A Century of U.S. Farm Productivity Growth: A Surge Then a Slowdown

Matthew A. Andersen, Julian M. Alston, Philip G. Pardey, and Aaron Smith

U.S. farm productivity growth has direct consequences for sustainably feeding the world's still rapidly growing population, as well as U.S. competitiveness in international markets. Using a newly expanded compilation of multifactor productivity (MFP) estimates and associated partial-factor productivity (PFP) measures, we examine changes in the pattern of U.S. agricultural productivity growth over the past century and more. Considering the evidence as a whole, we detect sizable and significant slowdowns in the rate of productivity growth in recent decades. U.S. multifactor productivity grew at an annual average rate of just 1.16% per year during 1990–2007 compared with 1.42% per year for the period 1910–2007. U.S. yields of major crops grew at an annual average rate of 1.17% per year for 1990–2009 compared with 1.81% per year for 1936–1990. More subtly, but with potentially profound implications, the relatively high rates of MFP growth during the third quarter of the century are an historical aberration relative to the long-run trend.

Key words: U.S. agriculture, multifactor productivity, land and labor productivity, crop yields.

JEL codes: C22, Q18.

It is widely perceived that U.S. farm productivity grew robustly and steadily throughout the twentieth century, and that the same pattern can be expected to persist well into the twenty-first century (see, e.g., Ball et al. 2016; OECD 2016). However, some studies have reported evidence of a slowdown in U.S. agricultural productivity growth (see, e.g., Alston, Babcock, and Pardey 2010), and the issue has become contentious among agricultural economists. The national and global economic stakes are high. First, sustaining a comparatively rapid rate of farm productivity growth is key to U.S. farmers remaining competitive in world markets. Second, global food supplies and prices depend directly and indirectly on U.S. farming innovations. The United States itself accounts for significant shares of global production in major food and feed crops, and many other countries adopt and adapt U.S. agricultural innovations, such that global farm output is significantly influenced by U.S. farm productivity growth and the factors driving it.

Concerns about a slowdown in the pace of productivity growth in the U.S. economy as a whole, or sectors of the economy, are not new. In a retrospective, Nordhaus (2004) noted that "… the [U.S.] productivity slowdown of the 1970s has survived three decades of scrutiny, conceptual refinements, and data revisions. The slowdown was primarily centered in those sectors that were most energy-intensive, were hardest hit by the energy shocks of the 1970s, and therefore had large output declines." But economists had mixed views at the time as to whether the U.S.

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economy experienced a productivity slowdown during the 1970s; and, if it did, about the timing of the onset, the amplitude, and the duration of the slowdown.

Likewise, today economists have various views about the existence, nature, extent, and likely duration of a slowdown in U.S. (and global) agricultural productivity growth. Specifically, Alston, Babcock, and Pardey (2010) concluded "There can be little doubt that the InSTePP *MFP* data exhibit evidence of a slowdown in multifactor productivity growth in the period 1990–2002 compared with the previous [1949–1990] period." However, in stark contrast, Ball, Wang, and Nehring (2010) reported that "... statistical analysis of the [USDA] data does not provide evidence of a long-run productivity slowdown", and Wang (2010) observed that "...statistical analyses of ERS productivity accounts through 2008 did not reveal a corresponding slowdown in long-term rates of [U.S.] agricultural productivity growth." More recently, Ball, Schimmelpfennig, and Wang (2013) reported having found a structural break in the path of agricultural productivity in 1974, concluding that productivity grew at an annual average rate of 1.71% per year prior to the breakpoint and 1.56% per year after. Similarly, though they noted a structural shift in 1985, Wang et al. (2015a) reported that "We found no statistical evidence of a recent productivity slowdown." (See, also, Wang et al. 2015b; Fuglie et al. 2017).

In brief, the predominant view in U.S. government reports and in other published work is to reject or downplay the slowdown hypothesis; indeed, sufficiently so that a pair of recent articles focused on U.S. agricultural productivity by prominent authors in the area (Ball et al. 2016; Shumway et al. 2016) made no mention of the possibility of a sustained slowdown in U.S. farm productivity growth.[1] In this paper, we challenge that conventional wisdom and propose an alternative view. Having assembled a range of agricultural productivity measures, we perform a battery of statistical procedures and tests designed to investigate the nature of changes in the rate of productivity growth over time. To provide a more informative context in which to understand the more recent productivity patterns, we take a longer-run perspective using data reaching back almost one hundred years, created expressly for this purpose.[2] For the period 1910–2007, we estimate and analyze national trends in multifactor productivity (MFP) and partial factor productivity (PFP) measures.[3] We also analyze the long-run pattern of growth of national average crop yields for selected commodities stretching back to the latter part of the nineteenth century. Using this range of measures and methods we find robust and compelling evidence of a structural slowing of productivity growth in U.S. agriculture following a surge that peaked in the third quarter of the twentieth century.

Productivity Measures: 1910–2007

The main analysis here uses indexes of U.S. agricultural productivity that are themselves based on indexes of the quantity of inputs used in U.S. agricultural production, and indexes of the quantity of the resulting output. Bias from the procedure used to aggregate inputs and outputs can be kept to a minimum by choosing an appropriate index, carefully selecting value weights for all inputs and outputs, and disaggregating inputs and outputs as finely as possible. The main indexes used here are computed using an appropriate formulation (Fisher indexes that are discrete approximations to Divisia indexes), and based on highly disaggregated data, with care taken to adjust for changes in the composition and quality of the aggregates over time.

InSTePP Production Accounts

The primary source of the data used in this paper is the University of Minnesota's International Science and Technology Practice and Policy center (InSTePP)

[1] The same is true in a global context (see, e.g., Fuglie 2010, and various chapters in Fuglie, Wang, and Ball 2012).

[2] The long-run path of U.S. agricultural inputs, outputs, innovations, and productivity has been the subject of a rich literature, including Cochrane (1958, 1993), Olmstead and Rhode (2000, 2008), Gardner (2002), Dimitri, Effland, and Conklin (2005), and a host of others cited and discussed by Alston et al. (2010).

[3] In the present context, as in many others, we are most interested in total factor productivity (TFP) since it is an encompassing measure that represents the full quantity of resources used to produce the total quantity of output produced. However, for most practical purposes we have incomplete measures of outputs and inputs, especially in agriculture where many of the environmental consequences of, or natural inputs to, agricultural production are rarely measured. Likewise, the contributions of public infrastructure investments are rarely considered or taken into account. We are thus forced to rely on MFP estimates that include less than a complete accounting of inputs and outputs, or PFP measures that express output relative to a particular input.

Production Accounts, Version 5 (available at www.instepp.umn.edu/united-states), supplemented by earlier and other data from various USDA sources (see Pardey et al. 2006 for a more complete description of the InSTePP Production Accounts). The InSTePP Production Accounts consist of state-specific measures of the prices and quantities of 74 categories of outputs and 58 categories of inputs for the 48 contiguous U.S. states for the years 1949–2007, as well as the corresponding national aggregate measures.

The 58 categories of inputs are grouped into four broad categories: land, labor, capital, and materials inputs. The land input is subdivided into service flows from three basic types of land, namely: pasture and rangeland, non-irrigated cropland, and irrigated cropland. The price weights used for aggregation of the land input are annual state- or region-specific cash rents for each of the three land types. The labor data consist of 30 categories of operator labor by age and education cohort (and adjusted for time spent off farm), as well as family labor and hired labor. State-specific wages were obtained for hired and family labor, whereas implicit wages for operators were developed using national data on income earned by "rural farm males," categorized by age and educational attainment. Capital inputs include seven classes of physical capital and five classes of biological capital. A physical inventory method, based on either counts of assets purchased or on assets in place, was used to compile the capital series as described in some detail in Andersen, Alston, and Pardey (2011) and Pardey et al. (2006).[4] Eleven types of materials inputs are included in this data set.

In the disaggregated form, the output data cover 74 output categories, including state-level data for 16 field crops, 22 fruits and nuts, 22 vegetables, implicit quantities of greenhouse and nursery products, nine livestock commodities, and four miscellaneous items that include implicit quantities of machines rented out by farmers, and Conservation Reserve Program (CRP) acreage. The commodity-specific prices used as weights to form aggregate output are state-specific prices received by farmers for all commodities, except machines for hire and greenhouse and nursery products, for which national average prices are used.

