Staff Paper P23-01 **January 2023**

Staff Paper Series

R&D Lags in Economic Models

by

Shanchao Wang, Julian M. Alston and Philip G. Pardey

Department of APPLIED ECONOMICS

INSTEPP INTERNATIONAL SCIENCE & TECHNOLOGY PRACTICE & POLICY

College of Food, Agricultural and Natural Resource Sciences

UNIVERSITY OF MINNESOTA

R&D Lags in Economic Models

January 21, 2023

Shanchao Wang[a], Julian M. Alston[b] and Philip G. Pardey[c]

Affiliations and Acknowledgments

Shanchao Wang is a data scientist at Meta. Julian Alston is a Distinguished Professor in the Department of Agricultural and Resource Economics and Director of the Robert Mondavi Institute Center for Wine Economics at the University of California, Davis, and a member of the Giannini Foundation of Agricultural Economics. Philip Pardey is a Professor in the Department of Applied Economics, Director of Global Research Initiatives for CFANS, Director of the International Science and Technology Practice and Policy (InSTePP) center, and Director of the GEMS Informatics Center, all at the University of Minnesota

The authors are grateful for the excellent research assistance provided by Connie Chan-Kang and Devin Serfas and for helpful comments from Kevin Novan and Aaron Smith. The work for this project was partially supported by the California Agricultural Experiment Station; the Giannini Foundation of Agricultural Economics; the Minnesota Agricultural Experiment Station (MIN-14-171); the University of Minnesota's GEMS Informatics Center; and the USDA National Research Initiative.

Abstract

Quite different R&D lag structures predominate in studies of agricultural R&D compared with studies of R&D in other industries, and compared with studies of economic growth more broadly. Here we compare the main models and their implications using long-run data for U.S. agriculture. We reject the models predominantly used in studies of economic growth and industrial R&D both on prior grounds and using various statistical tests. The preferred model is a 50-year gamma lag distribution model. The estimated elasticity of MFP with respect to the knowledge stock is 0.28 and the implied marginal benefit-cost ratio is 23:1.

Key words: R&D lags, model selection, agricultural productivity, rate of return

JEL Codes: D24, E23, O31, O47, Q16

R&D Lags in Economic Models

1. Introduction

Innovation resulting from organized investments in R&D is at the center of contemporary models of economic growth and is a focus of econometric models of research-induced increases in productivity in agriculture and other industries. Although these branches of applied economics share a common heritage—from work done decades ago by economists like Zvi Griliches, Edwin Mansfield, Jora Minasian, Robert Solow, and Theodore Schultz—, nowadays they employ quite different conceptual and empirical models to represent the process by which today's investments in R&D influence the future time path of productivity and economic growth. These substantial differences in models can be characterized, formally, in terms of differences in the detail of the specification of the R&D lag structure, which transforms measures of past and present investments in R&D into an R&D knowledge stock that affects current productivity.

In a companion paper, Alston et al. (2022b) flesh out those differences and explore their origins and implications, taking a broad perspective and drawing on a range of evidence about particular technologies. In the present paper, we focus more narrowly on comparing these alternative models empirically, using a particular data set for U.S. agriculture. These are high-quality data in a comparatively long time-series, which is advantageous for drawing comparisons among the alternative models that differ substantively in terms of their assumptions regarding lag length and shape. Our findings using agricultural data are relevant beyond agriculture; they are informative about comparable relationships for the economy as a whole and the many other industries for which comparably useful data have not been available.

We begin with a review of the relevant conceptual foundations and a synopsis of the predominant lag specifications used in applications to agricultural R&D, industrial R&D, and implicitly in economic growth models. This leads to an econometric specification that permits testing among these alternatives. Our application uses data for U.S. agriculture, which are available in long enough time series to enable estimating models with long lags, and for which we have strong priors about the plausible length and shape of the lag distribution, sufficient to reject at least some models. In practice, we are also able to reject some models on statistical grounds, and to select a model that is both statistically preferred and compatible with our prior views—a 50-year gamma lag distribution model with a shape similar to that used in several recent studies of agricultural R&D. The implied marginal benefit-cost ratio for research is 23:1 and the elasticity of productivity with respect to the R&D knowledge stock is 0.28; both also in keeping with priors.

The most striking aspect of our results is the remarkable similarity of findings regarding implied rates of return to research and elasticities of productivity with respect to R&D knowledge stocks among all the models tried, including totally implausible ones. A geometric lag distribution model with no gestation lag—as typically used in models of industrial R&D, for example—is totally implausible for these data, yet in practice might appear to be an adequate statistical model that yields estimated rates of return and elasticities that are consistent with published estimates for agriculture and other industries. But as we show, this model wholly misrepresents the true data-generating process. The upshot is that modelers should place greater emphasis on developing well-informed priors as a basis for imposing assumptions about the overall length and general shape of the R&D lag distribution, which are inevitable.

2. Economic Models of Knowledge Stocks

Economic studies linking R&D to productivity implicitly or explicitly entail a model in which multifactor productivity (MFP_t) depends on flows of services from an R&D knowledge stock, K_t, as well as other factors, X_t:

(1) $$MFP_t = f(K_t;\ X_t).$$

In the typical application, a double-log form is imposed in which the parameters are elasticities:

(2) $$\ln MFP_t = \beta_0 + \beta_K \ln K_t + \beta_X \ln X_t + \varepsilon_t.$$

Different assumptions about the processes of creation and utilization of knowledge can be characterized as different parameterizations of the R&D lag structure whereby past and present R&D investments contribute to the stock of knowledge in use today. Applying notation from Alston et al. (2011), the knowledge stock in year *t*, K_t, can be characterized as:

(3) $$K_t = \sum_{k=0}^{\infty} b_k R_{t-k},$$

where b_k is the weight assigned to lag period *k*, and R_{t-k} is the real (or inflation-adjusted) public agricultural R&D investment in year *t* – *k*, and (in most cases) these weights sum to one:

(4) $$\sum_{k=0}^{\infty} b_k = 1.$$

We are interested in three main categories of models, allowing for some variation within categories, namely: agricultural R&D models, industrial R&D models, and growth theory models. We characterize the differences among these models in terms of differences in the attributes of R&D lag distributions that are imposed implicitly or explicitly: (1) the total lag length, (2) a gestation lag period before research investments begin to contribute to the knowledge stock, (3) restrictions imposed on the functional form of the distribution, and (4) parameters associated with the functional form. In what follows we compare the lag structures used in agricultural R&D models, industrial R&D models, and growth theory models both conceptually and in an illustrative empirical application using data for U.S. agriculture.

2.1 Agricultural R&D Models

As discussed by Alston et al. (2022b), in applications to U.S. agriculture over the past half century (since Evenson 1967) it has been conventional to model agricultural productivity as a function of an R&D knowledge stock. The current knowledge stock in use, K_t in year t, is represented by lagged investments in agricultural R&D, with rising and falling lag weights reflecting successive phases of research, development, adoption, depreciation and disadoption of the resulting innovations. Though some have tried free-form weights the great majority of the hundreds of agricultural R&D studies have imposed a structure on the lag distribution so it can be represented by just a few parameters (see, e.g., Alston et al. 2022b).[1] As discussed by Pardey et al. (2010), from early beginnings with quite simple models and short lags the models have evolved to allow for longer lags and more complex shapes.

The two predominant models in use nowadays are the 35-year trapezoidal lag distribution model introduced by Huffman and Evenson (1993) thirty years ago, and the 50-year gamma lag distribution model proposed more recently by Alston et al. (2010). Alston et al. (2011)

[1] Alston et al. (2022a) report that 540 out of 2,963 estimates of rates of return to agricultural R&D were derived from models using free-form lags.

compared these two models applied to U.S. state-level MFP data for the period 1949–2007 from InSTePP, and found in favor of a gamma lag distribution model with a peak lag considerably later than that for the trapezoidal lag model, though otherwise reasonably similar in shape. Both of these models have initial periods of several years with negligible or zero impact of R&D on productivity (a gestation lag or a pre-technology research and development lag) followed successively by a period of rising impact (the adoption lag), and eventually a period of declining impact (reflecting disadoption and depreciation of knowledge in use), truncated to zero at 35 years (the trapezoidal lag distribution model) or 50 years (the 50-year gamma distribution).

In this paper we take the 50-year gamma lag distribution model from Alston et al. (2011) as our starting point. Alston et al. (2011) had state-level MFP data beginning in 1949 so they were constrained to estimating models for the period 1949–2007, but we are modeling national aggregate MFP for which we have data back to 1910. Given a 50-year lag, our first knowledge stock observation in 1940 is a weighted average of public R&D investments from 1890 to 1940, while the last observation in 2007 is a weighted average of investments from 1957 to 2007. With these measures of knowledge stocks, we can estimate models of MFP using national data for 1940–2007.

Some studies (e.g., Andersen and Song 2013; Khan and Salim 2015) have imposed the specific gamma lag distribution model weights, as estimated by Alston et al. (2011) in other contexts, whether using similar or totally different data. Here, we use a somewhat different model (i.e., including a different weather index, applied to a single time-series of national aggregate data rather than a panel of state-level data, and excluding extension expenditures to make for more direct comparability to models applied to other sectors of the economy) to model changes in agricultural MFP over a different time period (1940–2007 rather than 1949–2007). Therefore, we opted to re-estimate the gamma lag distribution parameters, using a grid search procedure as done by Alston et al. (2011) across 64 combinations given by 8 values each for the two gamma distribution coefficients. We also try the Huffman and Evenson (1993) trapezoidal lag model with its specific lag weight structure applied to these different data.

2.2 Industrial R&D Models

In models applied in studies of returns to research in other industries, the predominant R&D lag model in use is quite different: it is a perpetual inventory model (see, e.g., Hall 2010; Li and Hall 2018; Serfas et al. 2023). In this model, a proportional declining balance or geometric depreciation rule is used to represent changes in an aggregate stock of knowledge (Griliches 1980, 1986). As described by Alston et al. (2022b), using δ to denote the depreciation rate, and allowing for a gestation lag of g years between research spending and increments to knowledge, the aggregate stock of knowledge evolves over time according to:

(5) $$K_t = (1-\delta)K_{t-1} + R_{t-g} = \sum_{s=0}^{\infty}(1-\delta)^s R_{t-s-g}.$$

Equation (5) can be seen as a special case of equation (3) in which the entire (infinitely long) distribution of lag weights, b_k is represented by one parameter, δ (or two parameters if a nonzero gestation lag is included): $b_{s-g} = (1-\delta)^s$. While it is analytically and empirically convenient, this model imposes strong restrictions on both the length and shape of the R&D-productivity lag relationship.

As typically used, this model allows little or no time for the sequential processes of research, knowledge creation, and the development, diffusion and adoption of technology.[2] The assumed gestation lag is usually very short (if not absent) as is the effective overall lag: in the benchmark case, as described by Li and Hall (2018), $g \leq 2$ (and more often zero) and $\delta = 0.15$.[3] Research has its maximum impact on productivity immediately or almost immediately, and thereafter the lag weights decline rapidly given high assumed rates of knowledge depreciation.

This model seems highly implausible. Why is it so popular? We speculate that the amount and types of firm- or sectoral-level research expenditure data, as typically used in measures of industrial R&D knowledge stocks, are not amenable to estimating (and testing among) more plausible lag distribution models that have more flexible shapes and longer effective lags. Moreover, the perpetual inventory-cum-geometric lag distribution model is quite convenient for applications using data in a very short time-series or a cross-section since the current R&D knowledge stock can be calculated using just the current annual rate of spending, and measures of (or assumptions about) the growth rate of that spending, and the rate of depreciation of the stock.[4]

[2] This remains so in almost all models of industrial R&D lags, even though some 30 years ago, Griliches (1992, pp. S41–42) declared: "… the more or less contemporaneous timing of such effects is just not possible."

[3] Serfas et al. (2023) compiled 1,464 estimates of rates of return from 128 studies of industrial R&D. Of those 1,464 estimates, 97.3% were based on a perpetual inventory model; 88.2%, did not allow for any gestation lag; 64.4% used a knowledge depreciation rate of δ = 15% per year, and another 4.5% used a δ > 15% per year.

[4] The knowledge stock in the base period, B, can be approximated as $K_B = R_B / (\delta - \theta)$ where θ is the applicable (often assumed) growth rate of spending on research.

2.3 Growth Models

As described by Jones (1995), the R&D-based models of economic growth associated with Romer (1990), Grossman and Helpman (1991a, b, c), and Aghion and Howitt (1992) all imply scale effects: "…an increase in the *level* of resources devoted to R&D should increase the *growth* rate of the economy" (Jones 1995, p. 761, emphasis in original). Jones (1995, p. 760) points out that the "…prediction of scale effects is clearly at odds with empirical evidence" and attempts to revise the model to address that deficiency. Others also have found fault with that model and its implausible empirical implications (see, e.g., Jones and Summers 2020). Jones (2022) provides an up-to-date discussion of this model and variants.

These issues notwithstanding, the same (unrevised) Romer-Aghion-Howitt model was employed by Bloom et al. (2020) in recent work that included illustrative applications to several industries, including U.S. agriculture. Specifically, Bloom et al. (2020) presume the current rate of productivity growth is proportional to the current flow of research effort, represented by the number of scientists, *S*, measured as research spending divided by an index of the wage rate of scientists (which corresponds to *R* in our notation above). That is, in their equation (1):

(6) $$\frac{\dot{A}_t}{A_t} = \alpha S_t.$$

In terms of our notation, the growth rate of productivity is measured by *MFP*, and equation (6) can be written as:

(6') $$\frac{\Delta MFP_t}{MFP_t} = \alpha R_t \approx d \ln MFP_t,$$

or, equivalently:

(6”) $$\ln MFP_t = \alpha R_t + \ln MFP_{t-1}.$$

After repeated substitution for the lagged value of equation (6”), this can be rewritten as:

(7) $$\ln MFP_t = \alpha \sum_{n=0}^{\infty} R_{t-n} = \alpha K_t,$$

where the knowledge stock in year *t* is equal to the accumulated sum of research spending up to year *t*.

