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State Productivity Growth:

Catching-Up and the Business Cycle

V. Eldon Ball
Economic Research Service
U.S. Department of Agriculture
and
Institute of Economics
University Carlos III of Madrid

Carlos San Juan
Department of Economics
University Carlos III of Madrid

Camilo Ulloa
BBVA Research

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2012 AAEA Annual Meetings in Seattle, Washington, August 12-14, 2012

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Agricultural Productivity in the United States:
Catching-Up and the Business Cycle

Several recent studies of the agricultural sector provide evidence of convergence of total factor productivity (TFP) across the U.S. states. McCunn and Huffman (2000) found evidence of 'catching-up' in levels of TFP (*i.e.*, β-convergence), although they rejected the hypothesis of declining cross-sectional dispersion (*i.e.*, σ-convergence). Ball, Hallahan, and Nehring (2004) also found evidence of convergence in levels after controlling for differences in relative factor intensities (*i.e.*, embodiment). The speed of convergence and whether it is transitory or permanent in nature plays an important role in characterizing regional disparities in income (see Abramovitz, 1986; Baumol, 1986; Baumol and Wolff, 1988; and Dowrick and Nguyen, 1989) and, hence, have important implications for the design of agricultural policy.

The literature on growth empirics defines the convergence hypothesis in several different ways. Following Barro and Sala-i-Martin (1992), there is β-convergence if states with lower levels of productivity tend to grow faster than the technology leaders, and σ-convergence if the dispersion of their relative TFP levels tends to decrease over time. Thus, β-convergence is a necessary but not a sufficient condition for σ-convergence (Quah, 1993a, b). An important implication of this result is that income inequality across states or regions may persist due to shocks (*e.g.*, cyclical fluctuations in economic activity) that tend to increase dispersion.

This paper explores the relationship between the business cycle and

convergence of agricultural productivity. Two alternative explanations have been proposed in the literature to explain why convergence patterns may be related to the business cycle. The first is based on the pro-cyclical nature of the innovation process (Basu and Fernald, 2001; Geroski and Walters, 1995) and the time lags between technological innovations and diffusion processes (Jovanovic and MacDonald, 1994). According to this argument, productivity leaders tend to innovate more during periods of expansion in response to positive demand shocks. However, due to the existence of informational barriers productivity followers, who tend to learn by imitation, postpone the adoption of innovations made by the technology leaders until economic downturns. The second explanation is based on the relation between competition and productivity (Escribano and Stucchi, 2008). Productivity followers have more incentive to reduce their costs during downturns when negative demand shocks increase the probability that these firms will exit the industry.

Taken together, these arguments point to faster rates of convergence during contractions in economic activity and to slower rates of convergence, or even divergence, during periods of expansion. Yet few researchers have estimated the impact of the business cycle on convergence. Most either ignore the effects of the business cycle or adjust the productivity measures to eliminate the cyclical fluctuations. They do so by either controlling for capacity utilization (Wolff, 1991; Dollar and Wolff, 1994; Baumol et al., 2004) or by using standard smoothing procedures (Di Liberto, Mura and Pigliaru, 2008).

An exception is provided by Escribano and Stucchi (2008). Using firm

level data for the Spanish manufacturing sector, the authors test the catch-up hypothesis across different phases of the business cycle. They find strong evidence in support of the innovation-imitation hypothesis. Relative TFP levels tend to diverge during periods of expansion and to converge during recessions, a result of both time lags in the diffusion of technical information and the pro-cyclical nature of innovation.

In this paper, we follow closely the approach of Escribano and Stucchi (2008). First, we test the catch-up hypothesis using a model that ignores the business cycle. Then we investigate the possible impacts of the business cycle on the convergence process by showing how the speed of convergence changes across different phases of the business cycle.

However, we depart from the above mentioned study in several important ways. First, our focus is on the agricultural sector, considered by a number of authors as the sector with the lowest productivity levels (see Laitner, 2000; Tamura, 2002). This is an important departure since the impact of the business cycle on convergence will likely differ across sectors of the economy. If prices in the agricultural sector are more flexible than in manufacturing then the impact of the business cycle may be greater in agriculture due to 'overshooting' of prices (Rucker and Sumner, 1997).[1] On the other hand, and despite the initially low productivity levels, recent empirical evidence suggests that convergence in levels of productivity may be faster in agriculture, the result of relatively rapid dissemination of technical information (Martin and Mitra, 1999). This result points to a smaller impact of

the business cycle on convergence. The above examples underscore the empirical nature of the relationship between the business cycle and convergence and suggest that results obtained for other sectors may not be applicable to the agricultural sector.

Second, we use data at the state level. In using aggregate data, we fail to account for the effects of entry and exit of firms from the industry. As a result, our empirical results may be biased. The farm sector in each state is composed of a finite number of firms, and individual firms' decisions may have a non-negligible impact on the behavior of the aggregate variables. If exiting firms are less productive than surviving firms then their exit will contribute to each state's productivity growth, thereby leading to biased results if the entry and exit of firms depend on each state's initial productivity level (Baldwin and Gorecki, 1991; Foster, Haltiwanger and Kriza, 1998; Fujita, 2008).[2]

We also make a number of important empirical contributions. A common practice in studies of convergence is to include control variables to avoid omitted-variables bias. In particular, most studies include changes in relative capital intensities to capture the effects of technological innovations embodied in capital (Dollar and Wolff, 1994; Ball, Hallahan and Nehring, 2004). We note, however, that the optimal factor demands depend on TFP growth, so changes in relative capital intensities are not exogenous with respect to changes in TFP (Daveri and Jona-Lasino, 2007). As a result, the improvements achieved by previous studies through the reduction of omitted-variables bias can be potentially offset by the introduction of simultaneity bias in their econometric

specifications.

