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Knowledge productivity and the returns to agricultural research: a review

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This paper describes the identification, specification, estimation, and evaluation of econometric models of knowledge productivity and the returns-to-research. General issues related to these models are discussed and placed in context of the literature. The path from R&D investment to economic benefit is complex, convoluted, generally unknown and possibly misrepresented. The complexity arises from the intricate spatial spillover relationships and the very long time periods involved, which complicate any econometric analysis. The relevant R&D investment data are typically unavailable, incomplete and poorly measured (or approximated). The appropriate calculation of the financial benefit is not entirely clear. Some parsimonious suggestions for future research are presented.

Key words: agricultural productivity, agricultural R&D, rate of return.

1. Introduction

In economic models of knowledge productivity and the return to research, technological know-how is approximated by aggregating monetary investments in R&D over space and time to create knowledge stock variables. These knowledge stocks are subsequently treated as intellectual capital in the knowledge production function. The R&D investments result in new technology adopted by producers generating productivity gains and economic benefits; however, the path from investment to economic benefit is complex, convoluted, generally unknown and possibly misrepresented (Griliches 1979, 1987). The complexity arises from the intricate spatial spillover relationships and the very long time frames involved, which complicate any econometric analysis. The relevant R&D investment data are typically unavailable, incomplete and poorly measured (or approximated). The appropriate calculation of the economic benefit is not entirely clear and recently disputed in the literature (Alston *et al*. 2011; Hurley *et al*. 2017; Oehmke 2017).

This paper is not a survey of the economic literature focused on estimating the returns-to-research in agriculture, which can be found in Alston *et al*. (2000) and Hurley *et al*. (2014). This paper describes the identification, specification, estimation, and evaluation of parametric models of knowledge

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productivity and the returns-to-research. General issues related to these models are discussed, placed in context of the literature, and some parsimonious suggestions for future research are presented.

2. Endogenous growth theory

In models of endogenous economic growth (or New Growth Theory), technological knowledge is intellectual capital, which is treated similar to physical capital or other traditional inputs in the production process. The theory has deep roots in economics that can be traced through a vast body of literature dating back a century or more; however, a series of papers were published in the 1990s that helped to formalise the important implications of endogenous growth theory (Adams 1990; Romer 1990; Aghion and Howitt 1992; and Jones 1995). See also the 'Symposia on New Growth Theory' in the *Journal of Economic Perspectives* (1994). Microeconometric studies of the returns to research represent an application of endogenous growth theory, and the prototype study of the returns-to-research in agriculture is Griliches' (1957) study of hybrid corn in the United States. This and later papers by Griliches (1986, 1987) were seminal studies on the topic of endogenous economic growth in agriculture and fundamental in the subsequent development of endogenous growth theory. Agricultural economists conducted some of the first empirical studies of the returns-to-research, which are summarised by Norton and Davis (1981) and Davis (1980).

Econometric studies of knowledge productivity require two basic ingredients, a dependent variable that is a measure of productivity and an independent variable(s) representing the knowledge stock.[1] These variables allow for the econometric estimation of a knowledge production (or productivity) function. Let $Y = F(X, K)$ be a production function relating aggregate output Y to aggregate input X and the knowledge stock K, assuming separability of X and K. The knowledge stock is a function of investments in research R, with $K = \Gamma(B)R$, where $\Gamma(B)$ is a backshift operator that is a lag polynomial.[2] Assuming Cobb–Douglas production technology, we can write F as:

$$Y = CX^{\alpha}K^{\beta}e^{\tau t+u} \tag{1}$$

where C is a constant term, t is a time trend, u is a random error term, e is the base of the natural logarithms, and α,β and τ are parameters of interest. Assuming constant returns-to-scale in traditional inputs ($\alpha = 1$), let $A = Y/X$ be a measure of multifactor productivity,

[1] Technical aspects of constructing measures of agricultural productivity are not reviewed in this paper. The construction of knowledge stock variables is considered in the next section.