This model assumes research investments have their maximum impact on productivity immediately (i.e., in the same year), without any gestation lag—like the majority of studies of industrial R&D but in contrast to almost all the studies of agricultural R&D.[5] Further, it assumes these effects that begin immediately continue undiminished, forever. This is significantly different from both the predominant models used in studies of industrial R&D (which imply rapidly and geometrically declining lag weights) and those used in prominent recent studies of agricultural R&D (which allow for rising and falling lag weights over a 35 to 50-year horizon).[6]

---

[5] We are aware of just one study contemplating economic growth models and industrial R&D models together, and ironically it entails an application to agriculture—in Italy. Specifically, Esposito and Pierani (2003) employ a variant of the perpetual inventory model, with a lag distribution characterized by three parameters: (1) the knowledge depreciation rate, (2) a parameter that defines the length of the “gestation period” (before today’s R&D has its maximum impact on future productivity), and (3) a parameter that defines the shape of the lag distribution during the gestation period. This lag distribution model seems less plausible than either the gamma lag distribution model or the trapezoidal distribution model, for most cases, but in practice it might yield similar results.

[6] Jones and Summers (2020) begin with a model in the same spirit as Romer (1990) and Bloom et al. (2020) and examine several reasons why the implied benefit-cost ratio may be too high, including a mis-specified R&D lag model. They say “The above baseline assumes that the payoff from R&D investments occurs immediately. Yet there may be substantive delays in receiving the fruits of R&D investments” (Jones and Summers p. 13). “Aggregating across the different types of research, a middle-of-the-road delay estimate may be 6.5 years…” (Jones and Summers p. 14). These comments refer to the initial R&D lag and adoption processes, but do not address the issue of depreciation of knowledge in use.

Also, in its pertinent aspects, equation (7) is similar to equation (2) except that the knowledge stock enters linearly rather than in logarithmic form.

2.4 Synopsis of Models—Nested Structure

We have a total of four models to compare, namely: (1) the 50-year (truncated) gamma distribution model (associated with Alston et al. 2011) with its two parameters to be estimated using a grid search, (2) the 35-year trapezoidal model with its specific parameterization (associated with Huffman and Evenson 1993), (3) the geometric model (associated with Hall et al. 2010 among others) using depreciation rates of $\delta = 0.10$ or 0.15, and (4) the Romer-Aghion-Howitt model (used by Bloom et al. 2020 among others).[7] For the first three of these models we impose in common a two-year gestation lag and we limit the maximum length of the R&D lag to 50 years—as was already imposed by Huffman and Evenson (1993), by truncating at 35 years, and implicit as an approximation in the geometric lag model with $\delta = 0.10$ or 0.15 since $0.90^{50} = 0.005$ and $0.85^{50} = 0.0003$. Further, we divide by the 50-year sum of the weights to obtain normalized weights that sum to 1.0. For the Romer-Aghion-Howitt model we do not impose a gestation lag, we do not truncate the lags at 50 years, and we do not impose the restriction that the lag weights sum to 1 (indeed, they are all equal to 1).

Specifically, for each of the gamma, trapezoidal, and geometric lag distribution models we envision the following linear regression model:

$$\ln(MFP_t) = \beta_0 + \beta_1 \ln(K_t) + \beta_2 W_t + T_t + \varepsilon_t, \quad (8)$$

[7] Details on the parameterization of the knowledge stocks for these four models are provided in the supplementary online appendix (Appendix Table 1).

where MFP_t, K_t, and W_t are, respectively, multifactor productivity, the knowledge stock, and an agricultural weather index, T_t is a linear time trend (where 1940 is the starting point with T_t = 1), and ε_t is a residual, all in year *t*. In contrast, for the Romer-Aghion-Howitt model, the knowledge stock enters additively rather than in logarithms:[8]

(8')
$$\ln(MFP_t) = \beta_0 + \beta_1 K_t + \beta_2 W_t + T_t + \varepsilon_t.$$

In equation (8), the growth rate of productivity is proportional to the growth rate of the knowledge stock, and we can interpret β_1 as the elasticity of productivity with respect to the knowledge stock. However, in equation (8'), representing the Romer-Aghion-Howitt model, the growth rate of productivity is simply proportional to the knowledge stock; hence, the elasticity of productivity with respect to the knowledge stock is equal to $\beta_1 K_t$.[9]

3. Data

We compare the alternative models in an application to U.S. agriculture, drawing on long-run data developed specifically for use in models like these by us with colleagues at the International Science and Technology Practice and Policy (InSTePP) Center at the University of Minnesota. The data used in our analysis include (1) an annual index of U.S. agricultural multifactor productivity (MFP) for the period 1910–2007, obtained from InSTePP; (2) measures

[8] In our regression analysis we try a variant of this model in which we include the Romer-Aghion-Howitt R&D stock in logarithms rather than levels, to check the importance of this aspect of the difference between this model and the other seven models. We thank Aaron Smith for prompting us to take this diagnostic step.

[9] Since the knowledge stock enters linearly and accumulates additively, the estimate of β_1 in equation (8') does not depend on the size of the initial knowledge stock in 1939, or how it is estimated, prior to the first observation of MFP, in 1940. Changes in the initial knowledge stock will be absorbed as changes in the intercept without changing any of the slope coefficients. Indeed, for that reason it would be possible to fit that model using data back to 1910—the first year for which we have data available on both MFP and R (and hence, K).

of aggregate annual U.S. public agricultural R&D investments and the associated R&D deflator for the period 1890–2007, also sourced from InSTePP; and (3) a purpose-built weather index, which we compute based on crop yield data from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA), sourced from USDA-NASS (2017).

3.1 Multifactor Productivity Index

The InSTePP multifactor productivity (MFP) indexes are Fisher ideal discrete approximations of Divisia indexes derived from detailed data on quantities and prices of inputs and outputs in U.S. agriculture (see supplementary online appendix, Appendix Figure 1). Version 5 of the InSTePP data consists of annual observations of state-specific prices and quantities of 74 categories of outputs and 58 categories of inputs for the 48 contiguous U.S. states from 1949 to 2007, and a corresponding national aggregate. To obtain a longer time series for the national aggregate, MFP is backcast to 1910 using year-to-year changes in the Laspeyres indexes of MFP for the period 1910–1949 from USDA-ERS (1983). More details on the construction and backcasting of this MFP index can be found in the book by Alston et al. (2010) and the online appendix of Pardey and Alston (2021).

3.2 Public Agricultural R&D Investment

InSTePP also provides data on U.S. public agricultural research expenditures for the period 1890–2007, primarily reflecting funding from the federal government to support intramural research undertaken by USDA, and from both federal and state governments to provide for R&D undertaken by the State Agricultural Experiment Stations (SAESs), affiliated with land grant universities.[10] As well as funds from various federal and state government agencies, SAESs obtain funding from industry grants and contracts and income earned from sales, royalties, and various other sources. During the period 1903–1942, USDA intramural research and SAES research contributed almost equally to total public agricultural research spending in the United States. However, since WWII the paths have diverged, and SAES research spending has increasingly exceeded federal intramural research spending, peaking at 75 percent of total public agricultural R&D spending in 2002 (Pardey et al. 2013 and 2017).[11]

3.3 Agriculturally Relevant Weather Shocks

Year-to-year fluctuations in crop yields around trend are highly influenced by weather (Beddow et al. 2014), making yield deviations from trend a useful proxy of the transient agricultural productivity effects of weather. Our composite index of crop yield deviations from trend is based on an area-weighted average yield for the years 1940–2007, calculated using yield data for the top 10 crops (by harvested area) taken from USDA-NASS (2017). First, we ranked all 44 field crops in the USDA-NASS (2017) listing according to their average annual harvested areas for the period 1940–2007. Then we selected the top 10 field crops by area (accounting for 78 percent of total harvested area), namely: corn, hay, wheat, soybeans, oats, cotton, sorghum, barley, rice and flaxseed. Since yields vary considerably across crops, we used standardized

---

[10] For our analysis in this paper, expenditures were converted to constant (2019-dollar) values using the InSTePP R&D price deflator (unpublished series, updated from Pardey et al. 1989).

[11] These measures are plotted in the supplementary online appendix (Appendix Figure 2). More detail on these data and the history of U.S. agricultural R&D investments can be gleaned from Alston et al. (2010, chapter 6) and Pardey et al. (2013).

yields for each crop.[12] These standardized annual, national-average crop yields were aggregated by years using as weights each crop's annual share of the total U.S. value of production (also from USDA-NASS, 2017). The resulting series was then used in the following time-trend regression:[13]

$$yield_t = \alpha + T_t + {T_t}^3 + \varepsilon_t, \tag{9}$$

where $yield_t$ is aggregated standardized yield in year *t*, and T_t is the time trend created by calendar year minus 1939.

We constructed the agricultural weather index in year *t* as a composite of yield deviations from trend: $yield_t - \widehat{yield}_t$, where: $yield_t$ is the weighted average of the *observed* yields, aggregated across crops, and $\widehat{yield}_t$ is *fitted* yields from equation (1). U.S. agriculture suffered an extended drought in the 1950s (see, e.g., Nace and Pluhowski 1965), and the year 1988 was a severe drought year (see, e.g., GAO 1989), as is apparent in both the yield index and the plot of deviations around it.[14]

---

[12] Standardized annual yields were computed by subtracting the mean of the series from each observation and dividing by the standard deviation of the series to reduce the effects of differences in average yields among crops.

[13] Alternative specifications were tried. In particular, we estimated models that included the following terms on the right-hand side of equation (9) besides the constant coefficient α: (a) a linear time trend T_t; (b) a linear time trend T_t and a quadratic time trend ${T_t}^2$; (c) a linear time trend T_t, a quadratic time trend ${T_t}^2$, and a cubic time trend ${T_t}^3$. All these specifications, including the one in equation (9), are not statistically significantly different from one another based on F tests. However, equation (9) results in a slightly higher adjusted R^2 and a slightly lower AIC, which indicates a better fit to our data. Detailed results are included in the supplementary online appendix, Appendix Table 2.

[14] In the supplementary online appendix (Appendix Figure 3) the fitted aggregated yield, $\widehat{yield}_t$ is plotted against the observed aggregated yield, $yield_t$.

4. Time-Series Properties and Lag Model Selection

Ultimately, we aim to estimate the elasticity of productivity with respect to the knowledge stock and the implied benefit-cost ratio (BCR) for agricultural R&D, to see how those estimates compare among the models that differ in terms of the lag specification, and to make an informed choice from among those alternatives. Drawing on Andersen and Song (2013), we propose a systematic method for model selection, which begins with an examination of the time-series properties of the knowledge stocks from each of our lag distribution models (including 64 gamma lag distribution models, as well as the trapezoidal lag distribution model, two geometric lag distribution models, and the Romer-Aghion-Howitt model), and the relationship with other variables, namely MFP and the agricultural weather index.

Whether we are estimating (8) or (8'), we are primarily interested in the estimate of the response of MFP to changes in the knowledge stock, represented by β_1. But for the estimate of β_1 to be meaningful, either the sequences of $\ln(MFP_t)$, $\ln(K_t)$ (or K_t for the Romer-Aghion-Howitt model), and W_t must be stationary or some linear combination of these variables must be stationary. Otherwise, we will get what Granger and Newbold (1974) call spurious regressions resulting in misleading estimates of β_1. To address this aspect, we first test the stationarity of $\ln(MFP_t)$, its first difference, $\Delta \ln(MFP_t)$, and W_t using the GLS-ADF test (a modified version of the augmented Dickey-Fuller test) proposed by Elliott et al. (1996). Elliott et al. (1996) showed that the GLS-ADF test has better power than the standard ADF test when a linear time trend is present in the data (we can see a clear trend in $\ln(MFP_t)$ in online Appendix Figure 1).

The test results are summarized in the online appendix (Appendix Table 3). In the GLS-ADF test the null hypothesis is that the time series is nonstationary. The results indicate that W_t

is stationary. Although $\ln(MFP_t)$ is nonstationary, its first difference (i.e., $\Delta\ln(MFP_t)$) is stationary, which indicates $\ln(MFP_t)$ is integrated of order one, I(1). Therefore, to avoid running spurious regressions, requires that $\ln(K_t)$ (or K_t for the Romer-Aghion-Howitt model) also is I(1) and cointegrated with $\ln(MFP_t)$.[15] The stationarity criterion eliminates 46 of the 64 (i.e., 8 x 8) parameterizations of the gamma lag model included in our grid search.

Our next step is to test whether $\ln(K_t)$ and $\ln(MFP_t)$ are cointegrated. We opted to perform two cointegration tests: the Johansen (1998) test and the Phillips-Perron (1988) test. The main results are summarized in Table 1.[16] In brief, only three gamma lag models (designated here and henceforth as Models 1, 2, and 3) pass all the time-series tests. For purposes of comparison, we also include results for another gamma model (Model 4, using parameters from Alston et al. 2011), as well as the trapezoidal lag distribution model (Model 5), the two geometric lag distribution models (Models 6 and 7), the Romer-Aghion-Howitt model (Model 8), and a logarithmic variant of the Romer-Aghion-Howitt model (Model 9), none of which has entirely satisfactory time-series properties.