We address simultaneity bias using an instrumental variables approach. For the growth rate in relative capital intensities we use several demand-side instruments, including fiscal impulse, monetary shocks, energy prices, the expected growth rates in potential domestic and external demand, and market accessibility to Metropolitan Statistical Areas (MSA). Both the market accessibility and domestic and external demand variables are constructed using the market accessibility function proposed by Harris (1954). Their construction involves geographic and economic data for more than 3,000 counties, 25,000 cities, 300 MSAs, and 80 U.S. ports.

Our estimation employs state-by-year panel data. However, using asymptotic distributions based on panel data may lead to poor approximations of the actual distributions of the parameter estimates. Therefore, we apply time-series cross-sectional (TSCS) techniques in order to provide reliable standard errors and critical values. We perform unit-root tests for panel data to assess the time-series properties of the data. Then we correct for unobserved heterogeneity at both state- and time-specific levels by considering a two-way error components econometric specification. Finally, we use a TSCS Instrumental Variables Feasible GLS (TSCS IV-FGLS) regression method to obtain parameter estimates that are robust to endogeneity, heteroskedasticity, autocorrelation, and cross-sectional contemporaneous correlation.[3]

The tests of the catch-up hypothesis used in this paper were proposed by Barro and Sala-i-Martin (1992).[4] Building on more recent research, we include

in our tests of convergence a number of control variables. Following Dollar and Wolff (1994) and Ball, Hallahan and Nehring (2004), we include changes in relative capital intensities to capture technological embodiment. We also include two indicators of agricultural specialization—the relative crop and livestock output intensities—to control for differences in TFP growth rates between the livestock and crop subsectors (Evenson and Huffman, 2001). In addition to these variables, we include years of schooling and experience to capture possible technology spillovers from investment in human capital (Parman, 2009).

Our empirical results are as follows. First, we found strong evidence of convergence in TFP levels across states. Second, embodiment was an important source of TFP growth in agriculture. In fact, after correcting for endogeneity of the relative capital intensities, embodiment was found to be a more important source of productivity growth than was previously reported (see Ball, Hallahan, and Nehring, 2004). Third, productivity growth was inversely related to specialization. However, states that specialized in production of livestock had, on average, more rapid TFP growth than states that specialized in crop production. Fourth, there were significant spillovers from investment in human capital, leading to more rapid productivity growth. And finally, although we found strong evidence of catching-up and embodiment across the business cycle, these effects were more pronounced during periods of contraction in economic activity.

Tests of β-Convergence

This section presents the econometric models used to test the convergence

hypothesis. First, we describe the model gleaned from the literature, termed the benchmark model. Then we present the model used to investigate the relationship between catching-up and the business cycle.

The Benchmark Model

To test the convergence hypothesis, we employ the basic specification:

$$\Delta \ln(TFP_{i,t}) = \alpha + \theta_1 \ln(TFP_{i,t}) + \Theta_x^{'} X_{i,t} + v_{i,t}, \tag{1}$$

where $TFP_{i,t}$ is state i's productivity level in period t relative to the U.S. average and $X_{i,t}$ is a vector of possibly endogenous control variables. Testing for β-convergence is equivalent to testing H_0: $\theta_1 = 0$ (*i.e.*, no β-convergence) against H_1: $\theta_1 < 0$ (*i.e.*, β-convergence), where $\theta_1 = -(1-e^{\beta})$ and β is the rate of convergence.

The specification in equation (1) implies symmetric mean reversion (SMR). States with TFP levels above the average converge to the mean at the same speed as states with TFP levels below the average. To model asymmetric mean reversion (AMR), we include a dummy variable, $d_{i,t}^{AMR}$, defined as unity if the state's TFP level is above the U.S. average, that interacts with $\ln(TFP_{i,t})$:

$$\Delta \ln(TFP_{i,t}) = \alpha + \Theta_1 [D_{i,t}^{AMR} \times \ln(TFP_{i,t})] + \Theta_x^{'} X_{i,t} + v_{i,t}, \tag{2}$$

where

$$D_{i,t}^{AMR} = (1, d_{i,t}^{AMR})',$$

$$\Theta_1' = (\theta_1, \theta_{1,d}),$$

and

$$d_{i,t}^{AMR} = 1[TFP_{i,t} > 1],$$

where $1[\cdot]$ is an indicator function. Testing for asymmetric mean reversion in β-convergence is equivalent to testing H_0: $\theta_{1,d} = 0$ (*i.e.*, no asymmetric mean reversion) against H_1: $\theta_{1,d} \neq 0$ (*i.e.*, asymmetric mean reversion).

β-Convergence and the Business Cycle

To characterize the relationship between β-convergence and the business cycle, we model changes in the coefficient on the initial level of productivity across the different phases of the business cycle. We also look at the effects of the business cycle on embodiment.

