth rate. Farm size, however, has no significant impact on the long-run TFP growth rate. Its influence is limited to the short-run.

The finding of positive impacts of health care supply and privately-funded knowledge spillovers from other states and from other sectors could sound a call for more policy activism. Based on the existing agricultural growth literature, states could expect to increase productivity growth by increasing public investments in new knowledge creation, research spillover absorption, and agricultural worker education, and by promoting greater investment and possibly a redesigned funding plan at the federal level. This study provides evidence that public investments and incentives for private investment in rural health care supply and privately funded research spillovers can substantially strengthen agricultural productivity growth. Thus, it identifies a richer set of potential policies for raising long-run TFP levels and for accelerating the pace of reaching them.

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Table 1. Test for TFP σ-Convergence

Variable	Estimated Coefficients	Standard Error
Intercept	0.037*	0.001
t	0.00001	0.0001

[a] Critical t-value for the 1-tailed test is 1.684 at the 0.05 significance level. Significant coefficients are identified by an asterisk.

Table 2. Cross-Section Tests for TFP Absolute β-Convergence

	Estimated Coefficients	Standard Error [a]
s = 10	-0.204*	0.089
s = 5	-0.249*	0.099
s =3	-0.264*	0.100

[a] Critical t-value for these 1-tailed tests is 1.645 at the 0.05 significance level. Significant coefficients are identified by an asterisk.

Table 3. Hadri Panel Stationarity Tests

Variable [a]	Levels		1st Differences		2nd Differences	
	Statistic [b]	P-value	Statistic [b]	P-value	Statistic [b]	P-value
Ln(*TFP*)	35.558	0.000	-5.441	1.000		
Ln(*Edu*)	126.786	0.000	-5.583	1.000		
Ln(*Hs*)	57.701	0.000	-4.307	1.000		
Ln(*Rpri*)	249.752	0.000	16.362	0.000	-7.128	1.000
Ln(*Rpub*)	79.132	0.000	-2.529	0.994		
Ln(*Ext*)	81.702	0.000	2.324	0.010	-7.168	1.000
Ln(*Fs*)	125.088	0.000	35.034	0.000	-6.645	1.000
Ln(*RpubSpill*)	88.685	0.000	-1.595	0.945		
Ln(*RpriSpill*)	297.868	0.000	22.154	0.000	-6.865	1.000
Ln(*InterSpill*)	212.767	0.000	-1.817	0.965		

[a] Codes: Ln is logarithm, *Rpri* is private research investment, *Rpub* is public research investment, *Ext* is extension investment, Size is farm size, *RpriSpill* is private agricultural spillovers from other states, *RpubSpill* is public agricultural research spillovers from other states, *InterSpill* is spillovers from other industries to the agricultural sector, *Edu* is farmers' average education level, *Hs* is health care supply level in rural areas.

[b] When testing for stationarity in levels, a time trend was included. For the differences, stationarity was tested without a time trend.

Table 4. Pedroni Panel Cointegration Tests

Test Statistic [a]	
Panel v-statistic	3.845*
Panel ρ-statistic	-6.666*
Panel t-statistic (nonparametric)	-11.584*
Panel t-statistic (parametric)	-6.348*
Group ρ-statistic	4.863
Group t-statistic (nonparametric)	-11.510*
Group t-statistic (parametric)	-5.271*

[a] Critical 1-tailed test values for rejecting the hypothesis of no cointegration via the panel-v statistic is 1.645 at the 5% level. Critical values for the other statistics are the negatives of these values (Pedroni 1999). Significant coefficients are identified by an asterisk.

[b] When testing for cointegration, a time trend was included.

Table 5. Pesaran PMG Estimates for Conditional Growth Model

Variable [a]	ECM I		ECM II	
	Coefficient	Standard Error [b]	Coefficient	Standard Error [b]
Long-run Coefficients				
ln(*Edu*)	0.0149	0.0211	0.0497*	0.0212
ln(*Hs*)	0.5751*	0.0278	0.3766*	0.0307
Δln(*Fs*)	0.0504	0.0440	0.0212	0.0521
ln(*Rpub*)	0.0338*	0.0142	0.0404*	0.0139
Δln(*Rpri*)	-0.0054	0.0087	-0.0486*	0.0196
Δln(*Ext*)	0.1275*	0.0339	0.0165	0.0296
ln(*PubSpill*)	0.1724*	0.0163	0.1280*	0.0184
Δln(*PriSpill*)	-0.0274	0.0181	0.0980*	0.0330
ln(*InterSpill*)	0.0079	0.0106	0.0544*	0.0114
ln($G_{i,t-1}$) [c]	-0.4122*	0.0401	-0.4444*	0.0378
Short-run Coefficients				
Δln(*Edu*)	0.0061*	0.0006	0.0221*	0.0019
Δln(*Hs*)	0.2368*	0.0230	0.1674*	0.0142
Δ^2ln(*Fs*)	0.0207*	0.0020	0.0094*	0.0008
Δln(*Rpub*)	0.0139*	0.0014	0.0180*	0.0015
Δ^2ln(*Rpri*)	-0.0022*	0.0002	-0.0216*	0.0018
Δ^2ln(*Ext*)	0.0525*	0.0051	0.0073*	0.0006
Δln(*PubSpill*)	0.0710*	0.0069	0.0569*	0.0048
Δ^2ln(*PriSpil*)	-0.0113*	0.0011	0.0435*	0.0037
Δln(*InterSpill*)	0.0032*	0.0003	0.0242*	0.0021
Δ^2ln(*Edu*)			-0.8915*	0.1050
Δ^2ln(*Hs*)			0.3932*	0.1218
Δ^3ln(*Fs*)			-0.0521*	0.0171
Δ^2ln(*Rpub*)			-0.0213	0.0175
Δ^3ln(*Rpri*)			0.0076*	0.0029
Δ^3ln(*Ext*)			0.0494*	0.0204
Δ^2ln(*PubSpill*)			-0.0564	0.0302
Δ^3ln(*PriSpil*)			-0.0322*	0.0069
Δ^2ln(*InterSpill*)			-0.0670*	0.0100
D83	-0.1034*	0.0144	-0.1094*	0.0164
Constant	-2.1398*	0.2111	-1.8819*	0.1594
$\bar{R}^2$	0.2989		0.3362	

[a] D83 is a dummy variable included to pick up the impacts of the 1983 PIK program; $\bar{R}^2$ is an average of state-specific adjusted $\bar{R}^2$ values; ln(*Rpub*), ln(*Rpri*) and ln(*Ext*) are lagged 25 years for public research, 15 years for private research, and 7 years for extension investments. These optimal lags were selected by minimizing the AIC.

[b] The critical t-value is 1.96 for the 2-tailed tests and 1.645 for the 1-tailed tests at the 0.05 significance level. Significant coefficients are identified by an asterisk.

[c] The estimated parameter is the error correction coefficient.