Multifactor Productivity Estimates, 1910–2007

The InSTePP indexes of quantities and prices of output and input were formed using a Fisher discrete approximation to a Divisia index for the years 1949 through 2007. An index of multifactor productivity for each state and the nation was then constructed as the ratio of the index of aggregate output to the index of aggregate input. To form national estimates of aggregate input, output, and multifactor productivity for the longer period 1910–2007, it was necessary to obtain data for the earlier period, 1910–1948, and combine it with the national series for the period 1949–2007. To do this we used Laspeyres indexes for the period 1910–1949 reported in USDA Economic Research Service (ERS; 1983; see Table 69). These indexes were rebased to equal 100 in 1949, then spliced to the InSTePP Fisher indexes of national inputs, outputs, and productivity for the period 1949–2007, and finally the spliced series was rebased to equal 100 in 1910.[5]

U.S. Land and Labor Productivity Estimates, 1910–2007

Partial productivities for land and labor for the period 1949–2007 were calculated as the InSTePP index of aggregate land and labor use divided by the InSTePP index of aggregate output. These ratios of InSTePP Fisher indexes were then spliced in year 1949 to the respective Laspeyres indexes, for the period 1910–1949, taken from USDA sources as described next. The national index of labor productivity for the period 1910–1949 is from USDA ERS (1983; see table 45) and represents an index of farm output per hour. The index of land productivity for the period 1910–1949 represents an index of output per acre, where the output series is from USDA ERS (1983; see table 69), and the acreage data are "land in farms" from Olmstead and

[4] The capital series was identified as a particular source of discrepancies between the InSTePP measures of multi-factor productivity growth and the counterpart measures published by the USDA (see, for instance, Ball, Butault, and Nehring 2001). These discrepancies are more pronounced for particular states and subperiods than for the aggregate U.S. series over the full period for which both measures are available (see Andersen, Alston, and Pardey 2011 and 2012 for details and discussion).

[5] USDA data for years prior to 1910 were available but they were discarded for the statistical analysis of this study because of inconsistencies in the coverage and reliability of the underlying data.

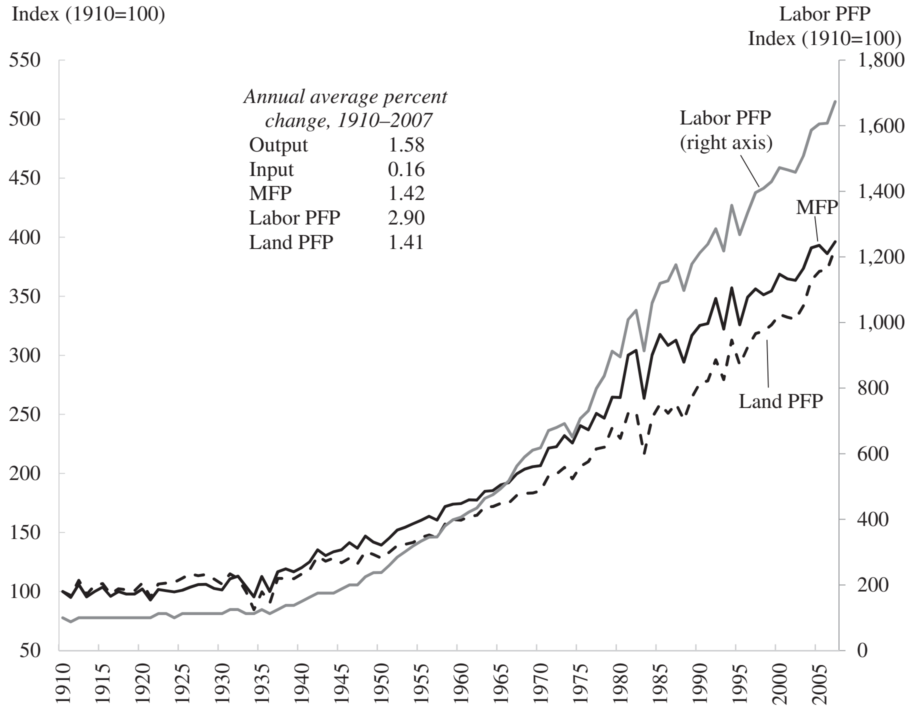

Figure 1. Measures of U.S. agricultural productivity, 1910–2007

Sources: Index numbers calculated by the authors using Version 5 of the InSTePP Production Accounts backcast with data taken from USDA ERS (1983; see table 45), USDA ERS (1983; see table 69), USDA ERS (1983; see table 1), and Olmstead and Rhode (2006; series Da-5).
Note: MFP and Land PFP, left axis, Labor PFP, right axis.

Rhode (2006). Once again, the spliced series was rebased to equal 100 in 1910.

As can be seen in figure 1, the time path of these indexes was not smooth or simple, but the overall growth was impressive. Over the 98 years represented from 1910–2007, the quantity index of total output (Q) grew at an average annual rate of 1.58%, while the quantity index of total inputs (X) grew at an average annual rate of 0.16%. Since MFP is defined as the ratio (i.e., $MFP = Q/X$), the growth rate of MFP is the difference between the growth rates of output and input: MFP grew at an average annual rate of 1.42%. Labor productivity grew considerably faster than MFP, at an average annual rate of 2.90%, reflecting the great reduction in labor relative to other inputs, while land productivity grew less rapidly, at an average annual rate of 1.41%.

In what follows we first use these newly extended estimates of MFP growth in the U.S. farm sector for the period 1910–2007 to examine two basic questions: (1) Did the long-run rate of MFP growth in U.S. agriculture remain constant over the past century? (2) Did the rate of growth in MFP exhibit a sustained slowdown in the latter part of the sample? Later, we apply similar procedures to land and labor PFP measures and data on crop yields, the results from which corroborate and reinforce the primary results based on MFP.

Multifactor Productivity Patterns: 1910–2007

Measuring productivity is a difficult task, but interpreting changes in productivity growth rates can be even more difficult. Substantial year-to-year variation in measured MFP and the associated year-to-year variation in aggregate output (and to a much lesser extent aggregate input use) also make it difficult to discern the onset, magnitude, and duration of a productivity slowdown (e.g., see figure 2). Year-to-year variations in measured productivity growth might reflect the influences of short-term, transient factors such as weather impacts or policy changes; they might also be the result of measurement errors such as those associated with variable capital utilization rates (see, e.g., Andersen 2005; Andersen, Alston, and Pardey 2011).