There are two reasons why we would expect asymmetries in the embodiment effect across the business cycle. First, capital and labor reallocations have been shown to have important cyclical patterns (see Eisfeldt and Rampini, 2006; Akerlof, Rose and Yellen, 1988; Foote, 1998). Second, the innovation-imitation hypothesis discussed in the introduction not only suggests that we should observe faster catching-up during periods of contraction, but also stronger embodiment effects. This is because productivity followers tend to learn by imitation, especially in downturns, and the innovations that they imitate may be embodied in capital.

From 1960 to 2004, the U.S. economy experienced seven recessions.

Figure 1 shows the year-over-year growth rates of GDP and the National Bureau of Economic Research (NBER) recession dating (boxed area). Two important facts emerge from this figure. First, expansions are longer than recessions (around 6 years on average against 1 year on average). Second, recessions have become less frequent since the middle 1980s. Given this asymmetry, we introduce in equation (2) interaction effects between a set of dummy variables that identify the different phases of the business cycle and the variables of interest, $\ln(TFP_{i,t})$ and $\Delta \ln(K/L)_{i,t}$.

We use the output gap and the NBER's Recession Dating Procedure to identify the different phases of the business cycle. A positive (negative) output gap indicates that the economy is operating below (above) its 'full employment' potential, thereby allowing us to distinguish periods of low economic activity (*i.e.*, contractions and recoveries) from periods with high economic activity (*i.e.*, booms). The NBER's Recession Dating Procedure determines the official peaks and troughs of the business cycle, thus identifying the periods when the economy is officially in a contraction phase (*i.e.*, from a peak to a trough) and, conversely, when in an expansion phase (*i.e.*, from a trough to a peak). Using this information, we partition the business cycle into a contraction phase, say Phase (C), a recovery phase, say Phase (R), and a late expansion phase, say Phase (E).

The model specification used to investigate the relationship between β-convergence and the business cycle is given in equation (3). To simplify the

notation, we present equation (3) assuming there is no asymmetric mean reversion (*i.e.*, that $\theta_{1,d} = 0$).

$$\begin{aligned} \Delta \ln(TFP_{i,t}) &= \alpha + \Theta'_{(1)}[Phase(BC)_t \times \ln(TFP_{i,t})] \\ &+ \Theta'_{(k)}[Phase(BC)_t \times \Delta \ln(K / L_{i,t})] \\ &+ \Theta'_{\tilde{x}} \tilde{X}_{i,t} + v_{i,t}, \end{aligned} \tag{3}$$

where

$$Phase(BC)_t = (Phase(C)_t, Phase(R)_t, Phase(E)_t)',$$

$$\Theta'_{(1)} = (\theta_{1,C}, \theta_{1,R}, \theta_{1,E}),$$

$$\Theta'_{(k)} = (\theta_{k,C}, \theta_{k,R}, \theta_{k,E}),$$

and

$Phase(C)_t = 1$ [In period t the U.S. economy is officially in a contraction phase],

$Phase(R)_t = 1$ [In period t the U.S. economy is officially in an expansion phase and the U.S. output gap is positive],

$Phase(E)_t = 1$ [In period t the U.S. economy is officially in an expansion phase and the U.S. output gap is negative],

where $1[\cdot]$ is an indicator function and $\tilde{X}_{i,t}$ is a vector of control variables.

Data

The following provides a brief overview of the data used to investigate the catch-up hypothesis. A full description of the underlying data sources and aggregation procedures can be found in Ball et al. (1999).

We construct state-specific aggregates of output and capital, labor, and materials inputs as Törnqvist indexes over detailed output and input accounts. Indexes of output are

formed by aggregating over agricultural goods and services using revenue-share weights based on shadow prices. The changing demographic character of the agricultural labor force is used to construct a quality adjusted index of labor input. Construction of the measure of capital input begins with estimating the stock of capital for each component of capital input. For depreciable assets, the capital stocks are the cumulation of past investments adjusted for discards of worn-out assets and loss of efficiency of assets over their service life. The capital stocks of land and inventories are measured as implicit quantities derived from balance sheet data. Indexes of capital input are then formed by aggregating over the various capital assets using cost-share weights based on asset-specific rental prices. Törnqvist indexes of energy consumption are calculated for each state by weighting the growth rates of petroleum fuels, natural gas, and electricity by their shares in the overall value of energy inputs. Fertilizers and pesticides are also important intermediate inputs, but their data require adjustment since these inputs have undergone significant changes in input quality. We estimate price indexes for fertilizers and pesticides using hedonic methods. The corresponding quantity indexes are formed implicitly by taking the ratio of the value of each aggregate to its hedonic price index. A Törnqvist index of intermediate input is calculated for each state by weighting the growth rates of each category of intermediate inputs by their value share in the overall value of intermediate inputs. Finally, following Caves, Christensen, and Diewert (1982), we construct output and input measures that have spatial as well as temporal integrity. The result is panel data that can be used for both cross section and time series analysis.

In our tests of the catch-up hypothesis, we include a number of control variables. Following Dollar and Wolff (1994) and Ball, Hallahan, and Nehring

(2004), we include changes in relative capital intensities, $\Delta \ln(K/L)_{i,t}$, to capture embodiment. We also include indexes of specialization to control for differences in TFP growth rates across agricultural subsectors. To capture possible human capital spillovers, we include differences in years of schooling and worker experience (Baier et al. (2007).

