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Agricultural Productivity in the United States:

Catching-Up and the Business Cycle

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A***BSTRACT:***

This paper examines the relation between the business cycle and convergence in levels of total factor productivity (TFP) across states. First, we find evidence of convergence in TFP levels across the different phases of the business cycle, but the speed of convergence was much greater during periods of contraction in economic activity than during periods of expansion. Second, we find that technology embodied in capital was an important source of productivity growth in agriculture. As with the rate of catch-up, the embodiment effect was much stronger during low economic activity phases of the business cycle.

KEY WORDS: Agriculture; convergence; total factor productivity.

Agricultural Productivity in the U. S. States:
Catching-Up and the Business Cycle

1. Introduction

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; 1995), 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).

This paper explores the relationship between the business cycle and convergence of agricultural productivity across the states. 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. Despite these predictions, few researchers have estimated the impact of the business cycle on productivity convergence. Most either ignore this effect 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. Firms 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 closely follow the methodology proposed by 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).[2] 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).[3]

We also make a number of important contributions to the literature. 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 uses panel data. However, using asymptotic distributions based on panel data results 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.

The tests of the catch-up hypothesis used in this paper were proposed by Barro and Sala-i-Martin (1992).[4] Building on earlier 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 results can be summarized 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). 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. There were significant spillovers from investment in human capital, leading to more rapid productivity growth. 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.

2. Tests of *β*-Convergence

This section presents the econometric model used to test the catch-up (*i.e.*, *β*-convergence) hypothesis. First, we describe the basic model found in the literature, termed the benchmark model. Next, we present the method used to explore the relationship between catching-up and the business cycle.

2.1 The Benchmark Model

To investigate 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. An element of $X_{i,t}$ is the rate of growth of the relative capital intensities, $\Delta \ln(K/L)_{i,t}$, which captures the effect of technological innovations embodied in capital. Testing for *β*-convergence is equivalent to testing H_0: $\theta_1 = 1$ (*i.e.*, no *β*-convergence) against H_1: $\theta_1 < 1$ (*i.e.*, *β*-convergence), where $\theta_1 = -(1 - e^{\beta})$ and β is the rate of convergence.

Without further modification, the specification given 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. In order 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 $\ln(TFP_{i,t})$:

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

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).

2.2 β-Convergence and the Business Cycle

In order to evaluate the relationship between β-convergence and the business cycle we pursue two different approaches. First, following Escribano and Stucchi (2008), we investigate how the coefficient on the initial level of productivity changes across the different phases of the business cycle. We then look at the effects 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 equations (1) and (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 above (below) its potential level, thereby allowing us to distinguish periods of high economic activity (i.e., booms) and periods with low economic activity (i.e., late contractions and recoveries). On the other hand, 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). Given these differences, we consider two alternative partitions of the business cycle. The first one only uses the output gap measures and divides the business cycle into a high economic activity phase, say Phase (H), and a low economic activity phase, say Phase(L). The second partition divides the business cycle into a contraction phase, say Phase (C), a recovery phase, say Phase (R), and a late expansion phase, say Phase (E).

In summary, we use four different model specifications to assess the relationship between phases of the business cycle and convergence in levels of TFP across states. The first two specifications, Models 1 and 2, take into account the effects of the business cycle through the rate of convergence (*i.e.*, the coefficient on $\ln(TFP_{i,t})$). The latter two specifications, Models 3 and 4, incorporate the effects of the business cycle through its impact on embodiment (*i.e.*, the coefficient on $\Delta\ln(K/L)_{i,t}$). In Models 1 and 3, we partition the business cycle into two phases, while in Models 2 and 4 we identify three phases of the business cycle. To simplify the notation, we present the models assuming that there is no asymmetric mean reversion (*i.e.*, that $\theta_{1,d} = 0$ in equation (2)).

Model 1:

$$\Delta \ln(TFP_{i,t}) = \alpha + \Theta'_{(1)}[Phase(BC)_t \times \ln(TFP_{i,t})] + \Theta'_x X_{i,t} + v_{i,t}, \tag{3}$$

where

$$Phase(BC)_t = (Phase(L)_t, Phase(H)_t)',$$

$$\Theta'_{(1)} = (\theta_{1,L}, \theta_{1,H}),$$

and

$Phase(L)_t$ = 1 [In period t the U.S. output gap is negative],

$Phase(H)_t$ = 1 [In period t the U.S. output gap is positive],

where $1[\cdot]$ is an indicator function. Testable hypotheses using Model 1 include:

1. β-convergence during low economic activity phase of the business cycle. The null and alternatives hypotheses are:

   H_0: There is no β-convergence during low economic activity phase, *i.e.*, $\theta_{1,L} = 0$.

   H_1: There is β-convergence during low economic activity phase, *i.e.*, $\theta_{1,L} < 0$.

2. β-convergence during high economic activity phase of the business cycle. The null and alternative hypotheses in this case are:

H_0: There is no β-convergence during high economic activity phase, *i.e.*, $\theta_{1,H} = 0$.

H_1: There is β-convergence during high economic activity phase, *i.e.*, $\theta_{1,H} < 0$.

3. Differences in β-convergence rates between low economic activity and high economic activity phases of the business cycle. The null and alternative hypotheses in this case are:

H_0: There is no difference in the β-convergence rates between low economic activity and high economic activity phases, *i.e.*, $\theta_{1,L} - \theta_{1,H} = 0$.

H_1: The β-convergence rate is faster during low economic activity phases than during high economic activity phases, *i.e.*, $\theta_{1,L} - \theta_{1,H} < 0$.

Model 2:

$$\Delta \ln(TFP_{i,t}) = \alpha + \Theta'_{(1)}[Phase(BC)_t \times \ln(TFP_{i,t})] + \Theta'_x X_{i,t} + v_{i,t}, \qquad (4)$$

where

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

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

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 negative],

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

where $1[\cdot]$ is an indicator function. The hypotheses to be tested using Model 2 are:

1. β-convergence during contractions. The null and alternatives hypotheses are:

   H_0: There is no β-convergence during contractions, *i.e.*, $\theta_{1,C} = 0$.

   H_1: There is β-convergence during contractions, *i.e.*, $\theta_{1,C} < 0$

2. β-convergence during recoveries. The null and alternative hypotheses in this case are:

   H_0: There is no β-convergence during recoveries, *i.e.*, $\theta_{1,R} = 0$

   H_1: There is β-convergence in recoveries, *i.e.*, $\theta_{1,R} < 0$

3. β-convergence during late expansions. The null and alternative hypotheses are:

   H_0: There is no β-convergence during late expansions, *i.e.*, $\theta_{1,E} = 0$.