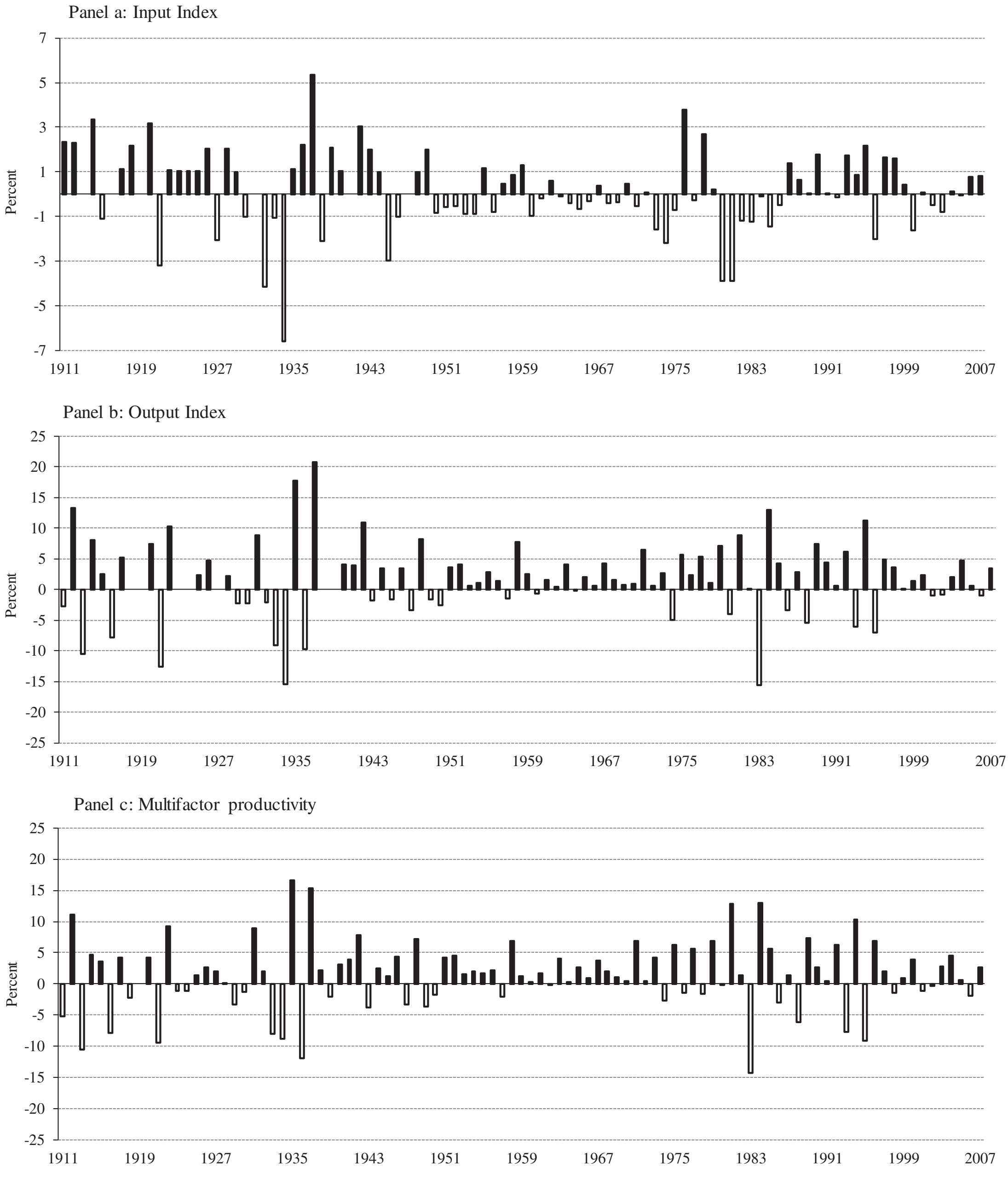

Figure 2. Year-to-year percentage changes in input, output and MFP, 1910–2007

Source: See figure 1. *Notes:* Annual growth rates were calculated as the annual change in the natural logarithms of the data.

To smooth the transient fluctuations and reveal long-run trends in MFP growth, we compute moving averages. Figure 3 shows 10-year, 20-year, and 30-year moving averages of MFP growth, with each point on the graph placed at the midpoint of the relevant sub period. The figure shows that the trend of moving-average MFP growth increased progressively from the beginning of the sample until the 1970s, when it started to decline. Annual average MFP growth was 1.18% in the last 20 years of the sample (1987–2007), which is substantially slower than the 2.06% per year experienced in the 1960s and 1970s, two decades in which growth was also much faster than the 0.10%

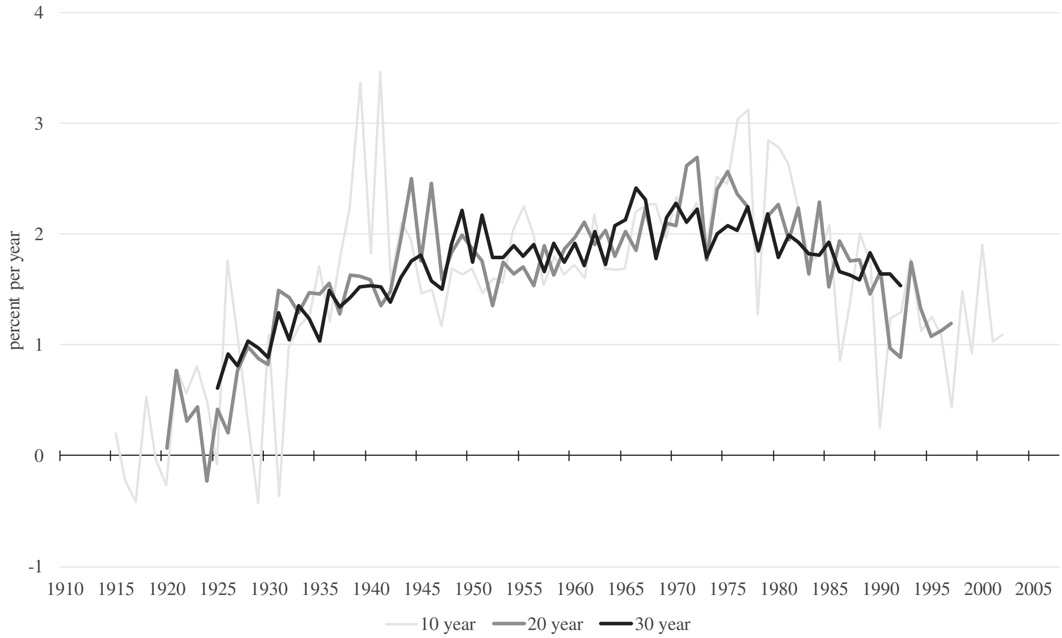

Figure 3. Moving averages of annual MFP growth rates, 1910–2007

Source: See figure 1.
Note: The lines represent moving averages of the annual change in the natural logarithm of MFP. Each point is centered at the midpoint of the range (e.g., the value for the 20-year moving average in 1960 is the average annual MFP growth between 1950 and 1970)

annual growth rate in the first 20 years (1910–1930) of the sample.[6]

We use time-series econometrics methods to estimate whether the acceleration in MFP growth in the third quarter of the twentieth century and the recent deceleration are better characterized as natural fluctuations around a constant trend growth rate, or rather as changes in the trend rate of growth. The first characterization would suggest that the observed accelerations and decelerations are transitory phenomena that average out over time as MFP reverts to a constant long-run growth path. In contrast, the second characterization implies that observed accelerations or decelerations are not self-correcting.

We fit the following model,

$$\ln\left(MFP_t\right) = f(t) + u_t$$

where $f(t)$ denotes a trend function and u_t is a stochastic term. We estimate two nonlinear specifications for $f(t)$ and test whether they fit the data significantly better than a linear specification. First, we apply a segmented linear trend model and use the tests of Bai and Perron (1998) to determine both the number of segments and the location of the breakpoints. Second, motivated by the apparent quadratic shape of the growth rate in figure 3, we specify $f(t)$ as a cubic function. Rejecting the linear specification in favor of a nonlinear model provides evidence of secular changes in the trend.

The stochastic term u_t may exhibit serial correlation, which allows persistent departures of MFP from the trend. This feature is crucial for assessing statistically whether a nonlinear trend fits the data well. To understand this point, suppose the data were generated by a process with a linear trend and substantial autocorrelation around the trend. Such data would exhibit multi-year departures from the trend line, but would eventually return to it. If the only two models we considered were a linear trend model without

[6] Annual growth rates in figure 2 were computed as the year-to-year changes in the natural logarithm of MFP. Period-specific average annual growth rates were computed as the relevant average of these annual rates, in this context. For example, the ten-year average annual MFP growth rate for the period 1910–1920 is equal to $\frac{1}{10}\sum_{t=1911}^{1920}\left(ln(MFP_t) - ln(MFP_{t-1})\right)$. For some other, similar computations in this paper we use fitted annual values from a linear regression of ln (MFP) on year.

autocorrelation (i.e., without multi-year departures from trend) and a model that allows the trend to change, the model with a changing trend would tend to fit better. Put another way, hypothesis tests on the nonlinear components of the trend will be oversized if we ignore the autocorrelation. Thus, in the statistical tests that follow, we report standard errors and test statistics that are robust to autocorrelation.