Cyclical fluctuations in aggregate economic activity and investment in human capital are likely exogenous sources of TFP growth in agriculture, but the growth rates of relative capital intensities and agricultural specialization may be endogenous. We address the potential endogeniety problems using instrumental variables.

Valid instruments for the capital intensities would be variables that are correlated with the inputs but are orthogonal to TFP shocks. One might conclude that a natural set of instruments would be the lagged values of the endogenous variables (Cungun and Swinnen, 2003). However, these lagged values may not be valid instruments because the optimal input demands may depend on past values of TFP (Levinson and Petrin, 2000), which leads to a violation of the weak exogeneity conditions. In this paper, we use two different sets of demand-side instrumental variables. The first set of instruments varies across time periods but not across states, while the second set of instruments varies across both time periods and states.

Following Groth, Nuñez and Srinivasan (2006), the first set of demand-side instruments includes monetary shocks, proxied by the changes in medium-

and long-term interest rates, and fiscal impulse, measured by the changes in the U.S. primary deficit as a percentage of GDP. The second set includes the growth rates in relative energy prices, the expected growth rates in potential domestic and external demand, and market accessibility to Metropolitan Statistical Areas (MSA).[5]

It can be argued that productivity growth also plays a role in determining production patterns (*i.e.*, specialization) across regions (see Gopinath and Upadhyaya, 2002), thereby leading to simultaneity bias. We address this problem by considering regional and time fixed effects and by introducing relative chemical and energy input intensities as instruments. The relative chemical and energy intensities are likely highly correlated with our measures of specialization because farms in a particular state that specialize in the production of, say crops, will also have relatively large chemical and energy input shares. In addition, the instruments should be a valid source of exogenous variation (*i.e.*, orthogonal to shocks in TFP) since the intermediate input indexes are adjusted for changes in input quality.

Empirical Results

This section details our empirical results. First, we discuss the results of our tests of β-convergence ignoring the business cycle (*i.e.*, the benchmark model). Then we present test results that take into account the effects of the business cycle on the rate of convergence and embodiment.

The Benchmark Model

Testing for Panel Unit Roots

To minimize the potential for spurious regression results, we first examine whether the variables in equation (2) exhibit a unit root. We perform panel unit root tests proposed by Levin, Lin, and Chu (2002), Im, Pesaran and Shin (2003) and Breitung (2000), respectively. Compared with individual unit root tests, such as the Augmented Dickey Fuller test or the Phillips and Perron (1988) test, all of these have common advantages when dealing with small samples. However, they also have their own limitations, which suggest a joint interpretation of the test results. The Levin, Lin, and Chu (2002) and Im, Pesaran and Shin (2003) tests face size distortions as the cross-section dimension gets large relative to the time series dimension. On the other hand, the Breitung (2002) and Levin, Lin, and Chu (2002) tests require homogeneity of the first-order autoregressive parameters, which restricts the parameters to be equal across all the cross-sections under the alternative hypothesis (Baltagi, 2005). Table 1 summarizes the results of the panel unit root tests. The tests include a constant term and, in the case of TFP growth rates, a time trend. All of the test statistics are less than the critical value of -1.65 at the 5% level. Therefore, we reject the null hypothesis of a unit root and proceed by estimating equation (2) assuming stationarity.

Pooled OLS Estimates

The first column of Table 2 reports pooled OLS estimates of equation (2). The results support the catch-up hypothesis, showing a highly significant inverse relation between the rate of TFP convergence and its initial level. The variable

$\Delta \ln(K/L)_{i,t}$ has a positive and significant coefficient, suggesting that embodiment of technology in capital is an important source of TFP growth. The relation between productivity growth and specialization is not statistically significant. Neither is the relationship between productivity growth and years of schooling or worker experience. Finally, the coefficient on the interaction term $d_{i,t}^{AMR} x \ln(TFP_{i,t})$, is not significant, suggesting there is no asymmetric mean reversión. We note, however, that the results in column (1) are consistent if and only if the orthogonality conditions on equation (2) hold (*i.e.*, the explanatory variables are uncorrelated with the error term $\upsilon_{i,t}$).

Unobserved State-Specific Effects

To control for unobservable state-specific effects, we perform three tests. First we perform the Breusch and Pagan (1980) Lagrangian Multiplier test for random effects against the pooled OLS estimates. Then we perform an F-test for fixed effects. Finally, we perform the Hausman (1978) specification test to compare the random- and fixed-effects specifications. The state-specific effects model (or one-way error components model) is given by equation (2) and:

$$v_{i,t} = \eta_i + u_{i,t}, \tag{4}$$

where η_i denotes the unobservable state-specific effect and $u_{i,t}$ is the remainder disturbance. Table 3 shows the results of the tests for state-specific effects. The Breusch and Pagan (1980) test for random effects and the F-test for fixed effects

yield p-values smaller than 0.05, which clearly points to the presence of state-specific effects. Furthermore, the Hausman (1978) specification test yields a p-value of 0.0000, which confirms that the differences between the random-effects and fixed-effects coefficients are systematic. We conclude that the fixed effects are relevant and that both the pooled OLS and random-effects GLS estimators are inconsistent.