   H_1: There is β-convergence during late expansions, *i.e.*, $\theta_{1,E} < 0$

4. Differences in β-convergence rates between contractions and recoveries. The null and alternative hypotheses are:

H$_0$: There is no difference in β-convergence rates between contractions and recoveries, *i.e.*, $\theta_{1,C} - \theta_{1,R} = 0$.

H$_1$: The β-convergence rate is faster during contractions than during recoveries, *i.e.*, $\theta_{1,C} - \theta_{1,R} < 0$.

5. Differences in β-convergence rates between contractions and late expansions. The null and alternative hypotheses are:

H$_0$: There is no difference in β-convergence rates between contractions and late expansions, *i.e.*, $\theta_{1,C} - \theta_{1,E} = 0$.

H$_1$: The β-convergence rate is faster during contractions than during late expansions, *i.e.*, $\theta_{1,C} - \theta_{1,E} < 0$.

Model 3:

$$\begin{aligned}
&\Delta \ln(TFP_{i,t}) = \alpha + \Theta'_{(1)}[Phase(BC)_t \times \ln(TFP_{i,t})] \\
&+\Theta'_{(k)}[Phase(BC)_t \times \Delta \ln(K/L_{i,t})] \qquad (5) \\
&+\Theta'_{\tilde{x}}\tilde{X}_{i,t} + v_{i,t},
\end{aligned}$$

where

$$Phase(BC)_t = (Phase(L)_t, Phase(H)_t)',$$

$$\Theta'_{(1)} = (\theta_{1,L}, \theta_{1,H}),$$

$$\Theta'_{(k)} = (\theta_{k,L}, \theta_{k,H}),$$

and

$Phase(L)_t$ = 1 [In period t the U.S. output gap is negative],

$Phase(H)_t$ = 1 [In period t the U.S. output gap is positive],

where $1[\cdot]$ is an indicator function, the parameters $\theta_{k,L}$ and $\theta_{k,H}$ capture the impact of the different phases of the business cycle on embodiment, and $\tilde{X}_{i,t}$ is the vector of control variables excluding the growth rates of relative capital intensities. The hypothesis tests using Model 3 include those of Model 1 plus:

1. Embodiment effects during low economic activity phases of the business cycle. The null and alternative hypotheses are:

H_0: There are no embodiment effects during low economic activity phases, *i.e.*, $\theta_{k,L} = 0$.

H_1: There are embodiment effects during low economic activity phases, *i.e.*, $\theta_{k,L} > 0$

2. Embodiment effects during high economic activity phases of the business cycle. The null and alternative hypotheses are:

H_0: There are no embodiment effects during high economic activity phases of the business cycle, *i.e.*, $\theta_{k,H} = 0$

H_1: There are embodiment effects during high economic activity phases of the business cycle, *i.e.*, $\theta_{k,H} > 0$

3. Differences in the embodiment effects between low economic activity phases and high economic activity phases of the business cycle. The null and alternative hypotheses in this case are:

H_0: There are no differences in the embodiment effects between low economic activity phases and high economic activity phases, *i.e.*, $\theta_{k,L} - \theta_{k,H} = 0$

H_1: The embodiment effects are larger during low economic activity phases than during high economic activity phases, *i.e.*, $\theta_{k,L} - \theta_{k,H} = 0$

Model 4:

$$\begin{aligned}&\Delta \ln(TFP_{i,t}) = \alpha + \Theta'_{(1)}[Phase(BC)_t \times \ln(TFP_{i,t})]\\&+\Theta'_{(k)}[Phase(BC)_t \times \Delta \ln(K/L_{i,t})]\\&+\Theta'_{\tilde{x}}\tilde{X}_{i,t} + v_{i,t},\end{aligned} \tag{6}$$

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 negative],

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

where $1[\cdot]$ is an indicator function, the parameters $\theta_{k,C}$, $\theta_{k,R}$ and $\theta_{k,E}$ capture the impacts of the contraction, recovery and late expansion phases of the business cycle on embodiment and $\tilde{X}_{i,t}$ is the vector of control variables excluding the rates of growth of the relative capital intensities. The hypotheses to be tested using Model 4 includes those of Model 2 plus:

1. Embodiment effects in contractions. The null and alternatives hypotheses are:

H_0: There are no embodiment effects during contractions, *i.e.*, $\theta_{k,C} = 0$.

H_1: There are embodiment effects during contractions, *i.e.*, $\theta_{k,C} > 0$.

2. Embodiment effects during recoveries. The null and alternatives hypotheses in this case are:

H_0: There are no embodiment effects during recoveries, *i.e.*, $\theta_{k,R} = 0$.

H_1: There are embodiment effects during recoveries, *i.e.*, $\theta_{k,R} > 0$.

3. Embodiment effects during late expansions. The null and alternatives hypotheses in this case are:

H_0: There are no embodiment effects during late expansions, *i.e.*, $\theta_{k,E} = 0$.

H_1: There are embodiment effects during late expansions, *i.e.*, $\theta_{k,E} > 0$.

4. Differences in the embodiment effects between contractions and recoveries. The null and alternatives hypotheses are:

H_0: There are no differences in the embodiment effects between contractions and recoveries, *i.e.*, $\theta_{k,C} - \theta_{k,R} = 0$.

H_1: The embodiment effects are larger during contractions than during recoveries, *i.e.*, $\theta_{k,C} - \theta_{k,R} > 0$.

5. Differences in the embodiment effects between contractions and late expansions. The null and alternatives hypotheses are:

H_0: There are no differences in the embodiment effects between contractions and late expansions, *i.e.*, $\theta_{k,C} - \theta_{k,E} = 0$.

H_1: The embodiment effects are larger during contractions than during late expansions, *i.e.*, $\theta_{k,C} - \theta_{k,E} > 0$.

3. Data

The following paragraphs provide 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. Törnqvist output indexes are formed by aggregating over agricultural goods and services using revenue-share weights based on shadow prices. Indexes of labor input are constructed using demographically cross-classified hours and compensation data. Our measure of capital input begins with data on the stock of capital for each component of capital input. For depreciable assets, the capital stocks are the cumulation of all past investments adjusted for discards of worn-out assets and loss of efficiency of assets over their service life. For land and inventories, capital stocks are measured as implicit quantities derived from balance sheet data. Indexes of capital input are 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. Price indexes for fertilizers and pesticides are constructed 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, considerable effort is expended to develop 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.[5]

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). We construct the market accessibility and domestic and external demand variables using the market accessibility function proposed by Harris (1954).[7]

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.