Segmented Trend Model

Bai and Perron (1998, 2003a, 2003b) devised procedures to test for, quantify, and draw inferences about the presence of structural changes in the linear regression model, allowing for multiple breaks. The Bai-Perron approach can be used to test for any number of breaks.[7] We specify the model

$$f(t) = \sum_{m=1}^{M} (\alpha_m + \beta_m t) 1\left(t_{m-1}^{*} \le t < t_m^{*}\right)$$

where $1(t_{m-1}^{*} \le t < t_m^{*})$ equals one for t within the specified range, and zero otherwise. For a given M, the procedure selects the break points $t_1^*, t_2^*, \ldots$ to provide the best least-squares fit to ln(MFP). Then, the procedure entails conducting a sequence of F-tests of the null hypothesis that the α and β parameters are equal across breaks. To conduct these F-tests, we compute the standard F statistic (Chow 1960) for each possible break point and record the maximum in this set. We compare the maximum F statistic to the critical values in Bai and Perron (2003b), which are adjusted for the fact that we maximize the statistic rather than evaluating it at a single break point. Following Bai and Perron (2003a), we proceed sequentially, first testing for one break, then a second conditional on the first, and so on.

Table 1 presents the results. First, estimating the model with a single break ($M = 1$) produces an estimated break point of 1937 and an F-statistic of 148.2. This statistic far exceeds the 5% critical value of 11.5, so we reject the null hypothesis of no breaks and conclude that there is at least one break. Next, we set $M = 2$ and search for a second break-point, which we locate in 1980. The test statistic of 18.5 exceeds the critical value, which suggests that the 1980 break is also statistically significant. When we condition on two breaks and search for a third break, we find an additional statistically significant break in 1961. The fourth break, which is the maximum feasible in this sample, is not statistically significant with the test statistic of 0.3 much smaller than the 5% critical value, 14.9.

The Bai-Perron procedure implies breaks in the rate of MFP growth in 1937, 1961, and 1980. The estimated trend annual growth rates during these sub-periods, shown in table 1, are 0.30% for 1910–1936, 1.74% for 1937–1960, 2.17% for 1961–1979, and 1.27% for 1980–2007; there is a surge in MFP growth between 1936 and 1980 and significantly slower growth since then. After fitting a segmented trend model that contains these breaks, the residuals are close to white noise, as can be seen from the small autocorrelations reported in table 1.[8]

Cubic Trend Regression Models

Taken as a whole, a plausible interpretation of the evidence in figure 3, and from the results of the Bai-Perron tests for multiple structural changes in table 1, is that (*a*) MFP growth slowed since 1981 compared with the measured history that preceded it but, more subtly, (*b*) the middle decades of the twentieth century, and especially the 1960s and 1970s, are historical anomalies when considered in the broad sweep of the past century, and the recent slowdown could be seen in part as a return to a more normal, long-run rate following a surge.

These findings are confirmed by a plot of the logarithm of MFP against time, and the results from estimation of polynomial trend models. In figure 4, panel c, the path of lnMFP is clearly (visibly) non-linear, whereas constant productivity growth implies a linear path, that is, $d\ln MFP/dt$ is constant. A cubic polynomial trend model (the dotted line) fits the data (the black line) very closely ($R^2 = 0.993$) and the hypothesis of the linear model with a constant growth

[7] Bai and Perron state that their test is appropriate only when there are no trending regressors. However, the test *is* valid if the trending regressor is defined as t/T rather than t—that is, their asymptotic theory allows a linear trend defined on the (0,1) domain but not the (0,T) domain. Section 3.1 of Perron (2006) elaborates on this point, and tables 3 and 4 of Bai (1999) show simulation evidence that the procedure works well for breaks in a linear trend.

[8] An augmented Dicky-Fuller test for a unit root in the residuals produces a t-statistic of –12.92, so we easily reject the null hypothesis of a unit root in this series.

Table 1. Bai-Perron Test Results, MFP, 1910–2007

Test	Null	Alternative	Break Year	Std. Error	Statistic	Critical Value
F(1|0)	$M=0$	$M=1$	1937	NW(5)	148.2	11.5
F(2|1)	$M=1$	$M=2$	1980	NW(0)	18.5	13.0
F(3|2)	$M=2$	$M=3$	1961	NW(0)	17.6	14.0
F(4|3)	$M=3$	$M=4$	1947	NW(0)	0.3	14.9
Dmax	$M=0$	$0<M\leq 4$		NW(5)	163.0	11.7
Estimated Growth Rates by Regime (3 breaks)						
Regime	α	β		Residual Autocorrelations in 3 break model		
1910–1936	–1.09	0.0030		Lag 1	–0.20	
1937–1960	–28.97	0.0174		Lag 2	–0.11	
1961–1979	–37.33	0.0217		Lag 3	0.00	
1980–2007	–19.49	0.0127		Lag 4	–0.03	

Source: Calculated by the authors using backcast version of the InSTePP production accounts (version 5) and Gauss code provided by Pierre Perron.
Note: Critical values are for 5% significance and are obtained from Bai and Perron (2003b). The minimum regime length is 15% of the sample. When computing test statistics, the parameter variance matrix was computed using either the Newey-West estimator with 5 lags (denoted *NW(5)*) or White's heteroscedasticity robust estimator (denoted *NW(0)*), whichever was larger.

rate—which is a nested special case of this model—is strongly rejected (see table 2, column 3).[9]

The estimated parameters of the cubic model imply that the rate of MFP growth accelerated over the years prior to 1966 and slowed after 1966. The year of the maximum growth rate is 1966 (the inflection point in the cubic trend relationship), with a 95% confidence interval between 1964 and 1968.[10] These estimates and the depiction in figure 4 support the view that U.S. farm productivity growth has slowed in recent decades, in the context of the post-war period (i.e., since 1950). But more than that, they also suggest that this slowdown came after a period of unusually high productivity growth in the middle of the full sample period, 1910–2007—that is, faster rates of productivity growth in the 50 years centered on 1966 (i.e., the 1940s through 1980s, especially in the middle of that period) and slower rates in the earlier decades (i.e., 1910–1930) and more recently (1990–2007).[11]

Figure 5 plots the estimated growth rates from the two trend models (i.e., the cubic polynomial model and the segmented linear model) along with the 10-year moving average annual growth rates. The two models impose different functional form restrictions—the segmented linear model allows for (and imposes) constant growth within segments, separated by discrete jumps, while the cubic polynomial model allows for a sigmoid shape but imposes smoothness.[12] Nevertheless, it is readily apparent from figure 5 that both models capture the same phenomena—an acceleration during the third quarter of the century and a deceleration since 1980 if not sooner—and there is little difference between them in terms of the implied (fitted) growth rate in any given year.[13] Neither model should be extrapolated out of sample. This

[9] The adjusted R^2 is higher for the cubic model ($\bar{R}^2 = 0.993$) than for a quadratic model ($\bar{R}^2 = 0.981$) or a linear model ($\bar{R}^2 = 0.972$). Because the residuals in the linear model are strongly autocorrelated, these adjusted R^2 differences should be interpreted with caution.

[10] The inflection points were calculated by running the following cubic trend regressions for each series $ln\, y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \varepsilon_t$, where t is (year –1909). The second-order partial derivatives of each estimation equation were then set equal to zero, and solving for t gives the inflection point: $\hat{t} = -\beta_2/3\beta_3$. Wald test-statistics and standard errors were then calculated for the nonlinear transformations of the parameters. The inflection year is $(\hat{t} + 1909)$.

[11] Johnson (1949) argued that the rapid run up in agricultural output during WWII and thereafter was attributable to the accumulation of technological improvements built up during the interwar period, the production consequences of which were obscured during this period owing to (*a*) bad weather (the dust bowl), (*b*) consequential crop pest epidemics (e.g., boll weevil infestations on cotton in the 1920s and recurring stem rust epidemics in wheat), and (*c*) limited domestic markets and shrinking international markets (see, e.g., Wilcox and Cochrane 1951) for agricultural outputs during the Great Depression.

[12] For comparison, in the supplementary online material we show the same figure, but with the addition of trend growth computed using the Hodrick-Prescott (HP) filter. The HP filter produces a trend growth rate pattern very similar to the cubic model until the late 1990s, when it flattens out at about 1.2% growth rather than continuing to decline as in the cubic model. However, we interpret this end-of-sample pattern from the HP filter with caution, as the filter can be unreliable at the end of the sample. Hamilton (2018) writes that "Filtered values at the end of the sample are very different from those in the middle, and are also characterized by spurious dynamics."