[Table 1. Cointegration Tests with Alternative Lag Distribution Models]

In Table 1, columns (4) and (5) refer to the results from applying the same time-series stationarity tests as above, but here with respect to the knowledge stock in order to determine its order of integration. The numbers in columns (4) and (5) indicate we reject the null hypothesis

---

[15] For the Romer-Aghion-Howitt model, we perform all the time-series tests with respect to K_t instead of $\ln(K_t)$.

[16] Further details regarding test statistics, optimal lags, and critical values are included in the supplementary online appendix, Appendix Tables 4.1–4.3.

at the specific percentage significance levels shown (i.e., 1%, 5%, or 10%). As discussed above, we require $\ln(K_t)$ to be $I(1)$, which implies we should fail to reject the hypothesis in column (4) but reject the nonstationary hypothesis in column (5). Models 1, 2, 3, 6, and 7 satisfy this criterion for $I(1)$ knowledge stocks.

Next, for the cointegration test, we regress $\ln(MFP_t)$ on $\ln(K_t)$ (or K_t for Model 8) and run Phillips-Perron tests on the residuals. The null hypothesis is that a unit root is present in the residuals. The results are shown in column (6) of Table 1. Models 1–5 pass this test but Models 6–8 fail. Finally, in Table 1, column (7) we denote that a model passes the Johansen test if it both (1) rejects the hypothesis that there is no cointegrating equation defined by linearly combining $\ln(MFP_t)$ and $\ln(K_t)$ (or K_t for Model 8), and (2) does not reject the hypothesis that no more than one cointegrating equation is defined by the two variables. In other words, $\ln(MFP_t)$ and $\ln(K_t)$ (or K_t for Model 8) form only a single stationary time series. All of the models except the trapezoidal lag model (Model 5) pass the Johansen test. Only the four gamma lag distribution models (Models 1–4) and the logarithmic variant of the Romer-Aghion-Howitt model (Model 9) pass both the Phillips-Perron and Johansen tests.[17]

[Figure 1: Lag Distribution Shapes for Models 1–7]

Based on this battery of statistical tests, and our strong priors regarding the general structure of the R&D lag, our preferred model is Model 1: a gamma model with $\gamma = 0.75$ and $\lambda = 0.80$. In Figure 1, we depict the distribution of lag weights assigned to past investments for

[17] These cointegration tests are strictly relevant only for the models that had satisfied the stationarity tests.

this model and Models 2 through 7 (i.e., all the models except for the Romer-Aghion-Howitt model and its variant, Models 8 and 9). We calculate the peak and average lag for each model and summarize the information in Table 2. Our preferred gamma model has its peak at year 13, which implies R&D investments make their greatest contribution to the useful knowledge stock 13 years later. Although the lag distribution from this model has a potential lag length of 50 years, its shape is much more similar to that of the trapezoidal model (Model 5, with an imposed lag length of 35 years) than that of Model 4 (with its much longer effective lag length), which was preferred by Alston et al. (2010, 2011).

[Table 2. Peak Lag Year and Mean Lag for Models 1–7]

5. Corrections for Autocorrelation and Heteroskedasticity

As noted by Anderson and Song (2013) in a similar context, ordinary least-squares (OLS) can provide consistent estimators given stationary relationships among the variables in our specification. However, the estimators and inferences may be biased if the residuals are not independent and identically distributed. The residuals from OLS estimates of equation (8) for the three gamma lag distribution models that pass the time-series tests (Models 1–3) are plotted in the supplementary online appendix (Appendix Figure 4). Although the knowledge stock differs across these models, the plots of the residuals are similar. From 1940 to 1970, the models seem to suffer from autocorrelation, and each of the three residual plots exhibits a wide apparent range of variance. Accordingly, we conduct tests for heteroskedasticity and autocorrelation, and ultimately utilize estimates from regression models with corrections for heteroskedasticity and autocorrelation.

Detailed results from formal tests for heteroskedasticity and autocorrelation are provided in the online appendix (Appendix Tables 5.1–5.3). To test for heteroskedasticity we use the White test for nonlinear forms of heteroskedasticity and the Breusch-Pagan test for linear forms of heteroskedasticity. The null hypothesis is that the errors have a constant variance. Since we do not have a large data set, we implemented Wooldridge's (2015) version of the White test to save degrees of freedom. The results indicate that we might have a nonlinear heteroskedasticity problem in the error terms: we reject the null hypothesis of constant error variance using the White test at a 5% significance level, though not at 1%. In our OLS and dynamic OLS regressions, we use Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors.[18] In the regressions that use the Cochrane-Orcutt procedure or the Prais-Winsten procedure to correct for autocorrelation we use Eicker-Huber-White standard errors to correct for heteroskedasticity. These corrections will not affect the point estimates of β_1. However, they will affect the confidence intervals.

We considered Durbin-Watson (DW) and Breusch-Godfrey (BG) tests to test for autocorrelation in the error terms. The DW test can be used to test for a first-order autoregressive structure in models where the error terms follow a normal distribution and the regressors are strictly exogeneous. The BG test can be used to test for higher orders of autoregressive structures, and it also does not require regressors to be strictly exogenous. From the test results, we reject the null hypothesis that there is no autocorrelation in the error terms up to the specified lags. The evidence strongly suggests that we should correct for at least first-

[18] We use Newey-West HAC estimators with pre-whitening and a finite sample adjustment. See the *R* manual on the function *NeweyWest* for details.

order autocorrelation in the error terms, and we consider three options for doing so: dynamic OLS (Stock and Watson, 1993), the Cochrane-Orcutt procedure, and the Prais-Winsten procedure. The dynamic OLS method does not specify the order of autocorrelation while the latter two procedures take care of AR(1) serial correlation in the errors. Compared with the Cochrane-Orcutt procedure, the Prais-Winsten procedure has the advantage of preserving the first observation in the data transformation step and, given a small sample size, it might produce different results.

6. Regression Results, Elasticities and Benefit-Cost Ratios

The dynamic OLS estimates are preferred because this procedure corrects for more general autocorrelation problems. In Table 3, we report complete results for all nine lag distribution models estimated using dynamic OLS with Newey-West HAC standard errors.[19] Corresponding results estimated with OLS, the Cochrane-Orcutt and the Prais-Winsten procedures are reported in the online appendix (Appendix Tables 6.1–6.3). In Table 3, the preferred R&D lag model (on both statistical and conceptual grounds) is Model 1, and the other models are presented for purposes of comparison and to illustrate the consequences of model specification choices.

---

[19] Stock and Watson (1993) did not provide an empirical procedure for selecting the optimal lags and leads for the first difference of the cointegrated regressors (i.e., $\Delta\ln(K_t) = \ln(K_t) - \ln(K_{t-1})$ for equation (8) and $\Delta K_t = K_t - K_{t-1}$ for equation (8′)). We follow a data-driven procedure as used by Choi and Kurozumi (2012) to select the optimal lags and leads. In particular, we first define the maximum numbers of lags and leads using $\text{floor}\left(4 \times (T/100)^{1/4}\right)$, where floor(*x*) is a floor function which gives the greatest integer less than or equal to *x*, and *T* is the total number of years in our data. The resulting maximum number of lags and leads in our sample is three. Next, we run dynamic OLS regressions with different combinations of lags and leads ($\Delta\ln(K_{t\pm i}) = \ln(K_{t\pm i}) - \ln(K_{t\pm i-1})$, where $i \in \{1,2,3\}$) and compute the BIC for each model. The model with the optimal lags and leads will produce the smallest BIC.

[Table 3. Dynamic OLS Regressions of MFP against Knowledge Stocks]

Estimation procedures might also matter for findings. In Table 4, we focus on the estimates of the elasticities of MFP with respect to the knowledge stock from those same regressions across the nine lag distribution models and the four different estimation procedures.

[Table 4. Estimated Elasticities from Alternative Models and Estimators]

6.1 Elasticity Estimates

In the OLS estimates (Table 4, column (1)), all of the coefficients except one are estimated quite precisely with small standard errors, they are all in keeping with prior expectations and the relevant economic theory, and they are quite similar across all but one of the nine models. The notable and sole exception is the coefficient on the knowledge stock in the Romer-Aghion-Howitt model (Model 8) for which the point estimate in column (3) is not statistically significantly different from zero at the 5% level of significance.[20]

Comparing the estimates across columns (1)–(4) of Table 4, we see that the corrections for autocorrelation had mostly modest effects on the point estimates of the elasticities of productivity with respect to the knowledge stock. The notable exceptions are meaningful increases, especially with dynamic OLS, in the point estimates of the elasticities for Models 3, 4, and 9—models with larger mean lags compared with the other methods. However, even when they did not increase the point estimates, the autocorrelation corrections affected the standard

[20] Recall, in the Romer-Aghion-Howitt model, the elasticity of productivity with respect to the knowledge stock is equal to $\beta_1 K_t$, whereas in the other models the elasticity of productivity with respect to the knowledge stock is equal to β_1.

errors on some of the estimates of elasticities of productivity with respect to the knowledge stock, sufficiently to change the inferences in some cases—notably in Models 3 and 4.

When the Cochrane-Orcutt procedure is employed (column (2)) nothing changes very much compared with OLS (column (1)), but more pronounced differences are observed when the Prais-Winsten procedure is employed (column (3)), reflecting the combination of smaller estimated standard errors and larger point estimates of elasticities. Now, compared with the OLS estimates (column (1)), the elasticity of productivity with respect to the knowledge stock in Model 2 is statistically significantly different from zero at the 1% level of significance, rather than 5%; the elasticities in Models 3, 4, 6, 7 and 9 are statistically significantly different from zero at the 5% level, but not 1%; and the elasticity from Model 8 is now statistically significant at the 10% level but not 5%.

Compared with OLS, the dynamic OLS regressions result in a slightly less precise and less statistically significant estimate of the elasticity of productivity with respect to the knowledge stock in the preferred model (from 1% to 5%) and significantly more precise estimates of the elasticities from three other models: elasticities from Models 3, 4, and 9 that were not statistically significant are now all significantly different from zero at the 1% level. This might be because the leads and lags of the first differences of the knowledge stock variables absorb short-term noise, resulting in more precise estimators of the long-run cointegration relationships (i.e., elasticities).

In what follows we focus on the estimates obtained using the dynamic OLS regressions. The elasticities reported in column (4) of Table 4 for lag distribution Models 1–7 and 9 range from 0.201 to 0.386. This is a remarkably narrow range given the considerable differences in the shapes of the lag distributions across the models. The largest value comes from Model 3. The point estimate of the elasticity for Model 1 is essentially the same across the different estimation methods (0.290 for OLS, 0.306 for Cochrane-Orcutt, 0.307 for Prais-Winsten, and 0.277 for dynamic OLS).

6.2 Benefit-Cost Ratios

As first suggested by Griliches (1958) the gross annual benefits from productivity growth are approximately equal to the product of the gross value of production, *V*, and the growth rate of multifactor productivity, *MFP*:

$$(10) \qquad B_t \approx \frac{\Delta MFP_t}{MFP_t} \times V_t \approx d \ln MFP_t \times V_t.$$

In equation (8), growth in multifactor productivity is linked to research spending through the knowledge stock, *K*:

$$(11) \qquad d \ln MFP_t = \beta_1 d \ln K_t \;\text{ where } K_t = \sum_{k=0}^{\infty} b_k R_{t-k}$$

An increase in research spending in the current year, *t*, by ΔR_t will give rise to a stream of benefits from its effects on the time path of the stock of knowledge and thus productivity:

$$(12) \qquad d \frac{\Delta MFP_{t+k}}{MFP_{t+k}}\bigg|_{\Delta R_t} = \beta_1 \frac{\Delta K_{t+k}}{K_{t+k}}\bigg|_{\Delta R_t} = \beta_1 \frac{b_k \Delta R_t}{K_{t+k}}.$$

Given a discount rate of 100 *r* percent per year, the discounted present value of benefits from an increase in research spending in the current year, *t*, is therefore equal to:

(13)
$$PVB_t = \sum_{k=0}^{\infty} \frac{\Delta MFP_{t+k}}{MFP_{t+k}}\bigg|_{\Delta R_t} V_{t+k}\,(1+r)^{-k}$$
$$= \sum_{k=0}^{\infty} \beta_1\, b_k\, \Delta R_t \frac{V_{t+k}}{K_{t+k}} (1+r)^{-k}$$

Hence, the benefit-cost ratio (BCR) for an increase in research spending in year *t* by ΔR_t is:[21]

(14)
$$BCR_t = \frac{PVB_t}{\Delta R_t} = \beta_1 \sum_{k=0}^{\infty} b_k \frac{V_{t+k}}{K_{t+k}} (1+r)^{-k}.$$

Table 5 presents the BCRs and 95% confidence intervals computed using a real discount rate of 3 percent per year (i.e., r = 0.03) for the seven models that yielded sensible results (Models 1–7). The BCRs were computed using equation (13) with the elasticities estimated by OLS (column (1)), or with corrections for autocorrelation using either the Cochrane-Orcutt procedure (column (2)), the Prais-Winsten procedure (column (3)), or dynamic OLS (column (4)), the last of which is the preferred estimation procedure.

[Table 5. Benefit-Cost Ratios from Various Models]

The first row of Table 5 refers to results for our preferred lag distribution model (Model 1). In column (4), the dynamic OLS estimate of the BCR is 23.4, and it is statistically

[21] Reflecting the difference between equations (8) and (8'), the benefit-cost ratio for the Romer-Aghion-Howitt model is different, specifically

$$BCR_t = \frac{PVB_t}{R_t} = \beta_1 \sum_{k=0}^{\infty} V_{t+k} (1+r)^{-k}\,.$$

significantly different from zero. In columns (1), (2) and (3), the alternative estimation procedures yield very similar estimates (24.5, 25.9, and 26.0) for Model 1. The same is true for the estimates of BCRs for Models 2–7: looking across columns in any specific row the estimates are very similar. Reflecting the results with respect to elasticities, the OLS estimates of BCRs are mostly statistically significantly different from zero. However only four lag distribution models yield statistically significant BCR estimates across all estimation procedures: the preferred gamma model (Model 1), the almost identical trapezoidal model (Model 5), the somewhat similar gamma model (Model 2), and the geometric model with 10% depreciation (Model 6). Recall, of these four models, only Models 1 and 2 satisfy the time-series conditions required for robust estimates.