4. Empirical Results

This section details our empirical findings. 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.

4.1 Benchmark Model

4.1.1 Testing for Panel Unit Roots

To avoid spurious regression results, we first examine whether the variables in equations (1) and (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 (1981) 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 parameter, 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 equations (1) and (2) assuming stationarity.

4.1.2 Pooled OLS

In Table 2 we report the pooled OLS estimates of equations (1) and (2). The results support the catch-up hypothesis, showing a highly significant inverse relation between the rate of TFP convergence by state and its initial TFP level relative to the United States (columns 1 through 5). The results for the embodiment hypothesis appear in columns 2 through 5. The variable $\Delta \ln(K/L)_{i,t}$ has a positive and significant coefficient, suggesting that embodiment of technology in capital was an important source of TFP growth. The relation between productivity growth and specialization is given in columns 3 through 5, while years of schooling and worker experience appear in columns 4 and 5. Neither is statistically significant. Finally, the coefficient on the interaction term, $d_{i,t}^{AMR} x \ln(TFP_{i,t})$, is not statistically significant, suggesting there is no asymmetric mean reversion (column 5). We note, however, that the results in Table 2 are consistent if and only if the orthogonality conditions on equations (1) and (2) hold (*i.e.*, the explanatory variables are uncorrelated with the error term $\upsilon_{i,t}$).

4.1.3 Testing for 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 (1) or (2) and:

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

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 for each of the econometric specifications described above. In all cases, the Breusch and Pagan (1980) test for random effects and the F-test for fixed effects yield a p-value smaller than 0.10, which clearly points to the presence of state-specific effects. Furthermore, in all cases 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.

4.1.4 Testing for 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. Technically speaking, this assumption does not compromise the consistency of the estimated parameters. The two-way error components model is given by (1) or (2) and:

$$v_{i,t} = \eta_i + \varepsilon_t + u_{i,t}, \tag{8}$$

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 $\varepsilon_t = 0, t = 1,...,T$. Table 4 summarizes the two-way fixed-effects estimation results for each of the econometric specifications described above. The bottom panel in Table 4 shows the F-test results for the two-way fixed effects model against the one-way fixed-effects model. In all cases, the F-test 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.

4.1.5 Testing for Endogeneity

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 (1) or (2) using as instruments all the exogenous variables in (1) or (2) and the excluded instruments described in Section 3 above. Then we perform the augmented two-way fixed-effects within regressions by including the first-step residuals. If the coefficients on those residuals are significantly different from zero the original two-way fixed effects estimates are not consistent (*i.e.*, $E(X_{i,t}, u_{i,t}) \neq 0$.

Table 5 reports the endogeneity tests results for each econometric specifications in which an explanatory variable is likely endogenous. In all cases, the coefficients on the residuals of $\Delta \ln(K/L)_t$ are significant at the 5% level, indicating that the relative capital intensities are endogenous variables. In the case of specialization, the results are mixed. The coefficients on the residuals of the livestock intensities are significant at the 10% level. But the results suggest that the crop intensities are exogenous since the coefficients on the residuals are 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 estimated equations (1) and (2).

Table 6 reports the two-steps IV two-way fixed-effects results. The bottom panel in Table 6 shows the results for the underidentification and overidentifying restrictions tests. In all cases the Kleibergen-Paap (2006) test for underidentification yield 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. In two cases, the test yields a p-value grater that 0.10, and the other two cases yield 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 Tables 4 and 6 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 $\Delta \ln(K/L)_t$ 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 the cyclical component. As a point of reference, however, Ball, Hallahan and Nehring (2004) find that the magnitude of the coefficient on $\Delta \ln(K/L)_t$ is, in absolute value, about 0.75 times the magnitude of the catch-up parameter. The results in Table 6 suggest that the coefficient on $\Delta \ln(K/L)_t$ 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.

4.1.6 Testing for Serial Correlation of the Error Components

The specifications given by equations (1) or (2) and (8) 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 (8) 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 (1) or (2), (8) and,

$$u_{it} = \rho u_{it-1} + e_{i,t}; |\rho| < 1, \tag{9}$$

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

Table 7 summarizes the estimation results for the two-way fixed-effects specification with AR(1) remaining disturbances. The results reported in columns 2 through 5 were obtained by the two-steps IV method. First, we estimate the endogenous right-hand side variables in (1) and (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. The bottom panel in Table 7 shows 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. Since we have that some explanatory variables in (1) and (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.

4.1.7 Testing for Heteroskedasticity

In order to control for possible groupwise heteroskedasticity, we perform the Modified Wald test in the specifications given by equations (1) or (2) and (8). Note that this test gives valid results even though the normality assumptions do not hold (see Green, 2003). Table 8 summarizes the heteroskedasticity test results. The results reported are robust to endogeneity. First, we estimate the endogenous right-hand side variables in equations (1) and (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. In all the cases, the test yields a p-value of 0.0000. Thus we can reject the null hypothesis of homoskedasticity.

4.1.8 Benchmark Model Specification

The final benchmark model 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:

$$v_{it} = \eta_i + \varepsilon_t + u_{i,t}, \tag{10}$$

$$u_{it} = \rho_i u_{it-1} + e_{it}; |\rho| < 1. \tag{11}$$

In order to correct for endogeneity, heteroskedasticity and autocorrelation, we proceed by estimating the model using a TSCS Instrumental Variables Feasible GLS (TSCS IV-FGLS) regression method. First, we estimate the endogenous right-hand side variables in (1) and (2) using a two-way fixed effects model and the set of valid instruments described in Section 3. 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 estimation results are summarized in Table 9. In contrast with previous studies, the results in Table 9 confirm that human capital spillovers contribute significantly to TFP growth. Moreover, there is evidence of asymmetric mean reversion; that is, those states with below average TFP levels converge to the mean level at a faster rate than states with TFP levels above the average.