[2] The knowledge stock variable is $K = \Gamma(B)R = \gamma_0 R_t + \gamma_1 R_{t-1} + \gamma_2 R_{t-2} + \ldots$.

$$A = Y/X = CK^{\beta}e^{\tau t + u} \tag{2}$$

which is a function of the knowledge stock, other factors affecting productivity that are embodied in the time trend, and random factors. We can model the relationship between productivity and investments in R&D provided we have accurate data for Y, X and R, specify the correct functional form for the production technology F, and the lag polynomial $\Gamma(B)$ and obtain a consistent estimate of the parameter β. Any measurement errors related to the calculation of the knowledge stock K will bias the estimated research elasticity, β. Also, the construction of an accurate index of agricultural productivity poses many challenges related to data availability and economic data construction methods. For example, the existence of market power by producers, or quality changes to input measures over time, has important implications for the proper construction of indexes of productivity. Diewert (1978), and Caves *et al.* (1982a,b), discusses the general theoretical properties of index numbers and the construction of indexes of productivity.

It should be noted that the focus of this study is on the econometric estimation of knowledge productivity functions and the financial return to agricultural R&D; however, a dual economic approach and the estimation of cost functions can also be used to calculate the rate of return to investments in R&D. See Plastina and Fulginiti (2012) and Esposti and Pierani (2003) for examples of the estimation of the rate of return to public investments in agricultural R&D using a cost function approach.

3. Knowledge stock variables

The calculation of knowledge stocks begins with data on investments in R&D over time and among different research institutions. It should be noted that these data are often difficult to obtain, especially private agricultural R&D funding which is usually proprietary. Data on public investment in agricultural R&D are more readily available, but given the very long time frames involved, data collection methods and data classifications typically evolve, making the construction of a consistent long-run series problematic. Furthermore, identification of the relevant set of R&D expenditures to include in the analysis is not clear. This is known as the 'attribution problem' in these models, where we have difficulty attributing productivity gains to specific effects or specific classifications of investments because we either fail to realise they are important to the model or we simply do not have access to all of the relevant investment data.

Institution-specific knowledge stocks can be constructed using current and lagged investments within each institution, as well as investments that spillover from other institutions (spatial spillovers). Let i, j = 1, 2, …, N denote the research institutions, t = 1, 2, …, T denote the number of periods with investment data, $s = 1, 2, \ldots, S$ denote the number of periods to calculate knowledge stocks, and $t = 1, 2, \ldots, M$ denote the number of periods in the research lag distribution with $T = M + S + 1$. The institution-specific knowledge stocks, $K_{i,s}$, are functions of: (i) investments in research by institution $j = 1, 2, \ldots, N$ in period t, $R_{j,t}$; (ii) parameters that define the shape of the research lag distribution, $\gamma_{t,s}$; and (iii) parameters that define the spillover relationships among the institutions, $\omega_{i,j}$. One approach is to aggregate all of the relevant research expenditures into a single knowledge stock variable per institution that includes spillovers. The knowledge stock at institution i and period s is defined as:

$$K_{i,s} = \sum_{j=1}^{N} \sum_{t=1}^{T} \omega_{i,j} R_{j,t} \gamma_{t,s} \tag{3}$$

The omegas, $\omega_{i,j}$, are weights that indicate the contribution of a unit of the stock of knowledge created at institution j to the stock of knowledge at institution i, with $0 \leq \omega_{i,j} \leq 1 \forall i \neq j$ and $\omega_{i,j} = 1 \forall i = j$. Jaffe (1986) proposed basing the strength of the spillover relationship between institutions i and j using the angular separation between vectors v_i and v_j, representing the shares of the total research budgets for each institution devoted to each research activity:

$$\omega_{i,j} = \frac{v_i v_j'}{\sqrt{\left(v_i v_i'\right)\left(v_j v_j'\right)}} \qquad 0 \leq \omega_{i,j} \leq 1 \tag{4}$$