The preferred estimates of BCRs are those in column (4), based on the dynamic OLS regressions. They are all statistically significantly different from zero across eight of the nine lag distribution models, the exception being the Romer-Aghion-Howitt Model. Looking down column (4), among the eight lag distribution models the estimated BCRs range from 18.5 (Model 7) to 27.3 (Model 3), a surprisingly narrow range at first blush. These differences in BCRs reflect the effects of differences in elasticities combined with different lag shapes and discounting—a lag distribution with a greater mean lag, everything else equal, will have a smaller BCR and more so if the discount rate is greater.

Compared with Model 1 (our preferred gamma lag model, with a BCR of 23.4), Model 5 (the trapezoidal lag model) has a slightly larger BCR (25.2) reflecting its combination of a slightly larger elasticity and a somewhat shorter lag—it peaks at years 9 to 15 compared with year 13 for Model 1. In contrast, Model 2 has a smaller elasticity and a somewhat longer lag resulting in a somewhat smaller BCR (20.5). The other two gamma lag distribution models (Models 3 and 4) both have substantially longer lags. In spite of its relatively long lag, Model 3 has the highest BCR (27.3) reflecting its considerably larger elasticity, while Model 4 has both a smaller elasticity and a long lag; hence, a relatively small BCR (18.9). Finally, while they too have smaller elasticities the two geometric lag distribution models (Models 6 and 7) also have much shorter lags, with offsetting effects on the estimated BCRs (21.0 and 18.5 respectively).

The results in Table 5 were obtained with a discount rate of 3 percent per year, which we think is appropriate for this application. In the supplementary online appendix (see Appendix Table 7) we show the consequences of alternative discount rates applied to compute BCRs with the dynamic OLS estimates of the elasticities. In every row of this table, as we increase the discount rate from a very low (r = 0.001, 0.1 percent per year) to a very high (r = 0.10, 10 percent per year) the estimated BCR falls—for our preferred model it falls from a high of 36.3 to a low of 9.8, still quite impressive, bracketing the BCR in column (2) of 23.4. But this effect is more pronounced for the models with the longer lags, with implications for the relative sizes of the BCRs across models and even the ranking of the models. In column (4), with a 10 percent discount rate the geometric models (Models 6, and 7) now have BCRs greater than that for the preferred model (Model 1).

One of the striking features of these results is the strong similarity and substantial size and statistical significance of the estimated BCRs regardless of whether the underlying lag distribution model is fully consistent with priors (Models 1 through 5) or totally at odds with them (Models 6, 7 and 8). That this is so can be partly understood by considering the extensive discussion of "Plausibility of Estimates" in the book by Alston et al. (2010, pp. 423–435). As they show there, the annual value of agricultural productivity growth is many times greater than annual public spending on agricultural R&D. Hence, if the productivity growth is attributed entirely or mostly to that R&D spending, the BCR must be very large even if a long R&D lag is imposed. This aspect of the analysis is common across all the models and the variants tried.[22]

7. Conclusion

The work in this paper was inspired by our observation of striking differences in the predominant R&D lag distribution models currently being used by economists studying the economics of agricultural R&D, compared with economists studying the economics of R&D in other industries or modeling economic growth more broadly. Specifically, recent applications to agricultural R&D typically employ a 35- to 50-year R&D lag distribution model, with phases of rising and falling lag weights as innovations are progressively created, introduced, adopted and eventually replaced. In contrast, stereotypical models of industrial R&D and popular economic growth models entail much less likely assumptions of very short or nonexistent R&D lags and very high (at one extreme) or zero (at the other extreme) rates of knowledge depreciation. In addition, the same models also imply that R&D spending has its maximum effect on productivity (or profits) in the year in which it is spent, or very shortly thereafter.

[22] A related consideration discussed by Alston et al. (2010) is the potential for attribution bias resulting from the omission of potentially relevant explanatory variables such as agricultural extension knowledge stocks (as included in the model used by Alston et al. 2010, 2011), private agricultural R&D knowledge stocks (as tried but without any empirical success by Huffman and Evenson 2006) or other sources of technology spillovers such as international agricultural R&D or other U.S. industrial R&D. These omissions might have resulted in upward-biased estimates of the elasticities and, consequently, the BCRs from all the models. However, we suspect these biases would be modest, for the reasons given by Alston et al. (2010).

We set out to codify these differences into a nested structure and conduct a comparative assessment of their empirical consequences using a comparatively rich data set in relatively long time-series. Our data set for U.S. agriculture is similar to those used by others in several recent studies (see, e.g., Alston et al. 2011; Andersen and Song 2013; Baldos et al. 2019), and it is a context in which we have strong priors, based on detailed evidence of various forms, about the credibility of models that entail assumptions of very short or nonexistent R&D lags and extreme assumptions about the rate of knowledge depreciation (see, e.g., Pardey et al., 2010 and Alston et al. 2010, 2011, and 2022b).

The quantitative results are surprising in some ways. First, apart from the Romer-Aghion-Howitt model, the models all yielded rather similar estimates of elasticities of productivity with respect to the R&D knowledge stock and, in turn, quite comparable estimates of BCRs—all well within the range of widely accepted status quo estimates (see, e.g., the review by Fuglie 2018). If someone had naïvely estimated just one (any one) of these models by OLS, viewing the estimates uncritically they might have been well pleased by the seemingly strong and apparently credible results.

But even if they work well as statistical models, two of these models (the geometric lag distribution models, Models 6 and 7) are not at all plausible in the application to U.S. agriculture, if anywhere (Alston et al. 2022a). Further, four of the seven models (Models 4, 5, 6, and 7) fail to satisfy time-series (stationarity and cointegration) tests. Notably, we rejected (Model 4) the specific gamma lag distribution model that was found to be best in the similar application by Alston et al. (2010, 2011). Fortunately, we were able to estimate two models (Models 1 and 2) that performed well as statistical models, that were not inconsistent with our prior expectations regarding the likely length and shape of the R&D lag distribution, and that yielded plausible and statistically significant results within the range of reasonable expectations.

Interestingly, our preferred gamma lag distribution model is quite different in its general shape from the model preferred by Alston et al. (2010, 2011). Even though it allows for a longer, 50-year, lag it has a very similar overall shape to the shorter (35-year) Huffman and Evenson (1993) trapezoidal lag model. It also appears to be very similar in shape to the preferred gamma lag model identified by Baldos et al. (2019), which also implies a similar value for the BCR. Moreover, the estimate of the elasticity of productivity with respect to the knowledge stock (0.28) from our preferred model is remarkably close to what Baldos et al. (2019) estimated (0.29) using a Bayesian hierarchical approach.[23]

Most researchers are not in a position to estimate a flexible lag distribution model and test among alternatives in the ways we have done here using data for U.S. agricultural R&D. Instead, almost all studies linking R&D to productivity simply impose untested assumptions about the length and shape of the R&D lag, which can potentially have profound implications for the results. Some such assumptions are inevitable and indeed desirable. Forty years ago, Zvi Griliches (1979, p. 106, emphasis in original) suggested "… it is probably best *to assume* a functional form for the lag distribution on the basis of prior knowledge and general considerations and not to expect the data to answer such fine questions."

[23] Fuglie (2018, p. 437) reports an elasticity of MFP with respect to national public agricultural R&D equal to 0.30 for North America, computed as the average of estimates across seven studies.

But Griliches does not tell us what to assume about the form for the R&D lag distribution, and at least some groups of economists—in particular, those measuring returns to industrial R&D or using R&D-based models of economic growth—have made a habit of imposing assumptions in their lag distribution models that seem to be significantly at odds with reality, even after allowing for differences in market settings and the types of data used in industrial versus agricultural applications (Alston et al. 2022b). It should be possible to make better judgments about this aspect of model specification. Getting these ideas right matters. Even though they might seem superficially similar—in terms of the estimated elasticities and BCRs—the alternative lag distribution models can have profoundly different implications for our economic understanding of the linkages between investments in R&D, productivity, and economic growth, and the temporal structure of those linkages.

References

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth through Creative Destruction." *Econometrica* 60 (2): 323–51.

Alston, Julian M., Matthew A. Andersen, Jennifer S. James and Philip G. Pardey. 2010. *Persistence Pays: U.S. Agricultural Productivity Growth and the Benefits from Public R&D Spending*. Springer: New York, NY.

Alston, Julian M., Matthew A. Andersen, Jennifer S. James and Philip G. Pardey. 2011. "The Economic Returns to U.S. Public Agricultural Research." *American Journal of Agricultural Economics* 93 (5): 1257–77.

Alston, Julian M. and Philip G. Pardey. 2021. "The Economics of Agricultural Innovation." Chapter 75 in *Handbook of Agricultural Economics*, Volume 5 edited by Christopher B. Barrett and David R. Just, 3895–3980. Amsterdam: Elsevier.

Alston, Julian M., Philip G. Pardey, and Xudong Rao. 2022a. "Payoffs to a Half Century of CGIAR Research." *American Journal of Agricultural Economics* 104(2): 502-529 doi.org/10.1111/ajae.12255.

Alston, Julian M., Philip G. Pardey, Devin Serfas and Shanchao Wang. 2022b. "Slow Magic: Agricultural vs Industrial R&D Lag Models." *Annual Review of Resource Economics* (in process, January 2023). Working Paper version available at https://ageconsearch.umn.edu/record/329835/.

Andersen, Matthew A., and Wenxing Song. 2013. "The Economic Impact of Public Agricultural Research and Development in the United States." *Agricultural Economics* 44 (3): 287–95.

Baldos, Uris Lantz C., Frederi G. Viens, Thomas W. Hertel, and Keith O. Fuglie. 2019. "R&D Spending, Knowledge Capital, and Agricultural Productivity Growth: A Bayesian Approach." *American Journal of Agricultural Economics* 101 (1): 291-310. doi.org/10.1093/ajae/aay039.

Beddow, Jason M., Philip G. Pardey and Terrance M. Hurley. "Reassessing the Effects of Weather on Agricultural Productivity." Selected paper presented at the Agricultural and Applied Economics Association's 2014 AAEA Annual meeting, Minneapolis, MN, July 27-29, 2014.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2020. "Are Ideas Getting Harder to Find?" *American Economic Review* 110 (4): 1104–44.

Choi, In, and Eiji Kurozumi. 2012. "Model Selection Criteria for the Leads-and-Lags Cointegrating Regression." *Journal of Econometrics* 169: 224-238.

Elliott, Graham, Thomas J. Rohenberg and James H. Stock. 1996. "Efficient Tests for an Autoregressive Unit Root." *Econometrica* 64(4): 813–836.

Esposti, Roberto, and Pierpaolo Pierani. 2003. "Building the Knowledge Stock: Lags, Depreciation, and Uncertainty in R&D Investment and Link with Productivity Growth." *Journal of Productivity Analysis 19: 33–58.*

Evenson, Robert E. 1967. "The Contribution of Agricultural Research to Production." *Journal of*

Farm Economics 49(5): 1415–1425.

Fuglie, Keith O. 2018. “R&D Capital, R&D Spillovers, and Productivity Growth in World Agriculture.” *Applied Economic Perspectives and Policy* 40 (3): 421–444.

Granger, Clive W. J., and Paul Newbold. 1974. “Spurious Regression in Econometrics.” *Journal of Econometrics* 2: 111-120.

Griliches, Zvi. 1958. “Research Costs and Social Returns: Hybrid Corn and Related Innovations.” *Journal of Political Economy* 66(5): 419-431.

Griliches, Zvi. 1979. “Issues in Assessing the Contribution of R&D to Productivity Growth.” *Bell Journal of Economics* 10(1): 92–116.

Griliches, Zvi. 1964. “Research Expenditures, Education and the Aggregate Agricultural Production Function.” *American Economic Review* 54(6): 961-974.

Griliches, Zvi. 1979. “Issues in Assessing the Contribution of R&D to Productivity Growth.” *Bell Journal of Economics* 10(1): 92-116.

Griliches, Zvi. 1980.“Returns to Research and Development Expenditures in the Private Sector.” Chapter 8 in John W. Kendrick and Beatrice N. Vaccara, eds. *New Developments in Productivity Measurement and Analysis*. Chicago: University of Chicago Press (for the National Bureau of Economic Research).

Griliches, Zvi. 1986. “Productivity, R&D, and Basic Research at the Firm Level in the 1970s.” *American Economic Review* 76:141-154.

Griliches, Zvi. 1992. “The Search for R&D Spillovers.” *Scandinavian Journal of Economics* 94 (Supplement): 29–47.

Griliches, Zvi. 1996. *R&D and Productivity: The Econometric Evidence*. Chicago: Chicago University Press.

Grossman, Gene M. and Ethanan Helpman. 1991a. *Innovation and Growth in the Global Economy*. Cambridge, Massachusetts: MIT Press.

Grossman, Gene M. and Ethanan Helpman. 1991b. “Quality Ladders and Product Cycles.” *Quarterly Journal of Economics* 106 (May): 557–586.

Grossman, Gene M. and Ethanan Helpman. 1991c. “Quality Ladders in the Theory of Growth.” *Review of Economic Studies* 58 (January): 43–61.