[13] In the cubic trend regression model of ln*MFP*, the adjusted R^2 is 0.993 and in the segmented trend model it is 0.993.

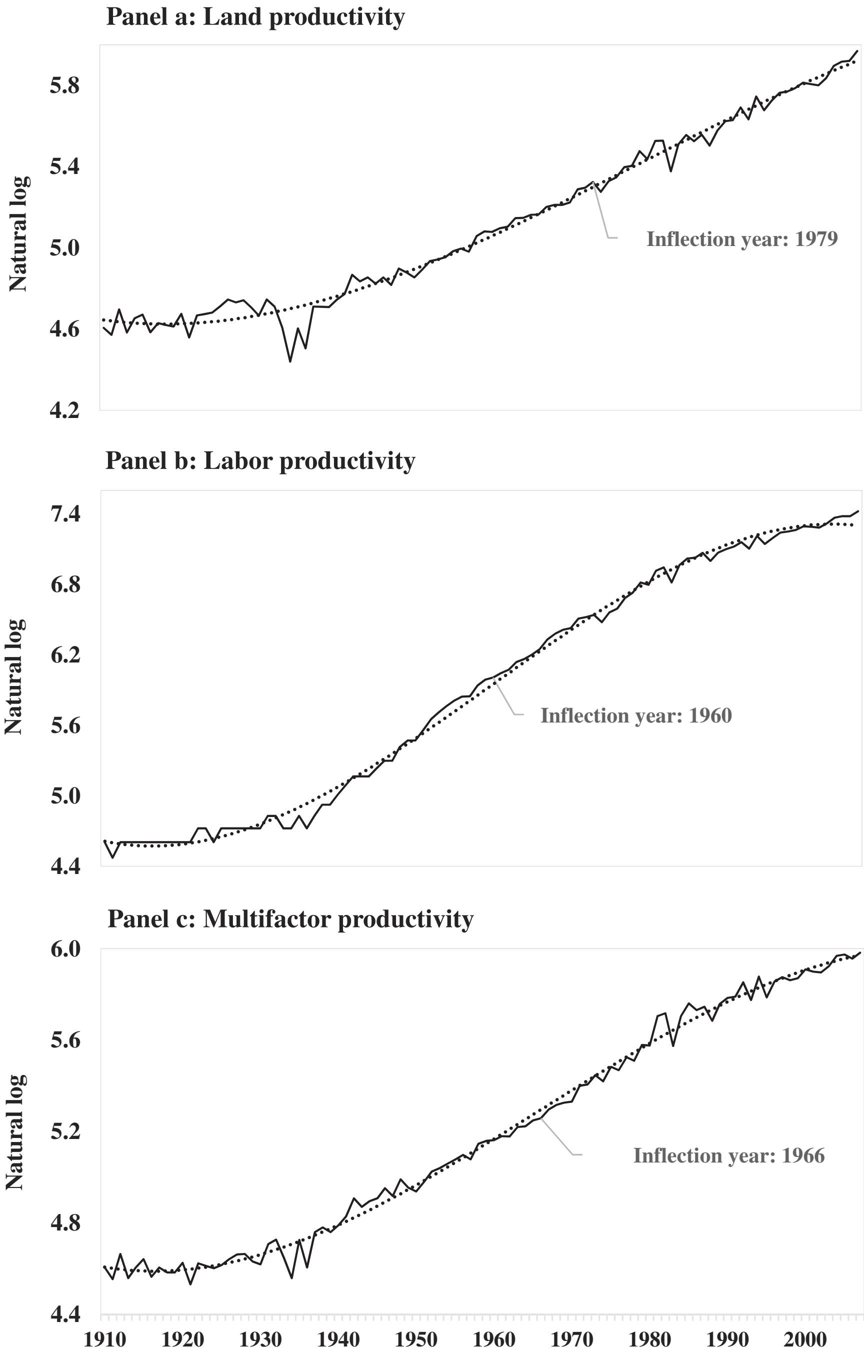

Figure 4. Cubic trend models of productivity indexes in natural logarithms, 1910–2007

Source: Alston, Andersen, and Pardey (2018).

analysis shows that the trend growth rate has slowed since 1980, but it should not be taken to imply that the slower growth rates in the more recent years will continue (as would be implied by extrapolating the segmented trend model), nor that the trend growth rate will continue to decline (as would be implied by extrapolating the cubic model).[14]

[14] In the supplementary online material, we report the results from breakpoint analysis using rolling regression procedures that

Table 2. Cubic Trend Models of MFP and PFP in Natural Logarithms, 1910–2007

	1910–2007		
	PFP		
	Land (1)	Labor (2)	MFP (3)
t	$-5.99\text{x}10^{-3}$*	$-1.63\text{x}10^{-2}$*	$-6.82\text{x}10^{-3}$*
	$(1.98\text{x}10^{-3})$	$(2.34\text{x}10^{-3})$	$(1.47\text{x}10^{-3})$
t^2	$3.62\text{x}10^{-4}$*	$1.24\text{x}10^{-3}$*	$4.94\text{x}10^{-4}$*
	$(4.63\text{x}10^{-5})$	$(5.47\text{x}10^{-5})$	$(3.45\text{x}10^{-5})$
t^3	$-1.72\text{x}10^{-6}$*	$-8.15\text{x}10^{-6}$*	$-2.89\text{x}10^{-6}$*
	$(3.08\text{x}10^{-7})$	$(3.63\text{x}10^{-7})$	$(2.29\text{x}10^{-7})$
Intercept	4.65*	4.63*	4.61*
	$(2.27\text{x}10^{-2})$	$(2.68\text{x}10^{-2})$	$(1.69\text{x}10^{-2})$
R^2	0.98	0.99	0.99
Number of observations	98	98	98
Inflection year	1979	1960	1966
95% confidence interval	[1971, 1987]	[1959, 1961]	[1964, 1968]

Source: Calculated by the authors using a backcast version of the InSTePP production accounts (Version 5).
Note: All models have the specification, $ln\ y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + u_t$. Trend is year minus 1909. The inflection years were calculated by adding 1909 to the estimated inflection points, rounded to the nearest whole year. Standard errors make no adjustment for heteroscedasticty or autocorrelation because we were unable to reject the null hypotheses of homoscedasticity or white noise errors. Moreover, using the Newey-West or White corrections made no material difference to the standard errors. Asterisk indicates statistical significance at the 5% level.

While the two models yield essentially the same results, the cubic polynomial model is comparatively straightforward to apply and the results are transparent and easy to interpret. In the remainder of the paper, we report results from applying the cubic model as a data description device to different measures of productivity or for different time periods to assess the robustness of findings to these aspects of the analysis.

Robustness Checks

Productivity growth seems clearly to have been slower after 1990 than before 1980, regardless of which model we use. Since 1990, MFP grew on average by 1.16% per year, which is less than the average rate of growth of 1.42% per year for 1910–2007, and substantially less than the rate for the Green Revolution decades of the mid-1960s to mid-1980s.[15] These and other specific findings could be influenced by end-point effects. In particular, the middle 1980s were characterized by relatively volatile productivity patterns, which make findings regarding a slowdown potentially sensitive to the location of a break-point within the 1980s.[16] To explore this aspect, we also calculated the annual average rate of growth for various subperiods, beginning in years ranging from 1981 to 1995 but all ending in 2007. The average annual growth rates during these various subperiods ranged from 0.80% to 1.70% (and from 0.65% to 1.66% if the terminal year was 2006), with 11 out of the 15 estimates well below the average rate of growth over the entire period of the data.[17]

yield comparable results, reinforcing the general findings from the two trend models reported here.

[15] The term "Green Revolution" was first coined in 1968 by William Gaud, then Administrator of USAID, to describe the rapid acceleration in crop (especially wheat and rice) yield growth that occurred throughout South-East Asia in the mid 1960s (Gaud 1968). The high-yielding, semi-dwarf wheat and rice varieties that were central to the Green Revolution in Asia also found their way onto the fields of U.S. farmers (Pardey et al. 1996).