Unobserved Time Specific Effects

Having confirmed the existence of state-specific fixed effects, we explore the existence of unobserved time-specific effects. For simplicity, we assume that if there exists unobserved time-specific effects common to all the states then it must be a fixed effect. This assumption does not compromise the consistency of the estimated parameters. The two-way error components model is given by equation (2) and:

$$v_{i,t} = \eta_i + \varepsilon_t + u_{i,t}, \tag{5}$$

where η_i and ε_t denote the unobservable state- and time-specific fixed effects and $u_{i,t}$ is the remaining stochastic disturbance. To test the time-specific effects hypothesis we estimate the two-way fixed effects model and then perform an F-test for time-specific fixed effects. The null hypothesis is that $\varepsilon_t = 0, t = 1,...,T$. Column (2) of Table 2 summarizes the two-way fixed-effects estimation results. The F-test for the two-way fixed effects model against the one-way fixed-effects model yields a p-value of 0.0000. Therefore, we can reject the null hypothesis at

the usual confidence levels. We conclude that both state- and time-specific fixed effects are significant.

Endogeneity of the Regressors

As previously noted, such variables as the relative factor intensities and specialization may be viewed as endogenous. We test for endogeneity using the Davidson and MacKinnon (1993) augmented regression test procedure. First, we estimate a two-way fixed effects model for each of the possibly endogenous right-hand side variables in equation (2) using as instruments all the exogenous variables in equation (2) and the excluded instruments described above. Then we perform the augmented two-way fixed-effects within regressions by including the first-step residuals. If the coefficients on the residuals are significantly different from zero, the original two-way fixed effects estimator is inconsistent

$(i.e.,\ E(X_{i,t}, u_{i,t}) \neq 0$

Table 4 reports the endogeneity tests results. The coefficient on the residuals of $\Delta \ln(K/L)_{i,t}$ is significant at the 5% level, indicating that the relative capital intensities are endogenous variables. In the case of specialization, the results are mixed. The coefficient on the residuals of the livestock intensities is significant at the 10% level. But the results suggest that the crop intensities are exogenous since the coefficient on the residuals is not significantly different from zero.

Having determined that a number of the regressors are endogenous, we test the relevance and validity of the instruments with the Kleibergen-Paap (2006) test

for underidentification and the Sargan-Hansen (1982) test for overidentifying restrictions. Both tests are robust to heteroskedasticity. The null hypothesis in the underidentification test is that the first-step equations are underidentified (*i.e.*, the excluded instruments are uncorrelated with the endogenous regressors). The joint null hypothesis in the test for overidentifying restrictions is that the instruments are valid (*i.e.*, uncorrelated with the error term $u_{i,t}$) and that the excluded instruments are correctly excluded from the estimation.

Column (3) of Table 2 reports the two-step IV two-way fixed-effects results, while Table 5 shows the results for the underidentification and overidentifying restrictions tests. The Kleibergen-Paap (2006) test for underidentification yields a *p*-value smaller than 0.05, indicating that the excluded instruments are significant. On the other hand, the Sargan-Hansen (1982) test for overidentifying restrictions yields borderline results. The test yields a *p*-value very close to 0.10. Given these results, we conclude that the instruments are valid.

A comparison of the parameter estimates reported in columns (2) and (3) of Table 2 yields two interesting results. First, embodiment is a more important source of TFP growth in agriculture than was previously reported (see Ball, Hallahan, and Nehring, 2004). In fact, once we addressed the problem of endogeneity, the coefficient on $\Delta \ln(K/L)_{i,t}$ increased by a factor of five. Unfortunately, these results are not strictly comparable with those of earlier studies because the time series and cross section coverage are quite different and because most studies attempt to purge the data of cyclical component. As a point

of reference, however, Ball, Hallahan and Nehring (2004) find that the magnitude of the coefficient on $\Delta \ln(K/L)_{i,t}$ is, in absolute value, about 0.75 times the magnitude of the catch-up parameter. Column (3) reports a coefficient on $\Delta \ln(K/L)_{i,t}$ that is nearly three times the catch-up parameter.

Second, we find that specialization and TFP growth are inversely related. Moreover, states that specialized in crop production achieved lower rates of productivity growth than did states that specialize in livestock production. These results are consistent with those obtained by McCunn and Huffman (2000) and Evenson and Huffman (2001). Highly specialized farms are the productivity leaders, but they achieved slower productivity growth than did less specialized farms.

Serial Correlation of the Error Components

The specification given by equations (2) and (5) assume that serial correlation in the model stems from the fact that the observations correspond to the same states across the panel. However, the remaining stochastic disturbance $u_{i,t}$ in (5) may be serially correlated. In general, if the autocorrelation problem is not corrected, the Gauss-Markov assumptions about the residuals will be violated and this will lead to consistent but inefficient parameter estimates, as well as biased standard errors (see Baltagi, 2005). The generalized two-way fixed effects model with AR(1) remainder disturbances is given by equations (2), (5) and

$$u_{it} = \rho u_{it-1} + e_{i,t}; |\rho| < 1, \qquad (6)$$

where

$e_{i,t}$ denotes the remaining stochastic error.

Column (4) of Table 2 reports the parameter estimates for the two-way fixed-effects specification with AR(1) remaining disturbances. The results were obtained by the two-step IV method. First, we estimate the endogenous right-hand side variables in equation (2) using a two-way fixed effects model and the set of valid instruments described above. Then we estimate the two-way fixed effects model with AR(1) disturbances using the fitted values of the first-step dependent variables as exogenous variables. Table 6 reports the AR (1) estimated coefficient $\hat{\rho}$, as well as the Baltagi and Li (1995) and Wooldridge (2002) test statistics for the non-serial correlation hypothesis.[6] Both tests yield *p*-values of 0.0000, hence we can reject the null hypothesis of no serial correlation. Given that some of the explanatory variables in equation (2) are endogenous, this confirms that lagged values of these explanatory variables may not be used as excluded instruments since this would violate the weak exogeneity conditions.