Hall, Bronwyn H. 2005. “Measuring the Returns to R&D: The Depreciation Problem,” *Annales d’Economie et de Statistique* 79/80: 341–381. Also available as National Bureau of Economic Research Working Paper 13473, October 2007.

Hall, Bronwyn H., Jacques Mairesse, and Pierre Mohnen. 2010. “Measuring the Returns to R&D,” Chapter 24 in Bronwyn Hall, and Nathan Rosenberg, eds., *Handbook of the Economics of Innovation, Volume 1*. Amsterdam: Elsevier.

Huffman, Wallace E., and Robert E. Evenson. 1993. *Science for Agriculture: A Long-Term Perspective*. Ames: Iowa State University Press.

Huffman, Wallace E., and Robert E. Evenson. 2006. “Do Formula or Competitive Grant Funds Have Greater Impacts on State Agricultural Productivity?” *American Journal of*

Agricultural Economics 88(4): 783–798.

InSTePP (International Science and Technology Practice and Policy) center. Unpublished InSTePP R&D Deflators. St Paul, MN: University of Minnesota, 2020.

Johansen, Soren. 1998. "Statistical Analysis of Cointegrated Vectors." *Journal of Economic Dynamics and Control* 12: 231–254.

Jones, Benjamin F., and Lawrence H. Summers. 2021. "A Calculation of the Social Returns to Innovation." In *Innovation and Public Policy* edited by Austan Goolsbee and Benjamin F. Jones. National Bureau of Economic Research Conference Report, University of Chicago Press. https://press.uchicago.edu/ucp/books/book/chicago/I/bo138500594.html

Jones, Charles I. 1995. "R&D Based Models of Economic Growth." *Journal of Political Economy* 103 (4): 759–84.

Jones, Charles I. 2005. "Growth and Ideas." In *Handbook of Economic Growth,* Vol. 1B, edited by Philippe Aghion and Steven A. Durlauf, 1063–1011, Oxford: North Holland.

Jones, Charles I. 2022. "The Past and Future of Economic Growth: A Semi-Endogenous Perspective." *Annual Review of Economics* 14: 125–52.

Khan, Farid, and Ruhul Salim. 2015. "The Public R&D and Productivity Growth in Australian Broadacre Agriculture: A Cointegration and Causality Approach." Contributed Paper, Australian Agricultural and Resource Economics Society 59th Annual Conference, Rotorua, New Zealand, February 10–13, 2015. doi:10.22004/ag.econ.204432.

Li, Wendy C.Y., and Bronwyn H. Hall. 2020. "Depreciation of Business R&D Capital." *Review of Income and Wealth* 66 (1):161-180. doi: 10.1111/roiw.12380 (also NBER Working Paper 22473).

Lobell, David B., Uris Lantz C. Baldos, and Thomas W. Hertel. 2013. "Climate Adaptation as Mitigation: The Case of Agricultural Investments." *Environmental Research Letters* 8 (1). Available at https://doi.org/doi:10.1088/1748-9326/8/1/015012.

Nace, R.L. and E.J. Pluhowski. 1965. "Drought of the 1950's with Special Reference to the Midcontinent." Geological Survey Water-Supply Paper 1804. Department of Interior. Washington, DC: United States Government Publishing Service. https://pubs.usgs.gov/wsp/1804/report.pdf

Pardey, Philip G. and Julian M. Alston. 2021. "Unpacking the Agricultural Black Box: The Rise and Fall of American Farm Productivity Growth." *The Journal of Economic History*. 81 (1): 114–155. doi:10.1017/S0022050720000649.

Pardey, Philip G., Julian M. Alston and Connie Chan-Kang. 2013. *Public Food and Agricultural Research in the United States: The Rise and Decline of Public Investments, and Policies for Renewal.* AGree Report. Washington D.C.: Agree. https://foodandagpolicy.org/research-and-innovation/.

Pardey, Philip G., Julian M. Alston and Vernon W. Ruttan. 2010. "The Economics of Innovation and Technical Change in Agriculture." Chapter 22 in Bronwyn Hall and Nathan Rosenberg, eds. *Handbook of the Economics of Innovation, Volume 1,* Amsterdam: Elsevier.

Pardey, Philip G., Matthew A. Andersen, Barbara J. Craig, and Julian M. Alston. 2009. Primary Data Documentation, U.S. Agricultural Input, Output, and Productivity Series, 1949–2002 (Version 4). InSTePP Data Documentation. St Paul, MN: International Science and Technology Practice and Policy Center, University of Minnesota.

______________. 2014 "InSTePP United States Production Accounts, version 5." St Paul, MN: International Science and Technology Practice and Policy Center. Available from www.instepp.umn.edu/united-states#Version%205.

Pardey, Philip G., Barbara J. Craig and Michelle L. Hallaway. 1989. "U.S. Agricultural Research Deflators: 1890–1985." *Research Policy* 18(5): 289–296.

Pardey, Philip G. and Vincent Smith. 2017. *Waste Not, Want Not—Transactional Politics, Research and Development and the US Farm Bill*. Policy Brief in the series "Agricultural Policy in Disarray, Reforming the Farm Bill." Washington D.C.: American Enterprise Institute.

Phillips, Peter C. and Pierre Perron. 1988. "Testing for a Unit Root in Time Series Regression." *Biometrika* 75(2): 335–346.

Plastina, Alejandro and Lilyan Fulginiti. 2011. "Rates of Return to Public Agricultural Research in 48 US States." *Journal of Productivity Analysis* 37 (2): 95–113.

Rao, Xudong, Terrance M. Hurley, and Philip G. Pardey. 2019. "Are Agricultural R&D Returns Declining and Development Dependent?" *World Development*, 122: 27–37. https://doi.org/10.1016/j.worlddev.2019.05.009.

Romer, Paul M. 1990. "Endogenous Technical Change." *Journal of Political Economy* 98 (5): S71–102.

Serfas, Devin, Julian M. Alston, and Philip G. Pardey. 2023. "The Returns to Industrial R&D: A Comprehensive Meta-Review and Reassessment of the Evidence." Staff Paper (in process). St Paul, MN: Department of Applied Economics, University of Minnesota.

Stock, James H, and Mark W. Watson. 1993. "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems." *Econometrica* 61(4): 783-820.

Ugur, Mehmet, Eshref Trushin, Edna Solomon, and Franceso Guidi. 2016. "R&D and Productivity in OECD Firms and Industries: A Hierarchical Meta-Regression Analysis." *Research Policy* 45(10): 2069–2086.

USDA-ERS (U.S. Department of Agriculture, Economic Research Service). 1983. *Economic Indicators of the Farm Sector: Production and Efficiency Statistics, 1981*. ECIFS 1-3, Washington, D.C.: USDA, Economic Research Service.

USDA National Agricultural Statistics Service. 2017. NASS – Quick Stats. USDA National Agricultural Statistics Service. https://data.nal.usda.gov/dataset/nass-quick-stats. Accessed 2020-12-31.

United States General Accounting Office (GAO). 1989. *Crop Production Outlook for Post-drought Recovery.* Briefing Report to the Chairman, Subcommittee on Agricultural Research and General Legislation, Committee on Agriculture, Nutrition, and Forestry, U.S. Senate. GAO/RCED-89-161BR, June.

https://fraser.stlouisfed.org/files/docs/publications/books/cropprod_gao_1989.pdf

Wang, Shanchao. 2022. *Essays on Energy Economics and Agricultural R&D*. Unpublished doctoral dissertation, Department of Agricultural and Resource Economics, University of California, Davis, September.

Wooldridge, Jeffrey M. 2015. *Introductory Econometrics: A Modern Approach*, 6th Ed. Mason, OH: South-Western Cengage Learning.

TABLE 1—COINTEGRATION TESTS WITH ALTERNATIVE LAG DISTRIBUTION MODELS

Model	*Model Specification*		*SSE*	*GLS-ADF*		*Phillips-Perron test*	*Johansen test*
				$\ln(K_t)$	$\Delta\ln(K_t)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1	Gamma	$\gamma = 0.75$ $\lambda = 0.80$	0.074	Fail	10%	1%	Pass
2		$\gamma = 0.75$ $\lambda = 0.85$	0.083	Fail	1%	1%	Pass
3		$\gamma = 0.85$ $\lambda = 0.80$	0.096	Fail	10%	1%	Pass
4		$\gamma = 0.90$ $\lambda = 0.70$	0.098	Fail	Fail	1%	Pass
5	Trapezoidal		0.073	10%	Fail	1%	Fail
6	Geometric	$\delta = 0.10$	0.077	Fail	10%	Fail	Pass
7		$\delta = 0.15$	0.078	Fail	5%	Fail	Pass
8	Romer-Aghion-Howitt	K_t	0.100	1%	Fail	Fail	Pass
9		$\ln(K_t)$	0.086	Fail	10%	1%	Pass

Sources: Developed by the authors.

Notes: SSE (sum of squared errors) is calculated from estimating equation (8) for models 1–7 and 9, and equation (8') for Model 8. In the case of the Romer-Aghion-Howitt model (Model 8), the entries in columns (4) and (5) refer to K_t and ΔK_t rather than $\ln(K_t)$ and $\Delta\ln(K_t)$. The numbers in columns (4) through (7) indicate we reject the null hypothesis at the specific percentage significance levels shown (i.e., 1%, 5%, or 10%).

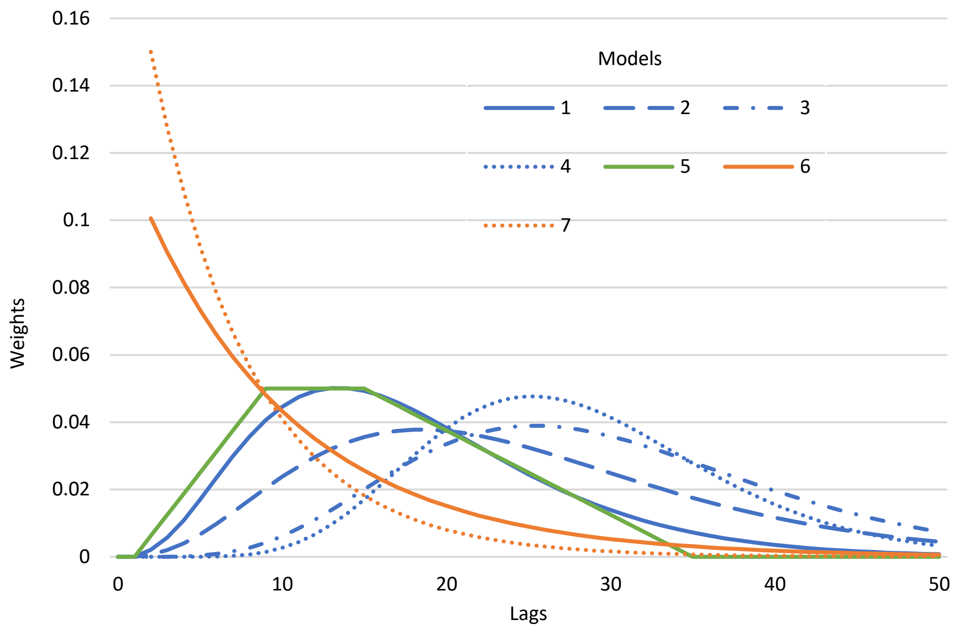


FIGURE 1—LAG DISTRIBUTION SHAPES FOR MODELS 1–7

Sources: Developed by the authors.

Notes: Gamma lag distribution models (Models 1–4) are shown in blue; the trapezoidal lag distribution (Model 5) is shown in green; the geometric lag distribution models (Models 6 and 7) are shown in orange; the Romer-Aghion-Howitt model (Model 8) is not depicted here. Table 1 includes a summary of the parametrizations of these lag distribution models.

TABLE 2—PEAK LAG YEAR AND MEAN LAG FOR MODELS 1–7

Model	*Model Specification*		*Lag (years)*		
			Peak	*Mean*	*Maximum*
1	Gamma	$\gamma = 0.75, \lambda = 0.80$	13	17.8	50
2		$\gamma = 0.75, \lambda = 0.85$	18	23.3	50
3		$\gamma = 0.85, \lambda = 0.80$	25	28.3	50
4		$\gamma = 0.90, \lambda = 0.70$	25	27.6	50
5	Trapezoidal		9	15.7	35
6	Geometric	$\delta = 0.10$	2	10.7	∞
7		$\delta = 0.15$	2	7.7	∞

Sources: Developed by the authors.

Notes: Derived from fitted models reported in Table 3.

TABLE 3—DYNAMIC OLS REGRESSIONS OF MFP AGAINST ALTERNATIVE KNOWLEDGE STOCKS

Model	*Lag Model (Parameters)*	*Regressors*						
		Constant (1)	$\ln(K_t)$ (2)	W_t (3)	T_t (4)	$\Delta\ln(K_t)$ (5)	$\Delta\ln(K_{t-1})$ (6)	$\Delta\ln(K_{t+1})$ (7)
1	Gamma	2.914***	0.277**	0.020***	0.010**	-8.200	9.156	
	(0.75, 0.80)	(0.639)	(0.106)	(0.006)	(0.004)	(6.608)	(6.256)	
2	Gamma	2.874***	0.260**	0.020***	0.012***	-12.334	17.354	
	(0.75, 0.85)	(0.654)	(0.109)	(0.006)	(0.004)	(12.319)	(11.676)	
3	Gamma	1.922***	0.386***	0.025***	0.009***	2.224	7.225	
	(0.85, 0.80)	(0.558)	(0.084)	(0.005)	(0.003)	(9.682)	(9.969)	
4	Gamma	2.455***	0.267***	0.026***	0.015***	88.593***		-72.038
	(0.90, 0.70)	(0.371)	(0.058)	(0.003)	(0.002)	(22.111)		(45.065)
5	Trapezoidal	2.843***	0.292***	0.020***	0.009**	9.489*		-9.561*
		(0.658)	(0.109)	(0.005)	(0.004)	(5.604)		(5.663)
6	Geometric	3.235***	0.232***	0.019***	0.011***	-0.206		-0.846
	($\delta = 0.10$)	(0.352)	(0.053)	(0.005)	(0.002)	(0.801)		(0.812)
7	Geometric	3.414***	0.201***	0.018***	0.012***	-0.256		-0.546
	($\delta = 0.15$)	(0.309)	(0.045)	(0.005)	(0.001)	(0.575)		(0.581)
8	Romer-Aghion-Howitt	4.703***	7.29E-07*	0.018***	0.007**	6.28E-05	3.45E-05	
	(K_t)	(0.018)	(4.08E-07) [0.082]	(0.006)	(0.003)	(3.96E-05)	(3.85E-05)	
9	[$\ln(K_t)$]	1.415	0.351***	0.018***	0.004	-0.645		-4.168
		(1.039)	(0.115)	(0.005)	(0.005)	(3.693)		(4.032)

Sources: Developed by the authors.