4.2 β-Convergence and the Business Cycle

In Section 2, we discussed four alternate model specifications to assess the impact of the business cycle on TFP convergence. The first two specifications, or Models 1 and 2, capture the effects of the business cycle through interaction with the initial level of productivity, while Models 3 and 4 also include an interaction term with the relative capital intensities. In Models 1 and 3, we partition the business cycle into phases of high economic activity (Phase H) and low economic activity (Phase L). In Models 2 and 4, we consider an alternative partition of the business cycle, a contraction phase (Phase C), a recovery phase (Phase R), and a late expansion phase (Phase E).

Each of the specifications is a two-way fixed effects model with state-specific error variances and state-specific AR(1) disturbances. As in the final benchmark specification, we proceed by estimating the model using a TSCS Instrumental Variables Feasible GLS (TSCS IV-FGLS) regression method. First we estimate the endogenous righthand side variables in equations (3) to (6) using a two-way fixed effects model and the set of valid instruments discussed previously. Then, using the fitted values for the first-step dependent variables, we estimate by TSCS Feasible GLS (TSCS FGLS) the two-way fixed-effects model robust to endogeneity, heteroskedasticity, autocorrelation and cross-sectional contemporaneous correlation. We include dummy variables for each year and each state to control for the state-specific and the time-specific fixed effects.

4.3 Rates of Convergence

Tables 10 and 11 summarize the estimation results for Models 1 and 2. The bottom panel in both tables shows the Wald χ^2-test results for differences in convergence rates across the different phases of the business cycle. The results in Table 10 indicate that there is convergence in levels of productivity during both the low economic activity and the high economic activity phases of the business cycle. The Wald χ^2-tests for differences in convergence rates yield a p-value smaller than 0.05 in all the cases. We conclude that there is a small but statistically significant difference in the rates of convergence across the different phases of the business cycle. Taking column (5) as the preferred specification, the model predicts that the convergence rate for productivity followers is 7.7% higher during low economic activity phases of the business cycle than during high economic activity phases. This difference is even greater for the productivity leaders, about 8.8% once we allow for asymmetric mean reversion.

On the other hand, the results in Table 11 indicate that there is convergence in TFP levels during the contraction, recovery, and late expansion phases of the business cycle. The Wald χ^2-tests for the differences in rates of convergence between contraction and recovery phases yield a p-value grater than 0.1 in four of the five cases. However, test results for differences in the rate of convergence during contraction and late expansion phases yield a p-value smaller than 0.1 in four of the five cases. These results suggest that there is a small but statistically significant difference in the convergence rates between the contraction and late expansion phases of the business cycle. Again taking column 5 as the preferred specification, the model predicts that the convergence rate for productivity followers is 6.8% higher during the contraction phase of the business cycle than during the late expansion phase. As in the previous case, the difference is even higher for the productivity leaders, about 7.3% once we allow for asymmetric mean reversion.

Overall, these results are consistent with theory. We observe faster catching-up during low economic activity and contractions phases of the business cycle and lower rates of convergence during high economic activity and late expansion phases of the business cycle. As noted earlier, this result is a direct consequence of both time lags in technological diffusion processes and the procyclical behavior of innovation. In contrast with evidence from the manufacturing sector, however, the magnitude of the effects of the business cycle on TFP convergence in agriculture appears relatively small. We attribute this result to the level of publicly funded 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 implies a smaller impact of the business cycle on TFP convergence.

4.4 Convergence, Embodiment, and The Business Cycle

Tables 12 and 13 summarize the results for Models 3 and 4. The bottom panel in both tables shows the Wald χ^2-test results for both differences in the rates of convergence and differences in the embodiment effect across different phases of the business cycle. The results in Table 12 confirm that there is convergence in TFP during both low economic activity and high economic activity phases of the business cycle. The Wald χ^2-test for differences in rates of convergence yields a p-value smaller than 0.05 in all the cases. Furthermore, the test for differences in the embodiment effect across the business cycle yields a p-value of 0.0000. These results lead us to two conclusions. First, there is a small but statistically significant difference in the rates of convergence across the different phases of the business cycle and, second, there is a large and statistically significant difference in the embodiment effect. Taking column 5 as the preferred specification, the model predicts that the rate of convergence for productivity followers is 5.7% higher during low economic activity phases of the business cycle than during high economic activity phases. As was seen earlier, that difference is even greater for the productivity leaders, about 6.1% once we allow for asymmetric mean reversion. Moreover, the model results point to a greater embodiment effect, some 40% greater, during low economic activity phases of the business cycle than during high economic activity phases.

The results in Table 13 also confirm that there is convergence in levels of TFP in the contraction, recovery, and late expansion phases of the business cycle. The Wald χ^2-test results for the differences in convergence rates between contractions and recoveries yield a p-value greater than 0.1 in three of the five cases. However, the test results for differences in rates of convergence during periods of contraction and late expansion yield a p-value less than 0.1 in four of the five cases. Furthermore, 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 a p-value of 0.0000 in all the cases. We conclude that there is a small but and statistically significant difference in the rates of convergence during contraction and late expansion phases of the business cycle. There is also a large and statistically significant difference in the embodiment effect during the contraction phase and the other two phases of the business cycle. Again taking column 5 as the preferred model, the results suggest that the rate of convergence for productivity followers is 4.8% faster during the contraction phase than during the late expansion phase. And that difference is even greater for the productivity leaders, about 5.1% once we allow for asymmetric mean reversion. Moreover, 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.

Again, these results are consistent with theory. We not only observe faster catching-up during the low economic activity and contraction phases of the business cycle, but we also observe stronger embodiment effects. Both the rate of convergence and the magnitude of the embodiment effect are lower during the high economic activity and the late expansions phases of the business cycle.

5. Summary and Conclusions

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 an econometric 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 do so using four different model specifications. First, we consider the effects of the business cycle on convergence using two alternative partitions of the business cycle. Initially, we partition the business cycle into periods of high and low economic activity. A second decomposes the business cycle into periods of contraction, recovery, and late expansion. Finally, we 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. In line with Dollar and Wolff (1994) and Ball, Hallahan, and Nehring (2004), we include growth rates in relative capital intensities to capture technological embodiment. Following Evenson and Hufman (2001), 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 (Parman, 2009). Since the relative capital intensities and the measures of specialization are endogenous variables we use an instrumental variables approach.

The results from our benchmark model can be summarized as follows. First, we find evidence of convergence in productivity 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, less specialized states had, on average, higher productivity growth rates than more specialized states. However, states that specialized in livestock production achieved faster growth rates than states that specialized in the production of crops. This result is consistent with the literature on agricultural productivity 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. Finally, we find that there are important human capital spillovers into agriculture. 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 expansion and high economic activity phases.