Heteroskedasticity

In order to control for possible groupwise heteroskedasticity, we perform the Modified Wald test in the specification given by equations (2) and (5). Note that this test gives valid results even though the normality assumptions do not hold (see Green, 2003). They are also robust to endogeneity. First, we estimate the endogenous right-hand side variables in equation (2) using a two-way fixed effects model and the above set of valid instruments. Then we estimate the two-way fixed-effects model using as instruments the fitted values for the first-step

dependent variables. Finally, we perform the Modified Wald test. The test yields a *p*-value of 0.0000. Thus we can reject the null hypothesis of homoskedasticity.

Final Benchmark Model

The final benchmark specification (*i.e.*, before introducing the effects of the business cycle) is a two-way fixed effects model with state-specific error variances and state-specific AR(1) disturbances:

$$v_{it} = \eta_i + \varepsilon_t + u_{i,t}, \tag{7}$$

$$u_{it} = \rho_i u_{it-1} + e_{it}; |\rho| < 1. \tag{8}$$

In order to correct for endogeneity, heteroskedasticity and autocorrelation, we proceed by estimating the model using TSCS Instrumental Variables Feasible GLS (TSCS IV-FGLS) regression. First, we estimate the endogenous right-hand side variables in equation (2) using a two-way fixed effects model and the set of valid instruments described above. Then, using the fitted values for the first-step dependent variables, we estimate using TSCS Feasible GLS (TSCS FGLS) the two-way fixed-effects model robust to endogeneity, hetersoskedasticity, autocorrelation and cross-sectional contemporaneous correlation. We include dummy variables for each year and each state to control for state-specific and time-specific fixed effects.

The results are summarized in column (5) of Table 2. In contrast with previous studies, the results confirm that human capital spillovers contribute significantly to TFP growth. Moreover, there is evidence of asymmetric mean reversion. Those states with below average TFP levels converge to the mean level

at a faster rate than states with TFP levels above the average.

β-Convergence and the Business Cycle

We investigate the impact of the business cycle on TFP convergence using the specification in (3) above. This specification captures the effects of the business cycle through interactions with the initial level of productivity. We also include interaction terms with the relative capital intensities. As in the final benchmark specification, we estimate equation (3) using TSCS Instrumental Variables Feasible GLS (TSCS IV-FGLS) regression.

Table 7 reports the parameter estimates. The results confirm that there is convergence in levels of TFP across the different phases of the business cycle. Table 8 presents the Wald χ^2-tests for differences in the rates of convergence across the different phases of the business cycle. The χ^2-test for different rates of convergence during the contraction and recovery phases of the business cycle yield a *p*-value greater than 0.1. However, the test result for different rates of convergence during periods of contraction and late expansion yields a *p*-value less than 0.05. Moreover, the Wald χ^2-test results for differences in the embodiment effect during the contraction phase and the other two phases of the business cycle yield *p*-values of 0.0000. We conclude that there is a small but statistically significant difference in the rates of convergence during contraction and late expansion phases of the business cycle. There are large and statistically significant differences in the embodiment effect during the contraction phase and the other two phases of the business cycle. The specification in (3) also allows for

asymmetric mean reversion. The model predicts that the rate of convergence for productivity followers is 4.8% faster during the contraction phase than during the late expansion phase. This difference is even greater for the productivity leaders, about 5.1%. Finally, the model predicts that the embodiment effects are 33.9% and 73.7% greater during the contraction phase of the business cycle than during the recovery phase and the late expansion phase, respectively.

Concluding Remarks

This paper examines the relation between the business cycle and convergence in levels of productivity across states. First, we test the catch-up hypothesis using a model specification that ignores cyclical fluctuations in economic activity (*i.e.*, our benchmark model). Then we show how the rate of convergence changes across the different phases of the business cycle. We also assess the impact of cyclical fluctuations in economic activity on embodiment.

To avoid omitted-variables bias, we include a number of control variables in our tests of convergence. We include growth rates in relative capital intensities to capture technological embodiment. We also include measures of specialization to control for differences in patterns of TFP growth between the livestock and crops subsectors. Finally, we include years of schooling and worker experience at the state level to capture possible human capital spillovers. Since the relative capital intensities and the measures of specialization are endogenous variables, we use an instrumental variables approach in estimation.

The results from our benchmark model can be summarized as follows.

First, we find evidence of convergence in productivity levels across the states. Second, embodiment was an important source of TFP growth in agriculture. In fact, after correcting for endogeneity of the relative capital intensities, embodiment was found to be a more important source of productivity growth than was previously reported in the literature. Third, less specialized states had, on average, higher productivity growth rates than more specialized states. This result is consistent with the literature and provides further evidence in support of the catch-up hypothesis. Highly specialized states are among the productivity leaders, yet they exhibited slower rates of productivity growth. And fourth, we find that there are important human capital spillovers. States with higher levels of educational attainment and worker experience achieved faster productivity growth.