[16] Other statistical procedures also might be sensitive to this volatility in the 1980s, giving rise to both false negatives and false positives. For example, this might account for the finding of a structural break in 1985 reported by Wang et al. (2015a, 2015b).

[17] The largest estimate of average annual growth of 1.71% per year is from 1983 to 2007. The year 1983 included a severe drought as well as the USDA Payment-in-Kind (PIK) program, both of which substantially decreased aggregate output and *MFP* in that year.

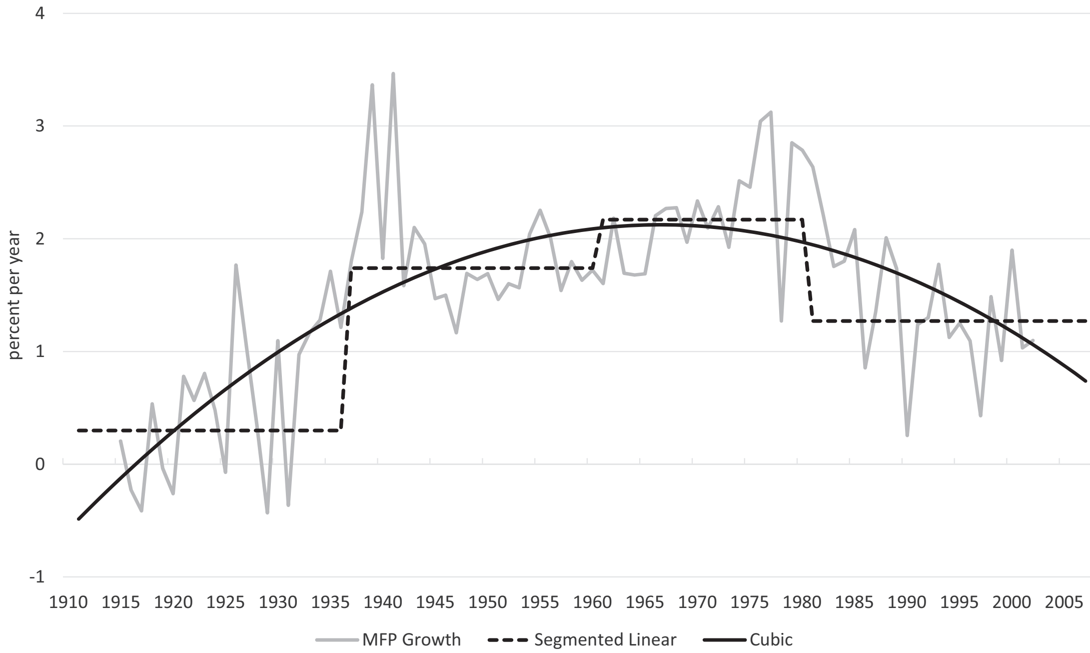

Figure 5. Moving average MFP growth rates and two estimates of the nonlinear trend, 1910–2007

Source: Calculated by the authors using a backcast version of the InSTePP Production Accounts (Version 5). *Note*: The segmented linear trend estimates are produced as in table 1 and the cubic estimates as in table 2. The MFP growth series is a ten-year moving average of the annual change in the natural logarithm of MFP. As in figure 3, each point is centered at the midpoint of the range.

Another potential issue is the dataset itself. As discussed by Acquaye, Alston, and Pardey (2003) and Andersen, Alston, and Pardey (2011, 2012), the InSTePP data used in this analysis differ from the data developed and published by the USDA Economic Research Service (USDA ERS) (see, e.g., Wang et al. 2015), and the USDA data include some more recent years.[18] Could these differences account for the differences between our findings and those of Ball, Wang, and Nehring (2010), Wang (2010), and Wang et al. (2015)? To check this possibility, we replicated parts of our analysis using U.S. agricultural TFP data for the period 1948–2015 obtained from USDA-ERS (2017) in place of the InSTePP data.[19]

First, to make a "head-to-head" comparison, we created a long-term version of the USDA data by splicing the MFP series for 1910–1948 (itself derived from USDA ERS indexes as described above) onto the USDA ERS TFP series for 1948–2015. Using these data, we estimated the cubic trend regression model and applied the Bai-Perron procedure for the sub-period 1910–2007, the same period as the InSTePP MFP series. The cubic trend regression results indicate a statistically significant slowdown, with an inflection in 1980 (a 95% confidence interval between 1970 and 1991), significantly later than the inflection in 1966 indicated by estimating the same model applied to the InSTePP data for the same period. The results from the Bai-Perron tests are more complicated to explain. These tests indicate a statistically significant break in 1936. The annual average year-to-year growth rate was 0.30% for the period 1910–1936, and 1.65% for 1937–2007. The next largest break is in 1983, but it is not statistically significant.

[18] See also Andersen, Alston, and Pardey (2011, 2012), who highlight conceptual and empirical differences in the InSTePP versus USDA capital accounts.

[19] This partial analysis using the USDA data is not a comprehensive analysis to test for the existence and timing of a slowdown in the USDA TFP measures, fully comparable to the analysis of our own (InSTePP) MFP data. Rather, it is meant to serve simply as a robustness check, to determine whether our results are contingent on our particular data set, which differs from the USDA data set in terms of data construction methods and time period covered. We previously conducted our robustness check using an earlier version of the USDA ERS TFP series for the period 1948–2013, which we had downloaded in January 2017, with no qualitative implications for differences from the results we present here.

However, the period since 1999 in this dataset is characterized by a marked slowdown. Splitting the post-1983 period into two halves, and using all the data to 2015, we see that the average annual growth rate was 2.22% for 1983–1999, and 0.82% for 2000–2015. But this decline is not statistically significant at the 95% level according to the (statistically demanding) Bai-Perron tests because it occurs too close to the end of the sample, with only 16 observations in the post-1999 subsample.

Next, to address the potential concern that the data for the earlier period (1910–1948) are not constructed on the same basis as those since then, we estimated the same cubic polynomial model applied to both the InSTePP MFP data and USDA TFP data for the period when both are available: 1949–2007. In both cases, when we exclude the data prior to 1949, the results still indicate a statistically significant slowdown, but somewhat later (1971 versus 1966 for InSTePP, and 1982 versus 1980 for USDA-ERS). In addition, we estimated the cubic trend model applied to the full USDA national data series 1948–2015, finding that the results are not affected materially when we include the most recent data available: they still indicate a statistically significant slowdown, with an inflection point in 1980 and a fairly narrow 95% confidence interval (between 1978 and 1982). However, when we apply the Bai-Perron procedure to the USDA-ERS data to check for evidence of structural changes in a linear model with multiple breaks in the data for 1948–2015, the Bai-Perron tests indicate no structural changes in this sub-sample. This contrast with the results from the cubic trend model arises at least in part because the Bai-Perron test procedure entails both searching for break points and testing for the statistical significance of the structural change, with a corresponding size adjustment. This makes the Bai-Perron tests low-powered compared with procedures that make use of priors about the timing of the break to restrict the alternatives considered.

Our findings using national aggregate data are further reinforced using state-level MFP data for the more recent period, 1949–2007, from InSTePP. Some initial results in this regard were published by Alston, Babcock, and Pardey (2010) using annual data for the period 1949–2002 for the 48 contiguous states. Alston, Andersen, and Pardey (2018) updated this work to 1949–2007, and their statistical comparisons of mean growth rates over selected sub-periods provide compelling evidence of a slowdown in MFP growth rates at the level of individual states. These authors also report fixed effects, panel data estimates of cubic trend models applied to the state-level MFP data (in logarithms) in which they find an inflection in 1969 (with a narrow 95% confidence interval, between 1966 and 1971). Similarly, estimating the same kind of model applied to USDA ERS state-specific data on TFP for the years 1960–2004, they find strong evidence of a statistically significant slowdown in TFP growth; now with an inflection in 1983 (and a 95% confidence interval, between 1981 and 1985).[20]

In short, using the USDA ERS national or state-level data in the cubic polynomial trend model we reach the same qualitative conclusion as with the InSTePP data. Specifically, the null hypothesis of a linear model with constant growth is rejected in every instance in favor of a cubic model that implies a mid-century surge in farm productivity growth, followed by a slowdown as we approach and enter the twenty-first century. The slowdown is statistically significant but, compared with the InSTePP data, the USDA data indicate a more recent inflection point—that is, a slowdown beginning in the early 1980s in the USDA data compared with 1966 (using the long-run InSTePP data, 1910–2007), 1969 (using the state-specific InSTePP data since 1949), or 1971 (using the national InSTePP data since 1949). All of the models support a view that U.S. farm productivity growth has been slower since the 1980s than in the prior decades.