The gammas $\gamma_{t,s}$ in Equation (3) are weights that indicate the contribution of current and lagged investments to the current knowledge stock, with $\sum_{t=1}^{M} \gamma_{t,s} = 1$ and $\gamma_{t,s} = 0 \forall T > M$. The research lag weights, $\gamma_{t,s}$, follow an assumed distribution and lag length that will depend on the application. The research lag distribution represents knowledge accumulation and depreciation and is unknown to the researcher. Very little empirical evidence exists regarding a particular shape for an agricultural research lag distribution. This is because agricultural R&D takes a long time to affect productivity and then affects productivity for a long time. This implies that the research lag distribution should include an appropriate gestation period (either implicit or direct), as well as a sufficient lag length, probably in the 35-year to 50-year range. A gamma distribution can take many different forms depending on the choice of shape δ and scale λ parameters:

$$\gamma_{t,s} = \frac{(t+1)^{(\delta/1-\delta)} \lambda^t}{\sum_{h=0}^{M} (h+1)^{(\delta/1-\delta)} \lambda^h} \qquad 0 \leq t \leq M \tag{5}$$

with $0 \leq \delta < 1$ and $0 \leq \lambda < 1$. Given its flexibility, relative simplicity and intuitive shape, the gamma distribution is a good choice for representing the research lag distribution. The correct lag length M for the research lag distribution is also an important consideration, and the tendency in the agricultural economics literature over the last few decades has been to include longer lags. Figure 1 shows a gamma distribution with a 50-year lag when the shape parameter δ is set to 0.9, and the scale parameter λ is varied from 0.5 to 0.8.

A priori we might expect that the research lag distribution approximates a bell shape as in Figure 1, but could be skewed or have a large tail in one direction or the other. The gamma distribution also encapsulates an implicit gestation period given that the early lags have minimal weight in the distribution.

An alternative approach to the calculation of knowledge stocks is to create a separate variable for R&D conducted within each institution, as well as R&D that spills-in from other institutions. A within-institution knowledge stock is defined as $K_{i,s} = \sum_{t=1}^{T} \gamma_{t,s} R_{i,t}$, and a spill-in stock for each institution is defined as $S_{i,s} = \sum_{j \neq i}^{n} \omega_{i,j} K_{j,s}$. The main difficulty with separating the expenditures into different knowledge stock variables is that the resulting measures are typically smooth trending and highly collinear, which creates problems in econometric estimation.

4. Model specification

The successful identification of the production technology, the research lag distribution and the matrix of spillover relationships among institutions is critical to any study of the returns-to-research; however, the functional forms of the production technology and the knowledge productivity function are unknown. Furthermore, the data used in the analysis are difficult to construct, prone to errors and typically have omitted effects because of a

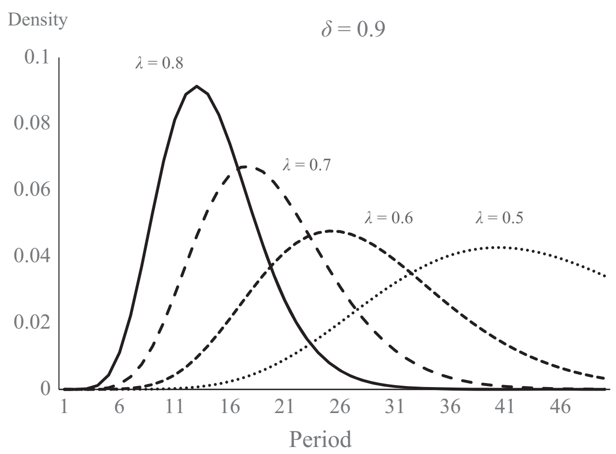

Figure 1 Gamma distribution with a 50-year lag, δ = 0.9 and λ = 0.5, 0.6, 0.7 and 0.8.
Note: Developed by author using Equation (5) from the text.

lack of availability of investment data. Perhaps the only commonly encountered form of specification error these models usually avoid is a simultaneity problem. This is because the knowledge stock variables are moving averages of lagged expenditures that usually include a gestation period and are therefore predetermined variables; however, as mentioned, models of knowledge productivity suffer from a persistent endogeneity problem in the form of omitted variables bias.