When we consider the effects of the business cycle only through convergence, we find that the rate of catch-up for the productivity followers is about 7.7% higher during low economic activity phases of the business cycle than during high economic activity phases. During contractions in economic activity, the rate of catch-up for these states is about 6.8% higher than during late expansions. The differences are even greater for the productivity leaders, about 8.8% and 7.3%, respectively, once we allow for asymmetric mean reversion.

The above mentioned results are robust to the presence of cyclical effects through embodiment. The catch-up rate for the productivity followers is about 5.7% higher during low economic activity phases than during the high economic activity phases. During contractions, the catch-up rate for those states is about 4.8% higher than during late expansions. These differences are even greater for the productivity leaders, about 6.1% and 5.1%, respectively.

Finally, the results indicate that there are significant differences in the magnitude of the embodiment effect across the business cycle. The embodiment effect is 40.4% higher during low economic activity phases of the business cycle than during high economic activity phases. Moreover, those effects are 33.9% and 73.7% higher during contractions than during recoveries and late expansions.

Overall, the results are consistent with the predictions of 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 point to a smaller impact of the business cycle on TFP convergence.

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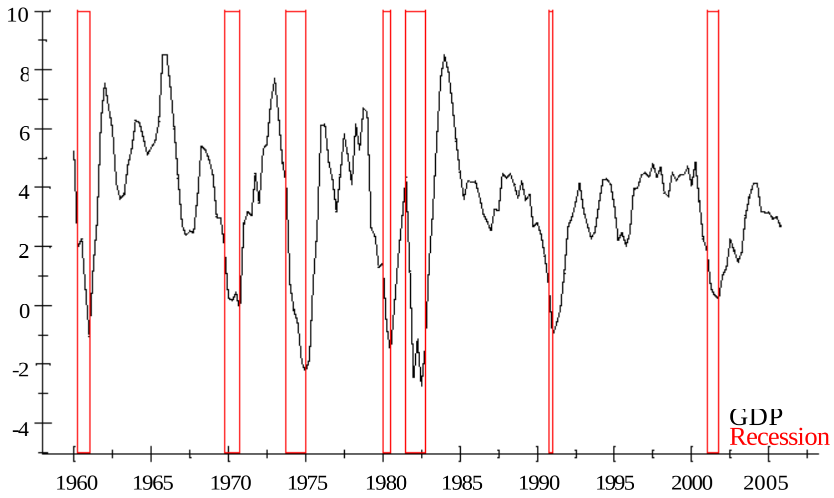
Notes

1. Overshooting of prices refers to temporary changes beyond long-run equilibrium levels.
2. Publically funded research and development (R&D) plays an important role in agriculture. Since innovations resulting from public R&D can be considered public goods that firms can imitate in a relatively short period of time diffusion of technical information may be faster in agriculture.
3. 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.
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. e.g., McCunn and Huffman, 2000; Ball, Hallahan, and Nehring, 2004).
5. These data were taken from Baier et al. (2007). They construct the state-level schooling and worker experience variables using a perpetual inventory method. The time series cover the period between 1840 and 2000. Figures for the period 2001-2004 are extrapolated using TRAMO. TRAMO is a program for MLE estimation of regression models with general non-stationary (ARIMA) errors, outliers, and long sequences of missing observations (Gómez and Maravall, 1997; Maravall 2005).
6. In this paper we perform the Baltagi and Li (1995) test and Wooldridge (2002) test since both tests can be applied under very few maintained assumptions (see Baltagi and Li, 1995 and Drukker, 2003).
7. 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.

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



Source: U.S. NBA and NBER.

Table 1: Panel Data Unit Root Tests

Variable	LLC' Statistic	IPS's Statistic	BRG's Statistic
$\Delta \ln(TFP_{i,t})$	—44.905	—50.343	—24.285
$\ln(TFP_{i,t})_{it}$	—18.125	—16.027	—9.881
$\Delta \ln(KIL)_{i;t}$	—47.091	—46.115	—34.825
$Livestock_{i,t}$	—17.152	—15.987	—8.101
$Crops_{i,t}$	—17.726	—17.240	—7.162
$\Delta \ln(Schooling_{i,t})$	—32.788	—31.572	—19.755
$\Delta \ln(Experience_{i,t})$	—23.955	—20.487	—23.311

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

Note: 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: Catching-Up in Agricultural TFP

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

Method: Pooled OLS

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.0621	-0.0585	-0.0593	-0.0593	-0.0719
	[0.008]***	[0.008]***	[0.008]***	[0.008]***	[0.012]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					0.0320
					[0.024]
$\Delta \ln(K/L)_{i,t}$		0.2094	0.2097	0.2093	0.2092
		[0.014]***	[0.014]***	[0.014]***	[0.014]***
$Livestock_{i,t}$			-0.0105	-0.0103	-0.0063
			[0.130]	[0.131]	[0.136]
$Crops_{i,t}$			-0.0130	-0.0130	-0.0084
			[0.014]	[0.014]	[0.014]
$\Delta \ln(Schooling)_{i,t}$				0.2906	-0.2886
				[0.312]	[0.312]
$\Delta \ln(Experience)_{i,t}$				0.0890	0.0842
				[0.160]	[0.144]
Constant	-0.0040	-0.0078	-0.0090	-0.0111	-0.0130
	[0.002]**	[0.002]***	[0.002]***	[0.003]***	[0.003]***
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
R^2	0.0280	0.1221	0.1225	0.1229	0.1236

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

Table 3: Panel Data State-Specific Effects' Tests

	(1)	(2)	(3)	(4)	(5)
Cross-section random effects					
BPLM X^2-statistic	4.91	3.51	3.85	4.14	4.99
Prob(X^2-statistic)	0.0266	0.0611	0.0497	0.0418	0.0255
Cross-section fixed effects					
F-statistic	10.07	9.44	10.00	10.15	10.15
Prob(F-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000
Cross-section fixed effects vs Cross-section random effects					
Hausman X^2-statistic	485.30	451.64	481.43	487.50	489.06
Prob(X^2-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000

Cross-sections included: 48

Total panel (balanced) observations: 2112

Table 4: Catching-Up in Agricultural TFP
Dependent Variable: $\Delta \ln TFP_{i,t}$
Method: FE (within regression)