Notes: Results using OLS and the Cochrane-Orcutt method are reported in the supplementary online appendix. The gamma model parameters in parentheses are (γ, λ). Newey-West heteroskedasticity and autocorrelation consistent standard errors in parentheses in columns (1) through (5). Coefficients in column (3) are elasticities of MFP with respect to the knowledge stock. In model 4 (but none of the other models) the preferred specification also included longer leads on the R&D knowledge stock. The estimated coefficients were -102.719** (45.755) on $\Delta\ln(K_{t+2})$ and 99.492*** (22.739) on $\Delta\ln(K_{t+3})$. In the Romer-Aghion-Howitt model (Model 8) the elasticity is shown in square brackets in column (4), calculated at the median of constructed Romer-Aghion-Howitt knowledge stock across the period 1940–2007. For Model 8, rather than $\ln K_t$ and $\Delta\ln K_t$ and so on, the regressors are K_t and ΔK_t and so on, as formulated in equation (8').

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 4—ESTIMATED ELASTICITIES FROM ALTERNATIVE MODELS AND ESTIMATORS

Model	*Lag Model (parameters)*	*Elasticity of MFP with respect to K*			
		OLS	*Cochrane-Orcutt* GLS	*Prais-Winsten GLS*	*Dynamic OLS*
		(1)	(2)	(3)	(4)
1	Gamma	0.290***	0.306***	0.307***	0.277**
	(0.75, 0.80)	(0.084)	(0.109)	(0.084)	(0.106)
2	Gamma	0.271**	0.317**	0.304***	0.260**
	(0.75, 0.85)	(0.130)	(0.143)	(0.092)	(0.109)
3	Gamma	0.184	0.248	0.247**	0.386***
	(0.85, 0.80)	(0.374)	(0.185)	(0.094)	(0.084)
4	Gamma	0.167	0.221	0.235**	0.267***
	(0.90, 0.70)	(0.466)	(0.192)	(0.098)	(0.058)
5	Trapezoidal	0.282***	0.292***	0.299***	0.292***
		(0.078)	(0.105)	(0.084)	(0.109)
6	Geometric	0.203***	0.212**	0.227**	0.232***
	($\delta = 0.10$)	(0.073)	(0.101)	(0.087)	(0.053)
7	Geometric	0.183**	0.190*	0.205**	0.201***
	($\delta = 0.15$)	(0.070)	(0.096)	(0.084)	(0.045)
8	Romer-Aghion-Howitt	-0.077	-0.083	-0.115*	0.082*
	(K_t)	(0.266)	(0.093)	(0.059)	(0.046)
9	[ln(K_t)]	0.247*	0.266*	0.290**	0.351***
		(0.144)	(0.150)	(0.116)	(0.115)

Sources: Developed by the authors.

Notes: The gamma model parameters in parentheses are (γ, λ). Eicker-Huber-White (for Cochrane-Orcutt and Prais-Winsten GLS estimators) and Newey-West heteroskedasticity and autocorrelation consistent (for OLS and dynamic OLS) standard errors in parentheses in columns (1) through (3). Elasticities for models 1 to 7 and 9 are just point estimates of β_1 in equation (8). In the Romer-Aghion-Howitt model in levels the elasticity is calculated as $\beta_1 K_t$ using the point estimate of β_1 in equation (8') with K_t as the median of the constructed Romer-Aghion-Howitt knowledge stock across the period 1940–2007.

*** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

TABLE 5—BENEFIT-COST RATIOS FROM VARIOUS MODELS AND ESTIMATORS

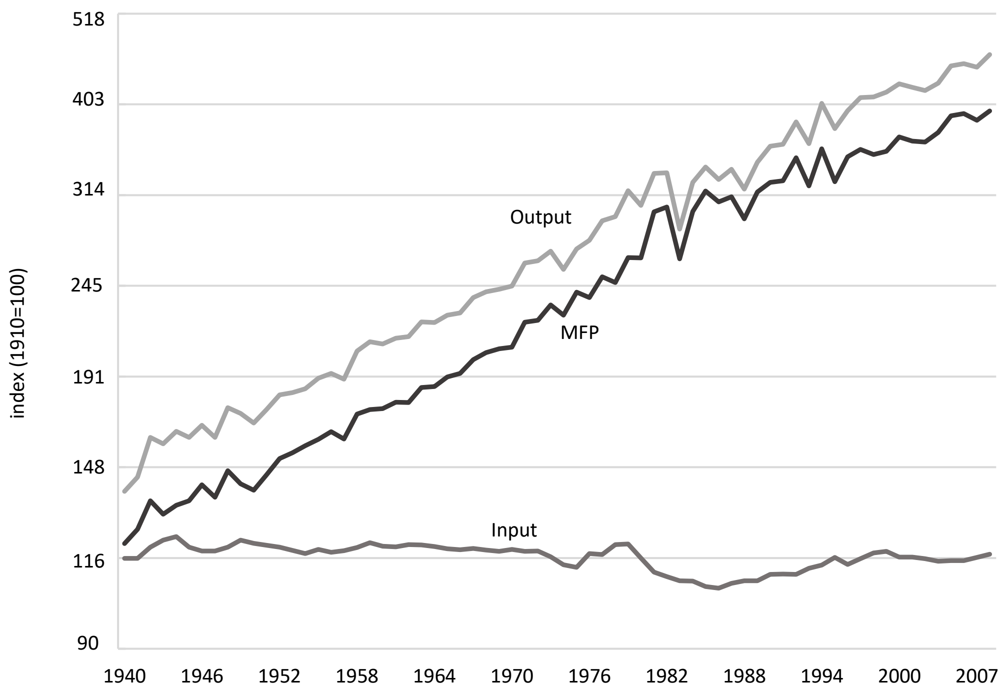
Model	*Lag Model (Parameters)*	*Mean Lag (years)*	*OLS* (1)	*Cochrane-Orcutt* (2)	*Prais-Winsten* (3)	*Dynamic OLS* (4)
1	Gamma	17.8	**24.5**	**25.9**	**26.0**	**23.4**
	(0.75, 0.80)		[10.3, 38.8]	[7.4, 44.3]	[11.8, 40.1]	[5.5, 41.3]
2	Gamma	23.3	**21.4**	**25.0**	**24.0**	**20.5**
	(0.75, 0.85)		[0.9, 42.0]	[2.5, 47.6]	[9.5, 38.5]	[3.3, 37.8]
3	Gamma	28.3	13.0	17.5	**17.5**	**27.3**
	(0.85, 0.80)		[-39.8, 65.8]	[-8.7, 43.8]	[4.2, 30.7]	[15.4, 39.2]
4	Gamma	27.6	11.8	15.6	**16.6**	**18.9**
	(0.90, 0.70)		[-54.1, 77.8]	[-11.5, 42.8]	[2.7, 30.5]	[10.7, 27.0]
5	Trapezoidal	15.7	**24.4**	**25.2**	**25.8**	**25.2**
			[11.0, 37.7]	[7.1, 43.3]	[11.3, 40.4]	[6.5, 44.0]
6	Geometric	10.7	**18.4**	**19.2**	**20.5**	**21.0**
	(0.10)		[5.2, 31.6]	[0.89, 37.5]	[4.8, 36.3]	[11.5, 30.5]
7	Geometric	7.7	**16.9**	17.5	**18.9**	**18.5**
	(0.15)		[4.1, 29.6]	[-0.15, 35.1]	[3.4, 34.3]	[10.2, 26.8]
8	Romer-Aghion-Howitt		-5.7	-6.1	-8.5	6.1
	(K_t)		[-45.1, 33.6]	[-19.9, 7.7]	[-17.3, 0.3]	[-0.7, 12.9]
9	$[\ln(K_t)]$		18.5	20.0	**21.7**	**26.3**
			[-3.1, 40.0]	[-2.6, 42.5]	[4.4, 39.1]	[9.1, 43.6]

Sources: Developed by the authors.

Notes: The gamma model parameters in parentheses are (γ, λ). Entries in the table are the marginal benefit-cost ratios (BCRs) for an incremental investment in 1957 calculated using equation 12 and elasticities from Table 4, and a real discount rate of 3 percent per year. Numbers in square brackets are the upper and lower bounds of the 95 percent confidence interval for the BCR, and BCRs in bold are statistically significantly different from zero since their respective confidence intervals do not include zero.

R&D Lags in Economic Models

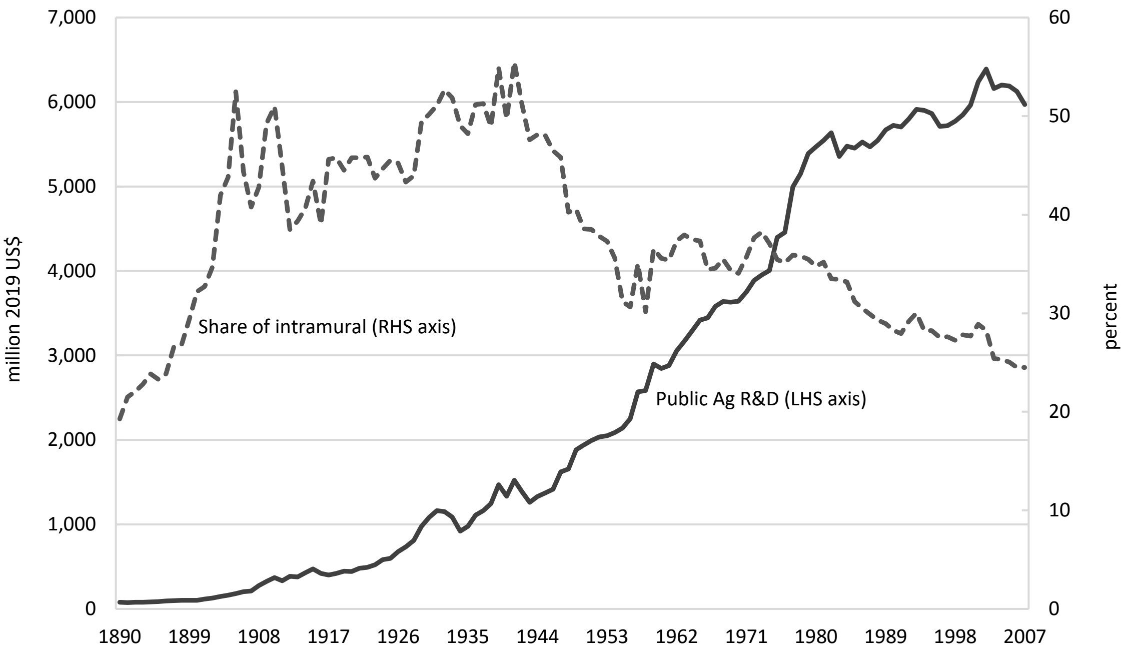
Appendix Supporting Material



APPENDIX FIGURE 1—U.S. AGRICULTURAL INPUTS, OUTPUTS AND MULTIFACTOR PRODUCTIVITY, LOGARITHMS, 1940–2007

Sources: University of Minnesota, InSTePP Center compilation drawing on InSTePP Production Accounts, version 5, augmented with data from USDA-ERS (1983).

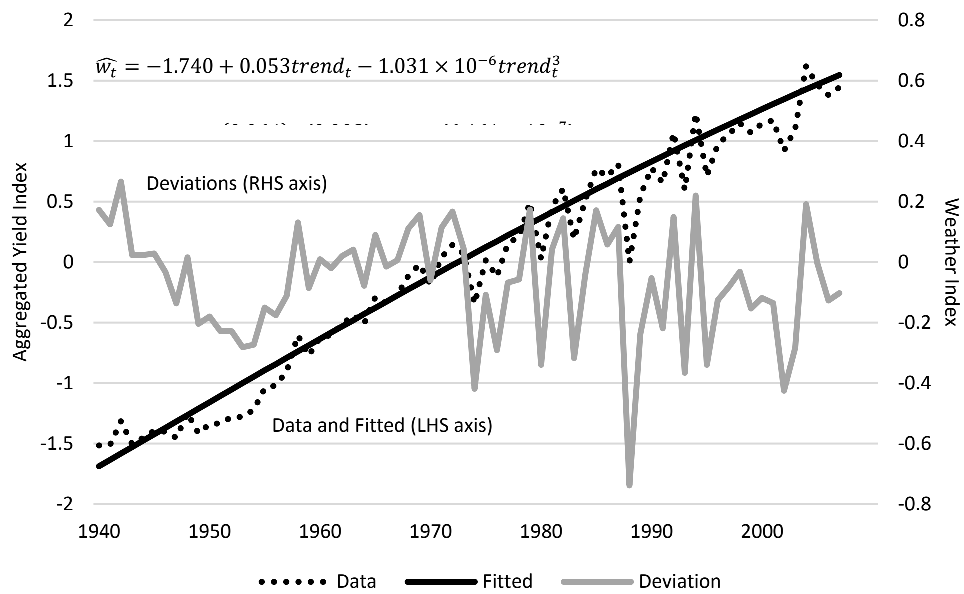
Notes: Plots are natural logs of the respective indexes with base year 1910=100. The Y axis reports the actual index values.