Research spillovers occur on different levels, including the effects from one location to another, from one branch of science to another (e.g. from basic to applied research), from one field of science to another (e.g. from genetics to plant science) and from private institutions to public ones, to name a few potential spillover relationships.[3] A matrix of spillover relationships representing closeness or similarity between institutions can be defined based on: (i) geographic proximity; (ii) cost shares of R&D activities; (iii) environmental or agro-ecological factors; (iv) value shares of outputs produced; and (v) scientific collaboration (citation networks for patents and/or research papers). Jaffe *et al.* (1993) examined the geographic location of patent spillovers. Katz (1994) found that citations to patents decline geometrically based on geographic proximity. The primary finding in the economics literature is that R&D spillovers are substantial but difficult to measure (Griliches 1992). The spillover effects of agricultural R&D are well-documented (Evenson 1989; Maredia *et al.* 1996; Gopinath and Roe 2000; Johnson and Evenson 2000; Maredia and Byerlee 2000; McCunn and Huffman 2000; Alston 2002; Alston *et al.* 2010).

The econometric evidence on research lag distributions is especially weak, and direct estimation is nonexistent. Many studies have utilised distributed lag and autoregressive distributed lag models, but these models still require critical assumptions regarding the shape and length of the research lag distribution, which ends up imposing a lot of structure on the estimation equation. The alternative approach is to assume some research lag distribution when constructing the knowledge stock variables or test different specifications using model selection criteria. Evenson (1967) used an inverted V-shape to represent the research lag distribution. Some additional lag structures found in the literature include a polynomial (Thirtle and Bottomley 1989), a trapezoid (Huffman and Evenson 1992, 2006) and a gamma distribution (Alston *et al.* 2010, 2011; Andersen and Song 2013). The gamma distribution can take many different forms depending on the choice of the shape and scale parameters that define the distribution. Alston *et al.* (2010) conducted a grid search of 64 different gamma distributions to represent the research lag distribution for U.S. agriculture, assuming a 50-year lag and

[3] Historically, there have been substantial international spillovers from agricultural technologies as documented in Fowler *et al.* (2000), Evenson *et al.* (1985), and Anderson *et al.* (1985). A study by Hall and Scobie (2006) examined the impact of international R&D spillovers on agricultural productivity in New Zealand, and a study by Pardey *et al.* (2006) examined international R&D spillovers to agriculture in Brazil.

covering a wide range of potential forms. They found an almost bell-shaped distribution that peaked in lag-year 24 provided the best fit to the data, meaning it takes nearly a quarter century for a given R&D expenditure to achieve its peak productivity-enhancing impact.

The econometric analysis should also include any relevant independent variables that are affecting productivity in a systematic way. These variables can range greatly depending on the application and the methods used to construct the data in the analysis. In some studies, quality-adjusted indexes of inputs are used in the construction of indexes of productivity, controlling for the influences of such factors as age and education on labour within the indexing procedure (Alston *et al.* 2011; Andersen and Song 2013). Other studies use unadjusted measures and include control variables directly in the estimation equation.