Next, we look at the speed of convergence across the different phases of the business cycle. We find that the rate of catch-up is faster during contraction and low economic activity phases of the business cycle than during late expansions. Allowing for asymmetric mean reversion, the catch-up rate for productivity followers is about 4.8% higher during contractions than during late expansions. These differences are even greater for the productivity leaders, about 5.1%.

Finally, the results indicate that there are significant differences in the magnitude of the embodiment effect across the business cycle. The embodiment effect is 33.9% and 73.7% higher during contractions than during recoveries and late expansions.

Overall, the results are consistent with theory. Time lags in the diffusion of technical information and the pro-cyclical behavior of innovations are the main forces driving the relation between fluctuations in the business cycle and convergence patterns. In contrast with evidence from the manufacturing sector, however, the magnitude of the effects of the business cycle through the rate of convergence appears to be smaller in the agricultural sector. We attribute this result to public funding of R&D in the agricultural sector. Since innovations resulting from public R&D can be considered public goods that firms can imitate relatively quickly the diffusion of technical information will be more rapid in agriculture, and this points to a smaller impact of the business cycle on TFP convergence.

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Notes

1. Overshooting of prices refers to temporary changes beyond long-run equilibrium levels.

2. If most exiting farms are concentrated in states with lower initial aggregate productivity the bias would be negative (*i.e.*, biased towards β-convergence). If most exiting farms are concentrated in the states with higher initial aggregate productivity (*i.e.*, in response to higher competitive pressures), the bias would be positive (*i.e.*, biased against β-convergence). Finally, if there are no statistically significant differences in the exit rates between the most productive states and the less productive states the results would be unbiased.

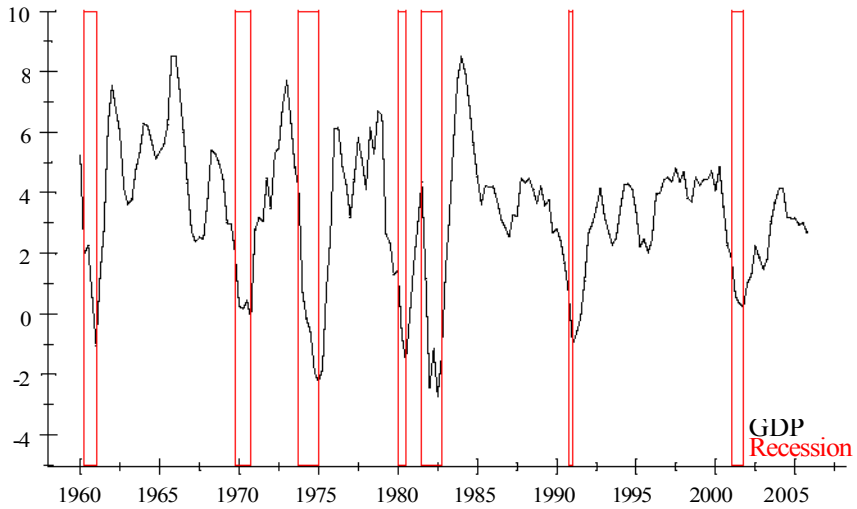
3. The model is estimated using STATA.

4. In the most basic specification of β-convergence only the initial and the final periods are considered. The advantage of using a specification for discrete or overlapping periods is that the estimates are less sensitive to the starting and ending dates of the panel data series (see McCunn and Huffman, 2000; Ball, Hallahan, and Nehring, 2004).

5. A complete description of methods and data used to construct the market accessibility and domestic and external demand variables is provided in an appendix available from the authors.

6. We perform the Baltagi and Li (1995) test and Wooldridge (2002) test since both tests can be applied under very few maintained assumptions.

Figure 1: U.S. GDP and NBER-Dated Recession.



Source: NBER.

Table 1: Panel Data Unit Root Tests

Variable	LLC Statistic	IPS Statistic	BRG Statistic
Δ ln (TFP)$_{I,t}$	—44.905	—50.343	—24.285
ln (TFP)$_{I,t}$	—18.125	—16.027	—9.881
$\Delta \ln(K/L)_{i,t}$	—47.091	—46.115	—34.825
Livestock$_{i,t}$	—17.152	—15.987	—8.101
Crops$_{i,t}$	—17.726	—17.240	—7.162
Δ ln(Schooling)$_{I,t}$	—32.788	—31.572	—19.755
Δ ln(Experience)$_{I,t}$	—23.955	—20.487	—23.311

Cross-sections included 48
Total panel (balanced) observations: 2112

Notes: Asymptotically standard normal distributed test statistics, 5% critical value —1.65. Automatic selection of lags based on SIC criteria. Newey-West bandwidth selection using Bartlett kernel