The Bai-Perron procedure yields a similar pattern of results across the alternative data sets: applied to the InSTePP national MFP data we obtain essentially the same results as with the cubic polynomial trend model; applied to the USDA-ERS national TFP data, the findings are also consistent with a structural break and a slowdown (albeit somewhat later and less-pronounced than in the InSTePP MFP data), but the difference in the growth rate after 1983 in the USDA-ERS data is not statistically significant at the 95% confidence level.

As we have documented elsewhere (Andersen, Alston, and Pardey 2011; Alston 2018) we have clear grounds for preferring the InSTePP measures for our purposes, and we should give less weight to the results from this sensitivity analysis using the USDA data

[20] The ERS state-specific productivity indexes are available at: https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/.

than to the results from our more exhaustive analysis using the preferred InSTePP data. In any event, across both data sets and the range of measures and tests, the weight of the evidence is generally consistent with the slowdown (following a surge) hypothesis and not consistent with the alternative hypothesis of a constant trend growth rate of productivity.

Partial Factor Productivity Measures: 1910–2007

To expand beyond the (InSTePP and USDA) *MFP* evidence, we now turn to an empirical assessment of long-run trends in land and labor productivity and in selected national average U.S. crop yields. Evidence of slowing growth in these *PFP* measures reinforces the more direct evidence of slowing *MFP* growth.

Land and Labor Productivity

U.S. agricultural land was 3.9 times more productive in 2007 than it was in 1910, and labor was 16.7 times more productive, reflecting the substantial exodus of farm labor out of agriculture. Figure 4 shows plots of logarithms of land productivity (panel a) and labor productivity (panel b). In each case, as for MFP, a cubic polynomial trend model (the dashed line) fits the data (the solid line) closely, and the quadratic and cubic terms are individually statistically significant; the hypothesis of the linear model with a constant growth rate is again strongly rejected (see table 2). However, the patterns are quite different between land and labor productivity. In the case of labor, the pattern shows a clear acceleration and slowdown with an inflection centered on 1960, whereas for land, a clear acceleration in the early decades is not mirrored by a corresponding slowdown in the later decades. The estimated inflection point of 1979 has a relatively wide 95% confidence interval and, visually, we see only weak if any indications of a slowdown at any time after 1950.[21]

A slowing rate of MFP growth can certainly be reconciled with a slowing rate of PFP growth for labor and a sustained (or possibly accelerating) rate of PFP growth for land. As discussed by Alston, Babcock, and Pardey (2010; see also the supplementary online material), a slowdown in MFP growth implies a slowdown in growth of the constituent factor PFPs in some “average” sense, but does not require a slowdown in PFP for every constituent factor. Setting aside other inputs, a weighted average of the labor PFP (with slowing growth) and the land PFP (with constant growth) would exhibit a slowdown; more so in view of the fact that, since 1990, labor’s share of total cost has been roughly constant, and about twice land’s, which has been shrinking. More broadly, the relative historical paths of the two PFP measures reflect the secular paths of the shifting balance in relative cost shares of land and labor, both relative to one another and relative to capital and purchased inputs, with labor-saving innovations being more pronounced in their effects earlier in the history. These patterns are complex but can be fairly easily reconciled with an observation of slowing growth of *MFP* and labor productivity growth in conjunction with (for now) a sustained or even accelerating rate of land productivity growth.

Trends in Crop Yields

Data on U.S. national average yields for barley, corn, oats, rice, soybeans, and wheat are available back to the late nineteenth century from USDA National Agricultural Statistical Service (NASS; 2010; see table 3). On average, over the entire period 1867–2009, national average yields per acre of soybeans and rice grew by approximately 1.60% per year and yields of corn grew by 1.34% per year, while yields of wheat, barley, and oats all grew at rates below 1.0% per year (see table 3, bottom section). A visual inspection of plots of these annual average data (available on request) suggests a structural change in U.S. crop yields during the mid-1930s, to begin a period of faster growth. In the period 1936–2009, yields for all six crops grew by more than 1.0% per year, with corn being the standout: corn yields grew by 2.99% per year on average for 1936–2009. The bottom section of table 3 also shows the annual average growth in yields during the period 1936–1990 (1.81% per year, averaging across all six crops) compared with the period 1990–2009 (1.17% per year). The difference in yield growth between these periods is striking, with a major slowdown in yield growth for barley, corn, oats, and wheat (and a less

[21] In the supplementary online material, we report the results from breakpoint analysis using rolling regressions procedures that yield similar results, in general, reinforcing the findings from the cubic polynomial regression models reported here.

Table 3. Crop Yields, and Absolute and Proportional Rates of Change in Yields, 1867–2009

	Barley	Corn	Oats	Rice	Soybeans	Wheat
Measure and Period						
Average			*Yield (pounds per acre)*			
1866[a]	1,152	1,361	938	1,144	660	660
2009	3,504	9,251	2,163	7,085	2,640	2,664
Entire period	1,581	3,138	1,226	3,382	1,563	1,294
Through 1935	1,090	1,452	904	1,671	804	812
1936–2009	2,046	4,733	1,530	4,330	1,686	1,750
1936–1990	1,748	3,733	1,392	3,648	1,465	1,523
1990–2009	2,898	7,580	1,928	6,266	2,311	2,403
1980s	2,427	5,930	1,739	5,138	1,818	2,149
1990s	2,795	6,907	1,854	5,764	2,203	2,318
2000–09	3,001	8,253	2,003	6,769	2,419	2,488
Average rate-of-change			*Average annual percentage change*			
Entire period	0.78	1.34	0.58	1.60	1.58	0.98
Through 1935	–0.05	–0.01	0.04	1.60	3.62	0.15
1936–2009	1.94	2.99	1.44	1.55	1.54	1.70
1936–1990	2.14	3.43	1.73	1.64	1.61	2.09
1990–2009	1.39	1.75	0.62	1.31	1.34	0.62
1950s	1.31	3.59	2.21	3.67	0.80	4.59
1960s	3.23	2.80	1.25	2.99	1.28	1.72
1970s	1.49	2.29	0.74	–0.45	–0.08	0.78
1980s	1.21	2.64	1.26	2.25	2.52	1.65
1990s	0.85	1.44	0.66	1.28	1.11	0.61
2000–2009	1.98	2.09	0.57	1.34	1.60	0.62

Source: Calculated by the authors using yield data from USDA NASS (2010). Superscript [a] indicates that the first observation for soybeans is 1924, and for rice it is 1895.

severe yet substantial slowdown for rice and soybeans).

Annual averages can be sensitive to the choice of terminal points for the periods being compared, and especially so given the year-to-year (often weather-induced) volatility in crop yields. To skirt this potential problem, we conducted a rolling regression (15-year) interval analysis of the (logarithms of the) average national yields of these six major field crops in the United States (this procedure is described in the supplementary online material, where it is applied to other productivity data series). Setting aside the rather truncated soybean time series, this evidence suggests that the (15-year) rate of growth in yields for barely, corn, oats, rice, and wheat has slowed in the recent several decades relative to the immediately preceding decades.

These results indicate that the 1950s, 1960s, 1970s, and 1980s were generally decades of abnormally high rates of yield growth during a longer period spanning the late nineteenth century and the entire twentieth century. The period of abnormally high MFP growth began a little later and was shorter lived, spanning the 1970s and 1980s. Up through 1935, the rate of growth in crop yields was, with some minor exceptions (for rice and soybeans), generally below the rate since then.[22] And, again like the MFP evidence, rates of growth in yield for all six crops since 1990 are more in line with the average rate of growth in yields over the entire period 1867–2009, that is, well below the rapid rates of the 1960s and 1970s.