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.4292	-0.4019	-0.3829	-0.3823	-0.3740
	[0.018]***	[0.018]***	[0.018]***	[0.018]***	[0.023]***
$d_{i,t}^{AMR} \times \ln TFP_{i,t}$					-0.0257
					[0.042]
$\Delta \ln(K/L)_{i,t}$		0.1704	0.1753	0.1753	0.1756
		[0.013]***	[0.013]***	[0.013]***	[0.013]***
$Livestock_{i,t}$			-0.0234	-0.0221	-0.0205
			[0.130]	[0.131]	[0.136]
$Crops_{i,t}$			-0.0959	-0.0959	-0.0946
			[0.023]***	[0.023]***	[0.023]***
$\Delta \ln(Schooling)_{i,t}$				0.3911	-0.3985
				[0.333]	[0.334]
$\Delta \ln(Experience)_{i,t}$				-0.0387	-0.0365
				[0.160]	[0.160]
Constant	-0.0407	-0.0463	-0.0513	-0.0525	-0.0508
	[0.009]***	[0.009]***	[0.009]***	[0.010]***	[0.010]***
Panel data Time-Specific Fixed Effects Test					
F-statistics	6.54	5.96	6.22	6.08	6.04
Prob(F-statistics)	0.0000	0.0000	0.0000	0.0000	0.0000
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
R^2	0.3039	0.3569	0.3672	0.3678	0.3679

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regressions use state and year fixed effects.

Table 5: Panel Data Endogeneity Tests

Variable	(2)	(3)	(4)	(5)
$\Delta \ln(K/L)_{i,t}$	-0.6131	-0.4320	-0.4411	-0.4481
	[0.177]***	[0.180]**	[0.178]**	[0.180]**
$Livestock_{i,t}$		0.2023	0.2025	0.2254
		[0.116]*	[0.115] *	[0.125]*
$Crops_{i,t}$		0.0842	0.0896	0.1190
		[0.176]	[0.172]	[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 6: Catching-Up in Agricultural TFP
Dependent Variable: $\Delta \ln TFP_{i,t}$
Method: IV-FE (within regression)

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.4292	-0.2965	-0.3034	-0.3004	-0.3000
	[0.018]***	[0.046]***	[0.049]***	[0.049]***	[0.061]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					-0.0074
					[0.076]
$\Delta \ln(K/L)_{i,t}$		0.8282	0.8329	0.8405	0.8345
		[0.213]***	[0.235]***	[0.235]***	[0.233]***
$Livestock_{i,t}$			-0.3069	-0.3086	-0.3145
			[0.118]***	[0.121]***	[0.123]***
$Crops_{i,t}$			-0.4345	-0.4387	-0.4445
			[0.133]***	[0.136]***	[0.138]***
$\Delta \ln(Schooling)_{i,t}$				-0.2426	-0.2388
				[0.566]	[0.564]
$\Delta \ln(Experience)_{i,t}$				-0.2002	-0.2005
				[0.249]	[0.248]
IV Identification tests (Instrumented: Δln(K/L)i,t, Livestocki,t)					
Underidentification test					
χ^2-statistics		15.715	15.306	15.269	15.350
Prob(χ^2-statistics)		0.0154	0.0323	0.0327	0.0318
Overidentification of all instruments					
χ^2-statistics		4.650	10.920	10.543	10.683
Prob(χ^2-statistics)		0.4601	0.0909	0.1036	0.0987
Cross-sections included: 48					
Total panel (balanced) observations: 2112					

Notes: * signiflcant at 10%; ** signiflcant at 5%; *** signiflcant at 1%. Robust Standard errors in brackets. All regresions use state and year fixed effects. The results reported in columns (2) to (5) are corrected for endogeneity. IV Identification tests robust to heteroskedasticity.

Table 7: Catching-Up in Agricultural TFP
Dependent Variable: $\Delta \ln TFP_{i,t}$
Method: IV-FE (within regression)

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.7411	-0.6008	-0.5590	-0.5628	-0.5782
	[0.022]***	[0.042]***	[0.041]***	[0.041]***	[0.041]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					0.0425
					[0.049]
$\Delta \ln(K/L)_{i,t}$		0.8840	1.0877	1.0454	1.0536
		[0.218]***	[0.237]***	[0.235]***	[0.235]***
$Livestock_{i,t}$			-0.5230	-0:.5040	-0.5340
			[0.130]***	[0.131]***	[0.136]***
$Crops_{i,t}$			-0.7326	-0.7106	-0.7417
			[0.148]***	[0.149]***	[0.153]***
$\Delta \ln(Schooling)_{i,t}$				0.0225	-0.0088
				[0.360]	[0.364]
$\Delta \ln(Experience)_{i,t}$				0.2213	0.2216
				[0.187]	[0.187]
Constant	-0.0537	0.0000	-0.1112	-0.1094	-0.1136
	[0.007]***	[0.011]	[0.017]***	[0.017]***	[0.018]***
AR(1) Reminder Disturbances Tests					
$\hat{\rho}$	-0.2699	-0.2722	-0.2608	-0.2611	-0.2608
BLI χ^2-statistic	43.976	46.404	38.067	38.135	37.944
Prob(χ^2-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000
WD F-statistic	336.608	334.002	303.683	298.339	297.079
Prob(F-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000

Cross-sections included: 48

Total panel (balanced) observations: 2064

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standarderrors in brackets. All regresions use state and year fixed effects and are robustto autocorrelation. The results reported in columns (2) to (5) are corrected forendogeneity. Instrumented variables: $\Delta\ln(K/L)_{i,t}$, $Livestock_{i,t}$

Table 8: Panel Data Heteroskedasticity Test

	(1)	(2)	(3)	(4)	(5)
Wald χ^2-statistic	585.88	555.36	569.04	564.87	566.23
Prob(χ^2-statistic)	0.0000	0.0000	0.0000	0.0000	0.0000

Cross-sections included: 48

Total panel (balanced) observations: 2112

Notes: The results reported in columns (2) to (5) are corrected for endogeneity. Instrumented variables: Δ ln(K/L)i,t, Livestocki,t