Table 2: Benchmark Model

Dependent Variable: $\Delta \ln TFP_{i,t}$

Method: (1) Pooled OLS; (2) and (3) IV-FE (within regression); (4) IV-FE (within regression); (5) IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.0719	-0.3740	-0.3000	-0.5782	-0.2995
	[0.012]***	[0.023]***	[0.061]***	[0.041]***	[0.012]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$	0.0320	-0.0257	-0.0074	0.0425	0.0253
	[0.024]	[0.042]	[0.076]	[0.049]	[0.010]***
$\Delta \ln(K/L)_{i,t}$	0.2092	0.1756	0.8345	1.0536	0.8624
	[0.014]***	[0.013]***	[0.233]***	[0.235]***	[0.043]***
$Livestock_{i,t}$	-0.0063	-0.0205	-0.3145	-0.5340	-0.4570
	[0.136]	[0.136]	[0.123]***	[0.136]***	[0.028]***
$Crops_{i,t}$	-0.0084	-0.0946	-0.4445	-0.7417	-0.5946
	[0.014]	[0.023]***	[0.138]***	[0.153]***	[0.031]***
$\Delta \ln(Schooling)_{i,t}$	-0.2886	-0.3985	-0.2388	-0.0088	0.1942
	[0.312]	[0.334]	[0.564]	[0.364]	[0.063]***
$\Delta \ln(Experience)_{i,t}$	0.0842	-0.0365	-0.2005	0.2216	0.2091
	[0.144]	[0.160]	[0.248]	[0.187]	[0.030]***
Constant	-0.0130	-0.0508	-	-0.1136	-0.2147
	[0.003]***	[0.010]***		[0.018]***	[0.011]***
Cross-sections included:	48	48	48	48	48
Total panel (balanced) observations:	2112	2112	2112	2112	2112

Notes: * Significant at 10%; ** Significant at 5%; *** Significant at 1%.Standard errors in brackets. All regressors use state and year fixed effects and are robust to autocorrelation. The results are corrected for endogeneity. Instrumented variables: $\ln(K/L)_{I,t}$, $Livestock_{i,t}$.

Table 3: Panel Data State-Specific Effects Tests

Cross-section random effects	
BPLM X^2-statistic	4.99
p-value	0.0255
Cross-section fixed effects	
F-statistic	10.15
p-value	0.0000
Cross-section fixed effects vs Cross-section random effects	
Hausman X^2-statistic	489.06
p-value	0.0000

Cross sections included: 48
Total panel (balanced) observations 2112

Table 4: Panel Data Endogeneity Tests

Variable	
$\Delta \ln(K/L)_{i,t}$	-0.4481
	[0.180]**
$Livestock_{i,t}$	0.2254
	[0.125]*
$Crops_{i,t}$	0.1190
	[0.184]

Cross sections included: 48
Total panel (balanced) observations 2112

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets.

Table 5: Identification Tests

IV Identification tests (Instrumented: Δln(K/L)i,t, Livestocki,t)	
Underidentification test	
χ^2-statistics	15.350
p-value	0.0318
Overidentification of all instruments	
χ^2-statistics	10.683
p-value	0.0987

Cross sections included: 48
Total panel (balanced) observations 2112

Table 6: Serial Correlation Tests

AR(1) Reminder Disturbances Tests	
$\hat{\rho}$	-0.2608
BLI χ^2-statistic	37.944
p-value	0.0000
WD F-statistic	297.079
p-value	0.0000

Table 7: Catching-Up and the Business Cycle

Dependent Variable: $\Delta \ln TFP_{i,t}$

Method: IV-FGLS

Variable	
$\text{Phase(C)}_t \times \ln(\text{TFP})_{i,t}$	-0.3103 [0.013]***
$\text{Phase(R)}_t \times \ln(\text{TFP})_{i,t}$	-0.3070 [0.012]***
$\text{Phase(E)}_t \times \ln(\text{TFP})_{i,t}$	-0.2985 [0.012]***
$d_{i,t}^{AMR} \times \ln TFP_{i,t}$	0.0251 [0.010]***
$\text{Phase(C)}_t \times \Delta \ln(K/L)_{i,t}$	1.1343 [0.052]***
$\text{Phase(R)}_t \times \Delta \ln(K/L)_{i,t}$	0.8473 [0.044]***
$\text{Phase(E)}_t \times \Delta \ln(K/L)_{i,t}$	0.6529 [0.047]***
$Livestock_{i,t}$	-0.4390 [0.028]***
$Crops_{i,t}$	-0.5715 [0.030]***
$\Delta \ln(Schooling)_{i,t}$	0.2136 [0.062]***
$\Delta \ln(Experience)_{i,t}$	0.2059 [0.030]***
Constant	-0.2079 [0.011]***
Cross-sections included: 48	
Total panel (balanced) observations: 2112	
Wald -statistic	9.8e+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regressions use state and year fixed effects and are robust to autocorrelation heteroskedasticity and cross-sectional contemporaneous correlation. The results are corrected for endogeneity. Instrumented variables: $\ln(K/L)_{I,t}$, $\text{Livestock}_{i,t}$.

Table 8: Wald χ^2–test Results for Differences in Rates of Convergence and Embodiment

Differences in β-convergence rates	
H_0 : $Phase(C)_t \times \ln(TFP)_{i,t} - Phase(R)_t \times \ln(TFP)_{i,t} = 0$	
χ^2-statistic	0.33
p-value	0.5672
H_0 : $Phase(C)_t \times \ln(TFP)_{i,t} - Phase(E)_t \times \ln(TFP)_{i,t} = 0$	
χ^2-statistic	4.21
p-value	0.0402
Differences in embodiment effects	
H_0 : $Phase(C)_t \times \ln(K/L)_{i,t} - Phase(R)_t \times \ln(K/L)_{i,t} = 0$	
χ^2-statistic	37.20
p-value	0.0000
H_0 : $Phase(C)_t \times \ln(K/L)_{i,t} - Phase(E)_t \times \ln(K/L)_{i,t} = 0$	
χ^2-statistic	97.73
p-value	0.0000