APPENDIX FIGURE 2—U.S. PUBLIC AGRICULTURAL R&D, USDA INTRAMURAL AND SAESS, 1890–2007

Sources: University of Minnesota, InSTePP Center unpublished data. The SAES R&D series (excluding forestry) prior to 1980 is from USDA sources cited in Alston et al. (2010, appendix III) and for more recent years are compiled from unpublished USDA, CRIS data files. The USDA intramural series for years prior to 2001 are also from the USDA sources cited in Alston et al. (2010, appendix III) and NSF (various years) thereafter.

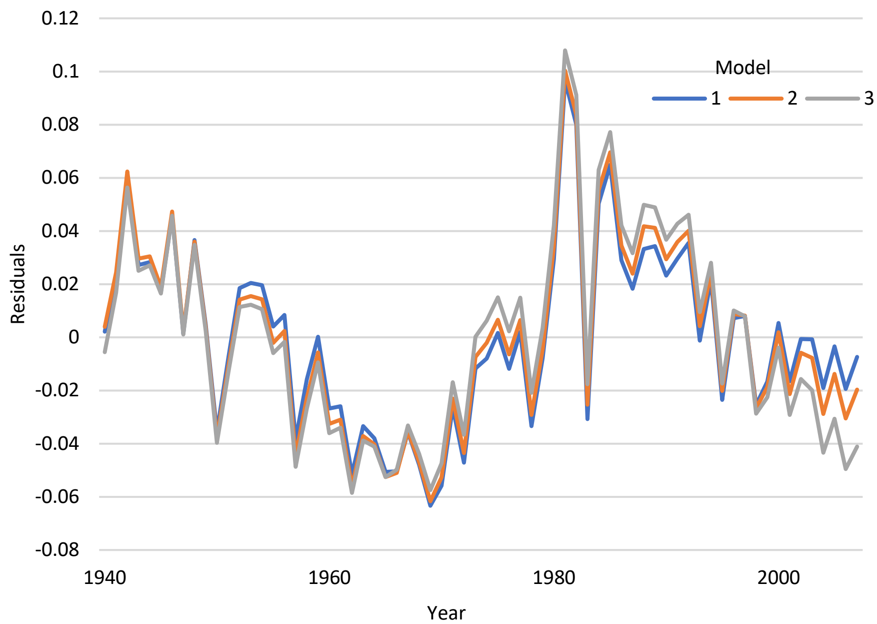
Notes: Public agricultural R&D includes SAES (state agricultural experiment station) and USDA intramural spending, excluding forestry research. The series were deflated using an agricultural R&D deflator from InSTePP.



APPENDIX FIGURE 3—*FITTED AND OBSERVED COMPOSITE CROP YIELD INDEX, 1940–2007*

Sources: Developed by the authors.

Notes: The observed annual aggregated yields in year *t*, yield_t, were constructed as weighted averages of standardized annual yields of the top 10 field crops for the years 1940–2007. Each crop's annual share of the total value of production was used as its weight. The equation presents the fitted (linear and cubic) time-trend regression with standard errors in parentheses under each of the point estimates. T_t is the time trend created by calendar year minus 1939. The agricultural weather index in year *t* is given by yield deviations from the fitted value: $yield_t - \widehat{yield}_t$.



APPENDIX FIGURE 4—RESIDUALS FROM THE MODELS THAT PASSED THE TIME-SERIES TESTS (MODELS 1–3)

Sources: Developed by the authors.

Notes: Derived from the fitted models estimated using OLS. Model numbers correspond to the first three gamma lag models in Tables 2 and 3. See Appendix Table 6.1 for detailed regression results.

APPENDIX TABLE 1—PARAMETERIZATION OF KNOWLEDGE STOCKS FOR THE ALTERNATIVE MODELS

Distributions	Parameters	Weights
Gamma	$\gamma, \lambda \in$ $\{x \times 0.05 + 0.6 \mid x \in Z, 0 \leq x \leq 7\}$, 64 combinations of γ and λ.	$b_k = \frac{(k-g+1)^{\gamma/\{(1-\gamma\})}\lambda^{(k-g)}}{\sum_{k=g+1}^{50}[(k-g+1)^{\gamma/(1-\gamma)}\lambda^{(k-g)}]}$ for $g < k \leq 50$; otherwise $b_k = 0$
Trapezoidal	a = 1, b = 9, c = 15, d = 35, two years of gestation lag, then weights increase linearly for seven years, then stay constant for six years, and finally decline linearly for 20 years.	$b'_k = \begin{cases} 0, k < a \; or \; k > d \\ \frac{2}{(d+c-a-b)}\frac{k-a}{b-a}, a \leq k < b \\ \frac{2}{(d+c-a-b)}, b \leq k < c \\ \frac{2}{(d+c-a-b)}\frac{d-k}{d-c}, c \leq k \leq d \end{cases}$ $b_k = \frac{b'_k}{\sum_{k=0}^{50} b'_k}$
Geometric	$\delta = 0.10$ or 0.15	$b'_k = (1-\delta)^k$ for $g < k \leq 50$; otherwise ${b_k}' = 0$ $b_k = \frac{b'_k}{\sum_{k=0}^{50} b'_k}$

Sources: Developed by the authors.

Notes: A two-year gestation period is equivalent to $g = 1$.

APPENDIX TABLE 2—REGRESSION RESULTS FOR ALTERNATIVE TIME TREND MODELS

	Models			
	Linear	*Quadratic*	*Cubic*	*Cubic*
	(1)	(2)	(3)	(4)
T_t	0.049***	0.056***	0.053***	0.045***
	(0.001)	(0.005)	(0.003)	(0.012)
T_t^2		-9.88E-05		2.96E-04
		(6.80E-05)		(4.15E-04)
T_t^3			-1.03E-06	-3.81E-06
			(6.46E-07)	(3.95E-06)
Constant	-1.672***	-1.752***	-1.740***	-1.686***
	(0.048)	(0.072)	(0.064)	(0.099)
Observations	68	68	68	68
R^2	0.961	0.962	0.963	0.963
Adjusted R^2	0.961	0.961	0.962	0.961
AIC	-25.510	-25.681	-26.124	-24.662

Sources: Developed by the authors.

Notes: The dependent variable is the annual weighted average yield of 10 field crops described in the data section of the main text. T_t is the time trend created by subtracting calendar year by 1939.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix Table 3—Tests for Nonstationary Time Series

Variable	*Optimal Lag (years)*	*Estimated Tau statistic*	*Critical Values of Tau*		
			1%	*5%*	*10%.*
$\ln(MFP_t)$	1	-2.43	-3.70	-3.13	-2.83
$\Delta\ln(MFP_t)$	1	-9.14	-3.71	-3.14	-2.84
W_t	1	-4.51	-3.70	-3.13	-2.83

Sources: Developed by the authors.

Notes: Results obtained using STATA 17 to conduct the GLS-ADF test. The optimal lag was determined using the minimum Schwarz (1978) information criterion (SIC).

APPENDIX TABLE 4.1—STATIONARITY TESTS FOR KNOWLEDGE STOCKS FROM ALTERNATIVE MODELS (DICKEY-FULLER GLS TEST)

Models	*Lag Model (Parameters)*	*DF-GLS on levels*					*DF-GLS on first differences*				
		lags	statistics	1%	5%	10%	lags	statistics	1%	5%	10%
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	Gamma (0.75, 0.80)	8	-2.500	-3.702	-2.839	-2.560	5	-2.766	-3.705	-2.982	-2.696
2	Gamma (0.75, 0.85)	5	-2.079	-3.702	-2.981	-2.695	1	-3.753	-3.705	-3.136	-2.837
3	Gamma (0.85, 0.80)	3	0.554	-3.702	-3.064	-2.772	2	-2.902	-3.705	-3.104	-2.809
4	Gamma (0.90, 0.70)	5	-0.640	-3.702	-2.981	-2.695	4	-1.683	-3.705	-3.026	-2.737
5	Trapezoidal	5	-2.822	-3.702	-2.981	-2.695	1	-2.654	-3.705	-3.136	-2.837
6	Geometric (0.10)	3	-0.762	-3.702	-3.064	-2.772	2	-3.015	-3.705	-3.104	-2.809
7	Geometric (0.15)	3	-0.629	-3.702	-3.064	-2.772	2	-3.301	-3.705	-3.104	-2.809
8	Romer-Aghion-Howitt (K_t)	1	-4.613	-3.702	-3.131	-2.833	2	-1.377	-3.705	-3.104	-2.809
9	[$\ln(K_t)$]	1	-1.948	-3.702	-3.131	-2.833	2	-2.883	-3.705	-3.104	-2.809

Sources: Developed by the authors.

Notes: The Dicky-Fuller GLS is used to test the order of integration of knowledge stock $\ln(K_t)$ (or K_t for the Romer-Aghion-Howitt model in levels) and its first differences $\Delta\ln(K_t)$ (or ΔK_t). The null hypothesis is that there exists a unit root in the tested time series, which implies the time series is nonstationary. The optimal lag length was chosen using the STATA 17 default minimum Schwarz (1978) information criterion (SIC). Critical values for significance levels (1%, 5%, and 10%) are listed following the test statistic.

APPENDIX TABLE 4.2—COINTEGRATION TESTS FOR KNOWLEDGE STOCKS AND MFP (PHILLIPS-PERRON TEST)

Model	*Lag Model (Parameters)*	*Phillips-Perron Tests*				
		lags	statistics	1%	5%	10%
		(1)	(2)	(3)	(4)	(5)
1	Gamma (0.75, 0.80)	3	-4.873	-4.113	-3.483	-3.170
2	Gamma (0.75, 0.85)	3	-4.812	-4.113	-3.483	-3.170
3	Gamma (0.85, 0.80)	3	-4.276	-4.113	-3.483	-3.170
4	Gamma (0.90, 0.70)	3	-4.151	-4.113	-3.483	-3.170
5	Trapezoidal	3	-4.715	-4.113	-3.483	-3.170
6	Geometric (0.10)	3	-3.116	-4.113	-3.483	-3.170
7	Geometric (0.15)	3	-2.556	-4.113	-3.483	-3.170
8	Romer-Aghion-Howitt (K_t)	3	-1.427	-4.113	-3.483	-3.170
9	[$\ln(K_t)$]	3	-4.866	-4.113	-3.483	-3.170

Sources: Developed by the authors.

Notes: The Phillips-Perron test is used to examine the cointegration relationship between $\ln(MFP_t)$ and $\ln(K_t)$ (or K_t for the Romer-Aghion-Howitt model). The null hypothesis is that the residual of regressing $\ln(MFP_t)$ on $\ln(K_t)$ (or K_t) contains a unit root (i.e., non-stationary). We imposed minimal restrictions by allowing the residual has a random walk, with or without drift, under the null hypothesis. Newey-West lags (lags=3) are used in the tests. Critical values for significance levels (1%, 5%, and 10%) are listed following the test statistics.

APPENDIX TABLE 4.3—COINTEGRATION TESTS FOR KNOWLEDGE STOCKS AND MFP (JOHANSEN TEST)

Model	*Lag Model (Parameters)*	*AIC*			*HQIC*			*SBIC*			*5% critical value*	
		Lags	Trace statistics		Lags	Trace statistics		Lags	Trace statistics			
			Maximum rank 0	Maximum rank 1		Maximum rank 0	Maximum rank 1		Maximum rank 0	Maximum rank 1	Maximum rank 0	Maximum rank 1
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	Gamma (0.75, 0.80)	9	32.154	12.045	8	39.907	9.574	4	42.647	7.572	25.320	12.250
2	Gamma (0.75, 0.85)	6	32.693	14.144	6	32.693	14.144	3	32.797	10.646	25.320	12.250
3	Gamma (0.85, 0.80)	5	34.381	7.495	4	37.081	8.239	4	37.081	8.239	25.320	12.250
4	Gamma (0.90, 0.70)	6	25.400	8.633	4	63.194	9.381	3	58.206	12.093	25.320	12.250
5	Trapezoidal	3	19.204	7.542	3	19.204	7.542	3	19.204	7.542	25.320	12.250
6	Geometric (0.10)	5	27.346	5.947	4	20.444	6.309	2	22.864	6.187	25.320	12.250
7	Geometric (0.15)	5	26.142	5.901	5	26.142	5.901	2	21.040	4.831	25.320	12.250
8	Romer-Aghion-Howitt (K_t)	5	40.901	8.916	4	32.712	6.839	2	38.815	13.526	25.320	12.250
9	[$\ln(K_t)$]	6	26.380	5.420	2	35.520	9.663	2	35.520	9.663	25.320	12.250

Sources: Developed by the authors.

Notes: The Johansen cointegration test is used to examine the cointegration relationship between $\ln(MFP_t)$ and $\ln(K_t)$ (or K_t for the Romer-Aghion-Howitt model). Maximum rank 0 (or 1) represents the case where the maximum rank of the cointegration matrix is 0 (or 1). The null hypothesis is that there exists up to r cointegration relations, where r starts from 0, then 1, and so on. In our specification, since there are two time-series, we perform Johannsen tests from r = 0 to r = 1. If according to the trace statistics, we reject the null that r = 0 but fail to reject r = 1, this means there only exists one cointegration relationship between $\ln(MFP_t)$ and $\ln(K_t)$ (or K_t). The 5% critical values for rank 0 and rank 1 are presented in columns (10) and (11). The optimal lags are selected by the Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC), and the Schwarz-Bayesian Information Criterion (SBIC).