In the case of agriculture, weather has a significant effect on production and productivity from year to year, and any analysis should control for this. A reduced form of the knowledge productivity function could take the following linear specification:

$$A_{i,t} = \alpha_i + \beta_k K_{i,t} + \beta_s S_{i,t} + \beta_z Z_{i,t} + \varepsilon_{i,t} \tag{6}$$

where $A_{i,t}$ is an index of multifactor productivity at institution i in period t, $K_{i,t}$ is the within-institution knowledge stock, $S_{i,t}$ is the spill-in knowledge stock, $Z_{i,t}$ is a weather index, the $\alpha' s$ and $\beta' s$ are parameters to estimate, and $\varepsilon_{i,t}$ is a random error term.[4] Another common specification is a double-log model, with all variables expressed in natural logarithms. Recall that we have implicitly assumed constant returns-to-scale in this model because we have not included an index of aggregate input as an explanatory variable as in Equation (2). If either diminishing or increasing returns-to-scale are present, the effect will be transmitted to the estimated research elasticity.[5] The knowledge productivity function could also be a second-order Taylor series expansion in natural logarithms representing a trans-log specification and including second-order effects in the analysis.

5. Econometric estimation

The previously described specification errors that are present in studies of knowledge productivity and the returns to research raise concerns about the consistency of any estimated parameters from a standard econometric

[4] The knowledge productivity function represented by Equation (6) does not include a time trend. This is because the inclusion of a time trend will typically result in a multicollinearity problem with the smooth trending knowledge stock variable(s), causing a statistically insignificant estimate of the research elasticity.

[5] Note that there are methods in the literature to decompose a measure of productivity into technical change, scale effects and efficiency effects using directional distance functions constructed via data envelopment analysis (DEA) methods. Applications to agriculture can be found in O'Donnell (2010, 2012, 2014), and Fulginiti (2010).

analysis. Given the fact that the knowledge stocks are predetermined, the current period error terms in Equation (6) are uncorrelated with the current and previous knowledge stocks; however, the knowledge stocks might be correlated with future shocks and this is a violation of strict exogeneity, which requires that the predetermined knowledge stocks be uncorrelated with current, past, and future shocks. The biggest issue for identification and estimation is an omitted variables problem, where the omitted effects include R&D investments by other institutions that are usually positively correlated with the included knowledge stock variables as well as agricultural productivity, implying that the estimated research elasticity would be biased upward. Some studies have attempted to use instrumental variables to proxy these omitted effects, such as the use of patent counts from private institutions as an instrument for the unobservable private R&D investments (Huffman and Evenson 2006).

Studies of knowledge productivity also typically involve long time frames, which can introduce time-series estimation issues related to nonstationary variables, autocorrelated error terms and cointegration of variables. Measures of agricultural productivity commonly have a strong time trend, either deterministic or stochastic. Most often they are nonstationary variables that become stationary after first-differencing, so they are integrated of order one, $I(1)$. The knowledge stock variables are also typically upward trending, although with much less volatility and certainty about the existence of a unit root compared to the productivity measures.

After collecting and constructing the relevant economic data, the next step should be to establish the time-series properties of the variables in the analysis. Some commonly used statistical tests of a unit root include the original Dickey and Fuller (1979) test based on linear regression, the Augmented Dickey and Fuller (1979) test if serial correlation is an issue, the Phillips and Perron (1988) test if autocorrelation and heteroscedasticity are an issue, the Zivot and Andrews (1992) test if a structural break is present, and the Elliott *et al.* (1996) test if a time trend is present. The last test listed is a modified version of the Augmented Dickey–Fuller (ADF) test for a unit root in which the series is first transformed by a generalised least squares (GLS) regression. The GLS test is superior to the standard ADF test when a linear time trend is present in the data.

If the findings indicate the productivity index and the measure(s) of knowledge stock have a unit root, then Johansen (1995) and Phillips and Perron (1988) tests for cointegration can be used to establish if a linear combination of the variables forms a stationary time series. In this case, the common specification of a knowledge productivity function estimated using standard econometric procedures such as ordinary least squares (OLS) will produce 'super-consistent' parameter estimates. Stock (1987) showed that these estimates converge to their probability limits faster than OLS estimates in stationary time-series models. Studies of the time-series properties of measures of productivity and research expenditures in agriculture include

Pardey and Craig (1989), Schimmelpfennig and Thirtle (1994), Makki *et al.* (1999b), Oehmke and Schimmelpfennig (2004), Thirtle *et al.* (2008), Balcombe *et al.* (2005), and Andersen and Song (2013).