Finally, figure 6 shows fitted cubic trend regressions of the crop yield data in natural logarithms (along with the calculated inflection year). In each case the cubic trend model was preferred over a linear model, and the estimated inflection point was statistically significant. As the only exception, soybeans has yield growth decelerating prior to 1975 and accelerating thereafter. The inflection points for the other five crops indicate accelerating yield growth before the inflection point and

[22] Notably, the annual rate of growth in rice yields before and after 1936 was little changed (1.64% per year and 1.31% per year, respectively), and the exceptionally high 3.62% per year rate of growth of soybean yields prior to 1936 likely reflects a small sample problem (in that we only have soybean yield observations beginning in 1924).

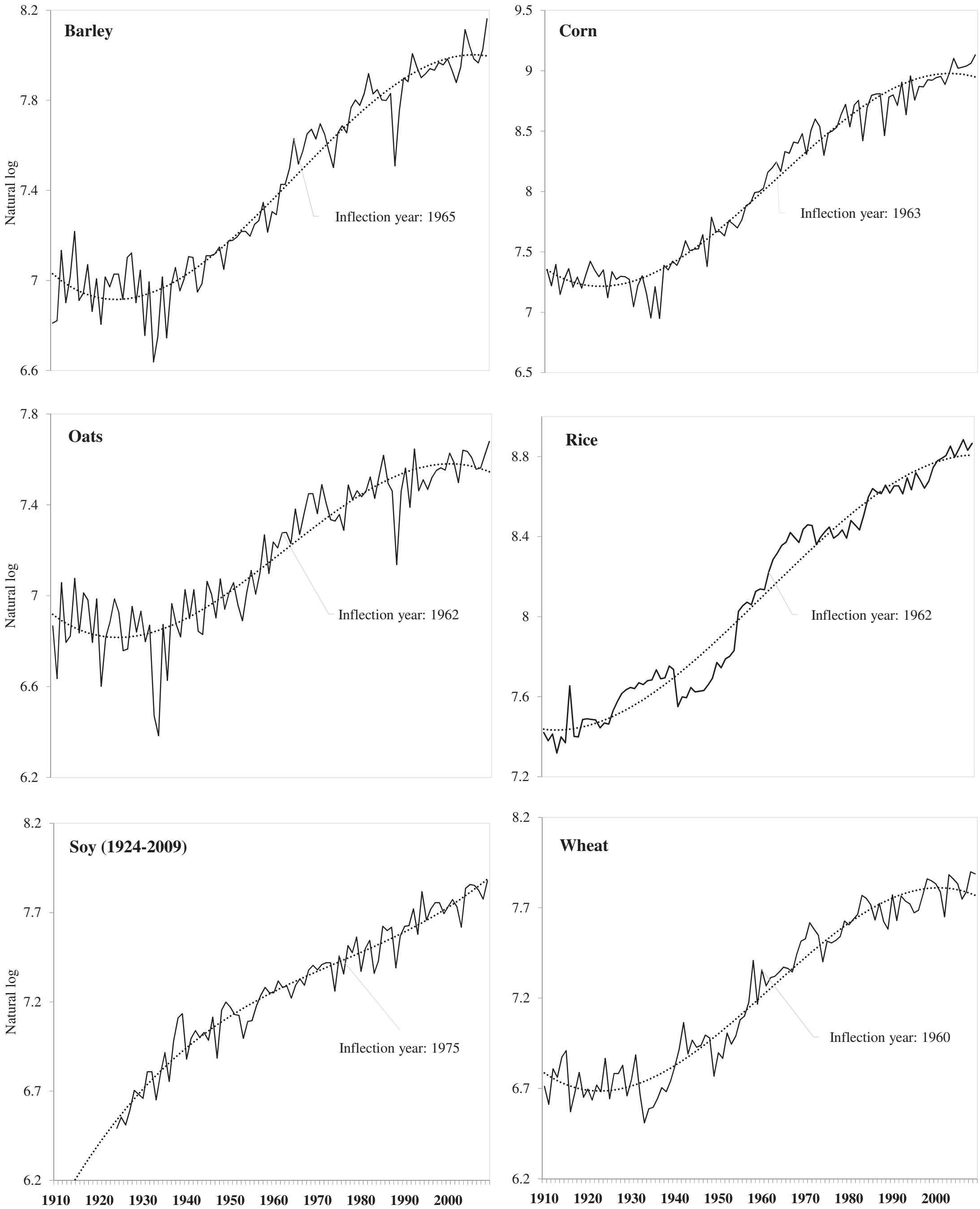

Figure 6. Cubic trend models of crop yields in natural logarithms, 1910–2009

Source: Calculated by the authors using yield data from USDA-NASS (2010).

decelerating thereafter, and the estimated years of maximum yield growth rates (i.e., the inflection points) range from 1960 for wheat to 1965 for barley.

In sum, the results from our analysis of crop yield data, and the land and labor PFP indexes, reinforce the results from our analysis of MFP indexes. These series generally exhibit a similar pattern of rise and fall providing persuasive evidence of a surge followed by a progressive structural slowdown in (multifactor) U.S. farm productivity growth that started in the latter decades of the twentieth century and continues into the twenty-first century.

Conclusion

In this paper we have used a range of data and methods to test for a slowdown in U.S. farm productivity growth, and the evidence is compelling. The results all confirm the existence of a surge and a slowdown in productivity but with some variation in timing, size, and statistical significance of the shifts. Alston, Andersen, and Pardey (2018) posit that a wave of technological progress through the middle of the twentieth century—reflecting the progressive adoption of various mechanical innovations, improved crop varieties and animal breeds, and synthetic fertilizers and other chemicals, each in a decades long process—contributed to an extended surge of faster-than-normal productivity growth throughout the third quarter of the century, and a subsequent slowdown toward the end of the twentieth century that has extended into the present era.

Over the most recent 10 to 20 years of our data, the annual average rate of MFP growth was half the rate that had been sustained for much of the twentieth century. More subtly, and of equal importance, the past century (and more) of statistics assembled here suggest the relatively rapid rates of productivity growth experienced during the 1960s, 1970s, and 1980s could be construed as aberrations (along with the relative rapid rates of growth experienced during a period spanning WWII), with the post-1990 rates of productivity growth now below the longer-run trend rate of growth.

The lags between investing in R&D and reaping the productivity growth dividends from those investments are long, spanning many decades (Alston, Babcock, and Pardey 2010). The stand-out productivity decades of the 1960s, 1970s, and 1980s were preceded by almost a century of sustained growth and accumulation of human, institutional, and scientific capital. Real investments in public agricultural R&D grew, on average, by 3.87% per year from 1953 to 1970, substantially faster than the corresponding rate of growth of agricultural output (an index of which grew by 1.42% per year over this period). Likewise, the precursor to the post-1990 slowdown in U.S. agricultural productivity growth was an earlier slowdown in the growth of total spending on agricultural R&D, and a gradual reduction in the share spent on productivity-enhancing agricultural research and development (Alston, Babcock, and Pardey 2010; Pardey, Alston, and Chan-Kang 2013; Alston 2018). However, the extent to which the surge and slowdown in productivity growth can be attributed to the evolving prior path of R&D spending remains a matter for speculation since this all took place in the context of a wholesale transformation of the farming sector, parts of which cannot be ascribed to innovation based on (publicly performed) agricultural science.

A failure to revive U.S. agricultural productivity growth during the decades ahead could have serious implications. If the 1990–2007 rate of MFP growth of 1.16% per year persists until 2060, for any given quantity of inputs, the quantity of U.S. agricultural output produced in that year will be approximately 10% less than if the 1910–2007 rate of 1.42% per year could be restored. Moreover, unless other countries with competing agricultural production experience comparable slowdowns in agricultural productivity growth, the United States will suffer a widening competitiveness gap. On the other hand, if other countries do experience comparable slowdowns in agricultural productivity growth, the consequences will be felt in a widening gap of a different sort: between growth in global supply and growth in global demand for agricultural products.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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