Table 9: Catching-Up in Agricultural TFP

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

Method: IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$\ln TFP_{i,t}$	-0.3852	-0.2592	-0.2900	-0.2891	-0.2995
	[0.016]***	[0.010]***	[0.012]***	[0.012]***	[0.012]***
$d^{AMR}_{i,t}$ x $\ln TFP_{i,t}$					0.0253
					[0.010]***
$\Delta \ln(K/L)_{i,t}$		0.6947	0.8885	0.8811	0.8624
		[0.024]***	[0.042]***	[0.043]***	[0.043]***
$Livestock_{i,t}$			-0.4581	-0.4407	-0.4570
			[0.026]***	[0.027]***	[0.028]***
$Crops_{i,t}$			-0.5948	-0.5776	-0.5946
			[0.028]***	[0.030]***	[0.031]***
$\Delta \ln(Schooling)_{i,t}$				0.2143	0.1942
				[0.063]***	[0.063]***
$\Delta \ln(Experience)_{i,t}$				0.2087	0.2091
				[0.030]***	[0.030]***
Constant	-0.0048	-0.0463	-0.2103	-0.2106	-0.2147
	[0.006]	[0.007]***	[0.011]***	[0.011]***	[0.011]***
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
Wald χ^2-statistic	3.26e+07	2.79e+06	1.15e+07	8.98e+06	8.73e+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regresions use state and year fixed effects and are robust to autocorrelation heteroskedasticity and cross-sectional contemporaneous correlation. The results reported in columns (2) to (5) are corrected for endogeneity. Instrumented variables: Δ ln(K/L)i,t, Livestocki,t.

Table 10: Catching-Up in Agricultural TFP and the Business Cycle

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

Method: IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$Phase(L)_t$ x $\ln TFP_{i,t}$	-0.3869	-0.2740	-0.2974	-0.2957	-0.3067
	[0.016]***	[0.016]***	[0.012]***	[0.012]***	[0.012]***
$Phase(H)_t$ x $\ln TFP_{i,t}$	-0.3772	-0.2631	-0.2789	-0.2773	-0.2883
	[0.016]***	[0.015]***	[0.011]***	[0.012]***	[0.013]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					0.0269
					[0.010]***
$\Delta \ln(K/L)_{i,t}$		0.6539	0.8878	0.8635	0.8551
		[0.052]***	[0.043]***	[0.043]***	[0.043]***
$Livestock_{i,t}$			-0.4558	-0.4390	-0.4556
			[0.026]***	[0.028]***	[0.029]***
$Crops_{i,t}$			-0.5932	-0.5768	-0.5940
			[0.029]***	[0.030]***	[0.031]***
$\Delta \ln(Schooling)_{i,t}$				0.2029	0.1820
				[0.064]***	[0.064]***
$\Delta \ln(Experience)_{i,t}$				0.1937	0.1943
				[0.030]***	[0.030]***
Constant	-0.0050	-0.0442	-0.2109	-0.2114	-0.2155
	[0.005]	[0.007]***	[0.011]***	[0.011]***	[0.011]***
Differences in β-convergence rates test					
$H_0: Phase(L)_t$ x $\ln TFP_{i,t} - Phase(H)_{i,t}$ x $\ln TFP_t = 0$					
χ^2-statistics	4.57	7.23	37.15	28.83	29.55
Prob(χ^2-statistics)	0.0326	0:0071	0.0000	0.0000	0.0000
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
Wald χ^2-statistic	4.25e+07	2.85e+07	1.03e+07	7.73e+06	7.25e+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors inbrackets. All regresions use state and year fixed effects and are robust to autocorrelationheteroskedasticity and cross-sectional contemporaneous correlation. The results reportedin columns (2) to (5) are corrected for endogeneity. Instrumented variables: $\Delta \ln(K/L)_{i,t}$, $Livestock_{i,t}$.

Table 11: Catching-Up in Agricultural TFP and the Business Cycle
Dependent Variable: $\Delta \ln TFP_{i,t}$
Method: IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$Phase(C)_t$ x $\ln TFP_{i,t}$	-0.3932	-0.2895	-0.2969	-0.2978	-0.3077
	[0.017]***	[0.017]***	[0.012]***	[0.013]***	[0.013]***
$Phase(R)_t$ x $\ln TFP_{i,t}$	-0.3863	-0.2762	-0.2946	-0.2925	-0.3027
	[0.016]***	[0.016]***	[0.012]***	[0.012]***	[0.012]***
$Phase(E)_t$ x $\ln TFP_{i,t}$	-0.3827	-0.2725	-0.2828	-0.2812	-0.2913
	[0.016]***	[0.016]***	[0.012]***	[0.016]***	[0.012]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					0.0242
					[0.010]***
$\Delta \ln(K/L)_{i,t}$		0.6186	0.8778	0.8518	0.8531
		[0.053]***	[0.042]***	[0.043]***	[0.043]***
$Livestock_{i,t}$			-0.4521	-0.4334	-0.4497
			[0.026]***	[0.028]***	[0.029]***
$Crops_{i,t}$			-0.5886	-0.5702	-0.5871
			[0.029]***	[0.030]***	[0.031]***
$\Delta \ln(Schooling)_{i,t}$				0.2147	0.1949
				[0.064]***	[0.064]***
$\Delta \ln(Experience)_{i,t}$				0.2028	0.2034
				[0.030]***	[0.030]***
Constant	-0.0047	-0.0418	-0.2088	-0.2090	-0.2130
	[0.006]	[0.007]***	[0.011]***	[0.011]***	[0.011]***
Differences in β-convergence rates test					
$H_0: Phase(C)_t$ x $\ln TFP_{i,t}$ - $Phase(R)_t$ x $\ln TFP_{i,t} = 0$					
χ^2-statistics	0.94	4.26	0.22	0.90	0.83
Prob(χ^2-statistics)	0.3325	0.0390	0.6367	0.3429	0.3627
$H_0: Phase(C)_t$ x $\ln TFP_{i,t}$ - $Phase(E)_t$ x $\ln TFP_{i,t} = 0$					
χ^2-statistics	2.04	6.78	8.06	8.67	8.73
Prob(χ^2-statistics)	0.1533	0.0092	0.0045	0.0032	0.0031
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
Wald χ^2-statistic	5.12e+07	2.91e+07	1.05e+07	7.8e+06	7.5e+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regresions use state and year fixed effects and are robust to autocorrelation heteroskedasticity and cross-sectional contemporaneous correlation. The results reported in columns (2) to (5) are corrected for endogeneity. Instrumented variables: $\Delta \ln(K/L)_{i,t}$, $Livestock_{i,t}$.