Given certain time-series properties of the variables, we can obtain consistent parameter estimates for the knowledge productivity function using an OLS estimation procedure or some common variant. Another primary consideration for the analysis is a multicollinearity problem between knowledge stock variables. Because of the fact that the knowledge stocks represent the spatial and temporal aggregation of investment data, they tend to be smooth trending variables; therefore, including multiple knowledge stocks in a standard econometric analysis almost always results in a multicollinearity problem. This puts the researcher in a difficult position in determining the level of aggregation to use in constructing the knowledge stock variables. For example, we can choose to aggregate all investment data into a single knowledge stock for each institution under an assumed research lag distribution and spillover matrix. Alternatively, we can create individual knowledge stock variables for 'within' institution and 'spillover' R&D. The advantage of the latter is to be able to estimate the differential effects of within-institution and spillover R&D directly from the estimation equation. The disadvantage is a likely multicollinearity problem between the within-institution and spillover knowledge stock variables.

In a panel data setting, we have additional assumptions concerning the error terms, $\varepsilon_{i,t}$. If the error terms are independent and homoscedastic among panels (institutions), then a fixed-effects (FE) or a random-effects (RE) estimator will be consistent, and Hausman's (1978) specification test can be used to establish the appropriate panel estimator. The error terms could be heteroscedastic but uncorrelated across panels, they could be heteroscedastic and correlated across panels, and they could also be autocorrelated (either with a common autocorrelation coefficient or a panel-specific one). These alternative assumptions can be handled using either a panel corrected standard error estimator or a feasible generalised least squares estimator as described in Beck and Katz (1995). Some panel data diagnostic tests include a modified Wald statistic for panel-level heteroscedasticity in the residuals of a FE model as described in Greene (2000), a Breusch and Pagan (1980) test for cross-sectional independence of the residuals in a FE or GLS panel data model, and a Wooldridge (2002) test for first-order serial correlation in the residuals of a linear panel data model.

Finally, published estimates of a research elasticity for public agricultural R&D are in the range of 0.2–0.5, according to studies by Makki *et al.* (1999a, b), Esposti and Pierani (2003), Alston *et al.* (2010), Andersen and Song (2013), Andersen (2015), and Jin and Huffman (2016). Differences in the estimated elasticities are the result of many factors, but the common finding of these studies is for a statistically significant research elasticity with a substantial magnitude, linking public investment in agricultural R&D to a productivity-enhancing benefit. The estimated research elasticities can be used in the financial calculations described in the next section.

6. Evaluating the financial return

Various metrics of financial return have been advocated in the literature on the returns-to-research, but no measure has been reported as extensively as the internal rate of return (IRR). Benefit cost (BC) ratios are also commonly reported. Alston *et al*. (2011) recently criticised the use of an IRR to evaluate the economic return to public investments in agricultural R&D and advocated instead for the use of a modified internal rate of return (MIRR). Subsequent research by Hurley *et al*. (2014) converted published estimates of the IRR to agricultural research to a MIRR and found very large differences in the resulting estimated return. We can easily convert a MIRR to a BC ratio given an assumed interest rate and length of a research lag distribution. Oehmke (2017) and Hurley *et al*. (2017) recently debated the appropriate measure of economic return to use in the case of public agricultural R&D.