APPENDIX TABLE 5.1—TESTS FOR PROPERTIES OF RESIDUALS FROM OLS ESTIMATES OF MODEL 1

Issue	*Test*	*Test statistic*	*P value*
Heteroskedasticity			
	White	$\chi^2_{(2)} = 6.22$	0.045
	Breusch-Pagan	$\chi^2_{(1)} = 0.05$	0.824
Autocorrelation			
First-order	Durbin-Watson	$\mathrm{DW} = 0.77$	0.000
	Breusch-Godfrey	$\chi^2_{(1)} = 25.86$	0.000
Second-order	Breusch-Godfrey	$\chi^2_{(2)} = 26.41$	0.000
Third-order	Breusch-Godfrey	$\chi^2_{(3)} = 29.88$	0.000

Sources: Developed by the authors.

Notes: P value for the Durbin-Watson test is calculated using a normal approximation with mean and variance of the Durbin-Watson test statistic. Details can be found in ‘lmtest’ package in R.

APPENDIX TABLE 5.2—HETEROSKEDASTICITY TESTS

Models	*Lag Model (Parameters)*	*Breusch-Pagan*		*White*	
		$\chi^2_{(1)}$	P value	$\chi^2_{(2)}$	P value
1	Gamma (0.75, 0.80)	0.050	0.824	6.219	0.045
2	Gamma (0.75, 0.85)	0.003	0.959	4.691	0.096
3	Gamma (0.85, 0.80)	1.212	0.271	3.939	0.140
4	Gamma (0.90, 0.70)	1.622	0.203	3.914	0.141
5	Trapezoidal	0.082	0.775	6.512	0.039
6	Geometric (0.10)	0.009	0.924	6.993	0.030
7	Geometric (0.15)	0.003	0.957	6.742	0.034
8	Romer-Aghion-Howitt (K_t)	2.877	0.090	4.897	0.086
9	[ln(K_t)]	0.092	0.762	5.317	0.070

Sources: Developed by the authors.

Notes: The Breusch-Pagan and White tests are chosen to test the heteroskedasticity of error terms in equations (8) and (8'). These two tests examine linear and non-linear heteroskedasticity, respectively.

APPENDIX TABLE 5.3—AUTOCORRELATION TESTS

Model	*Lag Model (Parameters)*	*Durbin-Watson First order*		*Breusch-Godfrey*					
				First order		*Second order*		*Third order*	
		DW statistics	P value	$\chi^2_{(1)}$	P value	$\chi^2_{(2)}$	P value	$\chi^2_{(3)}$	P value
1	Gamma (0.75, 0.80)	0.769	0.000	25.859	0.000	26.410	0.000	29.876	0.000
2	Gamma (0.75, 0.85)	0.677	0.000	29.671	0.000	30.233	0.000	33.732	0.000
3	Gamma (0.85, 0.80)	0.590	0.000	33.599	0.000	34.259	0.000	37.681	0.000
4	Gamma (0.90, 0.70)	0.580	0.000	34.085	0.000	34.737	0.000	38.092	0.000
5	Trapezoidal	0.790	0.000	25.066	0.000	25.705	0.000	29.288	0.000
6	Geometric (0.10)	0.797	0.000	25.321	0.000	26.577	0.000	30.652	0.000
7	Geometric (0.15)	0.799	0.000	25.337	0.000	26.704	0.000	30.860	0.000
8	Romer-Aghion-Howitt (K_t)	0.591	0.000	33.767	0.000	34.720	0.000	38.381	0.000
9	$[\ln(K_t)]$	0.696	0.000	29.298	0.000	30.339	0.000	34.047	0.000

Sources: Developed by the authors.

Notes: The Durbin-Watson and Breusch-Godfrey tests are chosen to test the autocorrelation of error terms in equations (8) and (8'). Test statistics and p values are presented. The results strongly indicate that the error term is at least first-order autocorrelated.

APPENDIX TABLE 6.1—REGRESSIONS OF MFP AGAINST KNOWLEDGE STOCKS WITH ALTERNATIVE LAG MODELS, OLS

Model	*Lag Model (Parameters)*	*Regressors*				
		Constant	$\ln(K_t)$	K_t	W_t	T_t
		(1)	(2)	(3)	(4)	(5)
1	Gamma	2.882***	0.290***		0.020***	0.009***
	(0.75, 0.80)	(0.555)	(0.084)		(0.006)	(0.003)
2	Gamma	3.078***	0.271**		0.021***	0.009*
	(0.75, 0.85)	(0.821)	(0.130)		(0.006)	(0.005)
3	Gamma	3.683	0.184		0.021***	0.012
	(0.85, 0.80)	(2.232)	(0.374)		(0.007)	(0.015)
4	Gamma	3.781	0.167		0.021***	0.012
	(0.90, 0.70)	(2.787)	(0.466)		(0.007)	(0.019)
5	Trapezoidal	2.911***	0.282***		0.020***	0.009***
		(0.517)	(0.078)		(0.006)	(0.002)
6	Geometric	3.385***	0.203***		0.018***	0.013***
	($\delta = 0.10$)	(0.500)	(0.073)		(0.006)	(0.002)
7	Geometric	3.502***	0.183**		0.017***	0.013***
	($\delta = 0.15$)	(0.483)	(0.070)		(0.005)	(0.002)
8	Romer-Aghion-Howitt	4.784***		-6.84E-07	0.019***	0.021**
	(K_t)	(0.024)		(2.35E-06) [-0.077]	(0.006)	(0.008)
9	[$\ln(K_t)$]	2.253	0.247*		0.019***	0.009*
		(1.474)	(0.144)		(0.006)	(0.005)

Sources: Developed by the authors.

Notes: Estimates obtained using OLS. The gamma model parameters in parentheses are (γ, λ). Newey-West heteroskedasticity and autocorrelation consistent errors (with pre-whitening and adjust for small sample) in parentheses in columns (1) through (5). Coefficients in column (3) are elasticities of MFP with respect to the knowledge stock. For the Romer-Aghion-Howitt model (Model 8) the elasticity is shown in square brackets in column (4), calculated at the median of constructed Romer-Bloom knowledge stock across the period 1940–2007.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

APPENDIX TABLE 6.2—REGRESSIONS OF MFP AGAINST ALTERNATIVE KNOWLEDGE STOCKS, COCHRANE-ORCUTT PROCEDURE

Model	*Lag Model (Parameters)*	*Regressors*				
		Constant	$\ln(K_t)$	K_t	W_t	T_t
		(1)	(2)	(3)	(4)	(5)
1	Gamma	2.781***	0.306***		0.026***	0.008**
	(0.75, 0.80)	(0.725)	(0.109)		(0.004)	(0.003)
2	Gamma	2.788***	0.317**		0.026***	0.007
	(0.75, 0.85)	(0.914)	(0.143)		(0.004)	(0.005)
3	Gamma	3.297***	0.248		0.026***	0.009
	(0.85, 0.80)	(1.135)	(0.185)		(0.004)	(0.007)
4	Gamma	3.460***	0.221		0.026***	0.010
	(0.90, 0.70)	(1.178)	(0.192)		(0.004)	(0.007)
5	Trapezoidal	2.845***	0.292***		0.026***	0.009***
		(0.705)	(0.105)		(0.004)	(0.003)
6	Geometric	3.331***	0.212**		0.026***	0.012***
	$(\delta = 0.10)$	(0.707)	(0.101)		(0.004)	(0.003)
7	Geometric	3.461***	0.190*		0.026***	0.013***
	$(\delta = 0.15)$	(0.682)	(0.096)		(0.004)	(0.002)
8	Romer–Aghion-Howitt	4.794***		-7.30E-07	0.026***	0.021***
	(K_t)	(0.034)		(8.26E-07) [-0.083]	(0.004)	(0.004)
9	$[\ln(K_t)]$	2.055	0.266*		0.026***	0.009
		(1.557)	(0.150)		(0.004)	(0.005)

Sources: Developed by the authors.

Notes: Estimates obtained using the Cochrane-Orcutt method. The gamma model parameters in parentheses are (γ, λ). Eicker-Huber-White standard errors in parentheses in columns (1) through (5). Coefficients in column (3) are elasticities of MFP with respect to the knowledge stock. For the Romer-Aghion-Howitt model (Model 8) the elasticity is shown in square brackets in column (4), calculated at the median of constructed Romer-Aghion-Howitt knowledge stock across the period 1940–2007.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

APPENDIX TABLE 6.3—REGRESSIONS OF MFP AGAINST ALTERNATIVE KNOWLEDGE STOCKS, PRAIS-WINSTEN PROCEDURE

		Regressors				
Model	*Lag Model (Parameters)*	*Constant*	$\ln(K_t)$	K_t	W_t	T_t
		(1)	(2)	(3)	(4)	(5)
1	Gamma	2.772***	0.307***		0.026***	0.008***
	(0.75, 0.80)	(0.550)	(0.084)		(0.004)	(0.003)
2	Gamma	2.873***	0.304***		0.026***	0.008**
	(0.75, 0.85)	(0.577)	(0.092)		(0.004)	(0.003)
3	Gamma	3.304***	0.247**		0.026***	0.009**
	(0.85, 0.80)	(0.559)	(0.094)		(0.004)	(0.004)
4	Gamma	3.373***	0.235**		0.026***	0.009**
	(0.90, 0.70)	(0.586)	(0.098)		(0.004)	(0.004)
5	Trapezoidal	2.798***	0.299***		0.026***	0.009***
		(0.561)	(0.084)		(0.004)	(0.003)
6	Geometric	3.222***	0.227**		0.026***	0.013***
	$(\delta = 0.10)$	(0.603)	(0.087)		(0.004)	(0.002)
7	Geometric	3.348***	0.205**		0.026***	0.013***
	$(\delta = 0.15)$	(0.592)	(0.084)		(0.004)	(0.002)
8	Romer-Aghion-Howitt	4.781***		-1.02E-06	0.026***	0.023***
	(K_t)	(0.018)		(5.26E-07) [-0.115]	(0.004)	(0.002)
9	$[\ln(K_t)]$	1.809	0.290**		0.026***	0.008*
		(1.191)	(0.116)		(0.004)	(0.004)

Sources: Developed by the authors.

Notes: Estimates obtained using the Prais-Winsten procedure. The gamma model parameters in parentheses are (γ, λ). Eicker-Huber-White standard errors in parentheses in columns (1) through (5). Coefficients in column (3) are elasticities of MFP with respect to the knowledge stock. In the Romer-Aghion-Howitt model (Model 8) the elasticity is shown in square brackets in column (4), calculated at the median of constructed Romer-Aghion-Howitt knowledge stock across the period 1940–2007.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

APPENDIX TABLE 7—EFFECTS OF THE DISCOUNT RATE ON THE BENEFIT-COST RATIOS FROM THE DIFFERENT LAG MODELS

Model	*Lag Model (Parameters)*	*Mean Lag (years)*	*Real Discount Rate* r = 0.001 (1)	r = 0.03 (2)	r = 0.05 (3)	r = 0.10 (4)
1	Gamma	17.8	**36.3**	**23.4**	**17.8**	**9.8**
	(0.75, 0.80)		[8.6, 64.1]	[5.5, 41.3]	[4.2, 31.5]	[2.3, 17.3]
2	Gamma	23.3	**35.5**	**20.5**	**14.7**	**7.1**
	(0.75, 0.85)		[5.7, 65.3]	[3.3, 37.8]	[2.4, 27.0]	[1.1, 13.1]
3	Gamma	28.3	**54.1**	**27.3**	**17.8**	**6.9**
	(0.85, 0.80)		[30.6, 77.7]	[15.4, 39.2]	[10.1, 25.6]	[3.9, 9.9]
4	Gamma	27.6	**37.6**	**18.9**	**12.1**	**4.5**
	(0.90, 0.70)		[21.4, 53.9]	[10.7, 27.0]	[6.9, 17.4]	[2.5, 6.4]
5	Trapezoidal	15.7	**37.6**	**25.2**	**19.6**	**11.4**
			[9.7, 65.6]	[6.5, 44.0]	[5.0, 34.2]	[2.9, 19.8]
6	Geometric	10.7	**26.9**	**21.0**	**18.1**	**13.3**
	(0.10)		[14.7, 39.1]	[11.5, 30.5]	[9.9, 26.4]	[7.3, 19.3]
7	Geometric	7.7	**22.4**	**18.5**	**16.5**	**12.8**
	(0.15)		[12.3, 32.4]	[10.2, 26.8]	[9.1, 23.8]	[7.0, 18.5]
8	Romer-Aghion-Howitt		11.7	6.1	4.3	2.3
	(K_t)		[-1.4, 24.8]	[-0.7, 12.9]	[-0.5, 9.1]	[-0.3, 4.9]
9	$[\ln(K_t)]$		**42.1**	**26.3**	**20.6**	**13.2**
			[14.5, 69.8]	[9.1, 43.6]	[7.1, 34.0]	[4.5, 21.8]

Sources: Developed by the authors.

Notes: The gamma model parameters in parentheses are (γ, λ). Entries in the table are the marginal benefit-cost ratios (BCRs) for an incremental investment in 1957 calculated using equation 12 and elasticities from column (4) of Table 4 (i.e., using the dynamic OLS estimators). Numbers in square brackets are the upper and lower bounds of the 95 percent confidence interval for the BCR, and BCRs in bold are statistically significantly different from zero since their respective confidence intervals do not include zero.