Table 12: Catching-Up in Agricultural TFP and the Business Cycle

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

Method: IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$Phase(L)_t$ x $\ln TFP_{i,t}$	-0.3869	-0.2687	-0.2980	-0.2968	-0.3067
	[0.016]***	[0.009]***	[0.011]***	[0.011]***	[0.012]***
$Phase(H)_t$ x $\ln TFP_{i,t}$	-0.3772	-0.2576	-0.2843	-0.2831	-0.2929
	[0.016]***	[0.009]***	[0.011]***	[0.011]***	[0.012]***
$d_{i,t}^{AMR}$ x $\ln TFP_{i,t}$					0.0274
					[0.009]***
$Phase(L)_t$ x $\Delta \ln (K/L)_{i,t}$		0.7935	0.9675	0.9368	0.9341
		[0.028]***	[0.041]***	[0.042]***	[0.042]***
$Phase(H)_t$ x $\Delta \ln (K/L)_{i,t}$		0.4611	0.6503	0.6474	0.6654
		[0.035]***	[0.047]***	[0.048]***	[0.048]***
$Livestock_{i,t}$			-0.4405	-0.4262	-0.4436
			[0.026]***	[0.028]***	[0.029]***
$Crops_{i,t}$			-0.5713	-0.5579	-0.5763
			[0.028]***	[0.030]***	[0.031]***
$\Delta \ln(Schooling)_{i,t}$				0.2106	0.1906
				[0.061]***	[0.060]***
$\Delta \ln(Experience)_{i,t}$				0.1921	0.1893
				[0.029]***	[0.029]***
Constant	-0.0506	-0.0489	-0.2082	-0.2090	-0.2134
	[0.006]	[0.007]***	[0.011]***	[0.011]***	[0.011]***
Differences in β-convergence rates test					
H_0 : $Phase(L)_t$ x $\ln TFP_{i,t}$ - $Phase(H)_t$ x $\ln TFP_{i,t}$ = 0					
χ^2-statistics	4.57	13.81	20.87	0.90	16.23
Prob(χ^2-statistics)	0.0326	0.0002	0.0000	16.15	0.0001
Differences in embodiment effects test					
H_0 : $Phase(L)_t$ x $\Delta \ln (K/L)_{i,t}$ - $Phase(H)_t$ x $\Delta \ln (K/L)_{i,t}$ = 0					
χ^2-statistics		63.93	99.89	76.08	65.37
Prob(χ^2-statistics)		0.0000	0.0000	0.0000	0.0000
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
Wald χ^2-statistic	4.25e+07	2.60e+06	8.1e+06	6.4e+06	6.2e+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regresions use state and year fixed effects and are robust to autocorrelation heteroskedasticity and cross-sectional contemporaneous correlation. The results reported in columns (2) to (5) are corrected for endogeneity. Instrumented variables: $\Delta \ln(K/L)_{i,t}$, $Livestock_{i,t}$.

Table 13: Catching-Up in Agricultural TFP and the Business Cycle

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

Method: IV-FGLS

Variable	(1)	(2)	(3)	(4)	(5)
$Phase(C)_t \times \ln TFP_{i,t}$	-0.3932	-0.2987	-0.3021	-0.3022	-0.3103
	[0.017]***	[0.017]***	[0.013]***	[0.012]***	[0.013]***
$Phase(R)_t \times \ln TFP_{i,t}$	-0.3863	-0.2872	-0.2936	-0.2984	-0.3070
	[0.016]***	[0.015]***	[0.012]***	[0.011]***	[0.012]***
$Phase(E)_t \times \ln TFP_{i,t}$	-0.3827	-0.2874	-0.2859	-0.2898	-0.2985
	[0.016]***	[0.015]***	[0.012]***	[0.011]***	[0.012]***
$d_{i,t}^{AMR} \times \ln TFP_{i,t}$					0.0251
					[0.010]***
$Phase(C)_t \times \Delta \ln (K/L)_{i,t}$		1.0195	1.1719	1.1850	1.1343
		[0.078]***	[0.052]***	[0.053]***	[0.052]***
$Phase(R)_t \times \Delta \ln (K/L)_{i,t}$		0.5981	0.8250	0.8324	0.8473
		[0.057]***	[0.045]***	[0.044]***	[0.044]***
$Phase(E)_t \times \Delta \ln (K/L)_{i,t}$		0.3242	0.6015	0.6301	0.6529
		[0.065]***	[0.048]***	[0.046]***	[0.047]***
$Livestock_{i,t}$			-0.4197	-0.4196	-0.4390
			[0.026]***	[0.027]***	[0.028]***
$Crops_{i,t}$			-0.5460	-0.5503	-0.5715
			[0.029]***	[0.029]***	[0.030]***
$\Delta \ln(Schooling)_{i,t}$				0.2414	0.2136
				[0.062]***	[0.062]***
$\Delta \ln(Experience)_{i,t}$				0.2058	0.2059
				[0.029]***	[0.030]***
Constant	-0.0047	-0.0404	-0.1940	-0.2023	-0.2079
	[0.006]	[0.007]***	[0.011]***	[0.011]***	[0.011]***
Differences in β-convergence rates test					
H_0 : $Phase(C)_t \times \ln TFP_{i,t} - Phase(R)_t \times \ln TFP_{i,t} = 0$					
	0.94	3.36	2.80	0.44	0.33
	0.3325	0.0667	0.0944	0.5057	0.5672
H_0 : $Phase(C)_t \times \ln TFP_{i,t} - Phase(E)_t \times \ln TFP_{i,t} = 0$					
	2.04	3.16	10.21	4.50	4.21
	0.1533	0.0753	0.0014	0.0338	0.0402
Differences in embodiment effects test					
H_0 : $Phase(C)_t \times \Delta\ln (K/L)_{i,t} - Phase(R)_t \times \Delta\ln (K/L)_{i,t} = 0$					
		26.00	59.90	55.64	37.20
		0.0000	0.0000	0.0000	0.0000
H_0 : $Phase(C)_t \times \Delta\ln (K/L)_{i,t} - Phase(E)_t \times \Delta\ln (K/L)_{i,t} = 0$					
		64.32	149.26	128.62	97.73
		0.0000	0.0000	0.0000	0.0000
Cross-sections included: 48					
Total panel (balanced) observations: 2112					
Wald -statistic	5.12e+07	2.18e+07	1.24e+07	7.8e+06	9.8+06

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%. Standard errors in brackets. All regresions use state and year fixed effects and are robust to autocorrelation heteroskedasticity and cross-sectional contemporaneous correlation. The results reported in columns (2) to (5) are corrected for endogeneity. Instrumented variables: $\Delta \ln(K/L)_{i,t}$, $Livestock_{i,t}$.