Let $t = 0, 1, \ldots, M$ denote the number of years in the research lag distribution. Let $\overline{K}_t$ be the simulated knowledge stock that includes a \$1,000 increase in investment at $t = 0$. The annual percentage increase in the knowledge stock from the \$1,000 investment is $k_t = ln(\overline{K}_t/K_t)$. Let V_t denote the real value of output in period t. Given a discrete annual real discount rate r and an estimate of the research elasticity $\hat{\beta}$, the future value of benefits (FVB) is:

$$\mathrm{FVB} = \hat{\beta}\sum\nolimits_{t=0}^{M} k_t V_t (1+r)^{M-t} \tag{7}$$

The present value of cost (PVC) is the \$1,000 simulated investment at $t = 0$. The MIRR is then defined as:

$$\mathrm{MIRR} = \left(\frac{\mathrm{FVB}}{\mathrm{PVC}}\right)^{\frac{1}{M}} - 1 \tag{8}$$

A BC ratio can be calculated as:

$$\mathrm{BC} = \left(\frac{\mathrm{PVB}}{\mathrm{PVC}}\right) = \left(\frac{\mathrm{MIRR}+1}{1+r}\right)^{M} \tag{9}$$

The net present value (NPV) of the \$1,000 investment is

$$\mathrm{NPV} = (\mathrm{PVB} - \mathrm{PVC}) = \hat{\beta}\sum\nolimits_{t=0}^{M} k_t V_t (1+r)^{-t} - 1{,}000 \tag{10}$$

The IRR is the rate of return that equates the PVB to the PVC, has no analytical solution except for simple cases and therefore typically requires numerical methods to solve for the discount rate. If the investment opportunity includes a single upfront cost at $t = 0$, and a single lump sum benefit at $t = M$, then the MIRR = IRR, and the discount rate can be calculated from Equation (8). The discrete annual discount rate can be converted to a continuous discount rate r_c using the formula, $r_c = \ln(1 + r)$.

The basic ingredients for the financial calculations are the research elasticity, the simulated growth in the knowledge stock, the real value of agricultural output and the discount rate, r. The first two ingredients are very difficult to obtain. The value data are generally easier to obtain although subject to additional data construction issues, such as an appropriate price deflator to use when calculating the real value of output. The choice of discount rate is also not entirely clear and should vary depending on the application. When evaluating the return to public spending on agricultural R&D, recent studies by Alston *et al.* (2010, 2011) used a real discount rate equal to 3 per cent per annum. Andersen and Song (2013) examined the sensitivity of the estimated return-to-research to the choice of discount rate (varied from 0 to 4 per cent per annum). They found that the estimated MIRR was 8.19 per cent assuming a zero discount rate and 10.41 per cent assuming a 4 per cent discount rate.[6] One simplifying suggestion for models of the returns-to-research is to utilise estimates of the research elasticity based on annual averages, rather than the marginal estimates obtained from econometric estimation of knowledge productivity functions. Andersen (2015) describes the calculation of research elasticities based on annual averages of the data, and some potential advantages of this approach over econometrically estimated elasticities.

The IRR is applicable in the context of evaluating private research investments, where the investor retains all of the benefits generated over time. In the case of public investment, the benefits are distributed to producers and consumers over time in the form of price and quantity changes that generate economic surplus. The MIRR requires the assumption of a reinvestment rate for the stream of benefits generated from a simulated \$1,000 investment. The uncertainty about the reinvestment rate comes from issues related to who receives the benefits from agricultural R&D and how those benefits are either consumed or reinvested over time. The benefits that accrue from agricultural R&D take the form of changes in the prices and quantities of agricultural products and their inputs, and therefore the benefits go to producers and consumers of agricultural products, and are not reinvested in agricultural R&D. This provides justification for using an exogenous reinvestment rate tied to the general economy such as the real return on bonds. One possible measure of an exogenous market interest rate is the annual yield on Moody's BAA corporate bonds, minus the rate of inflation as measured by the rate of growth of the implicit price deflator for gross domestic product – the GDP

[6] Note that the discount rate is used to calculate the future value of the stream of benefits, and therefore, the MIRR increases with an increase in the assumed discount rate.

deflator. The real discount rate (reinvestment rate) in the MIRR calculation would be the annual average of this measure. It should be noted that the reinvestment rate could also be assumed to be zero, or the MIRR can be calculated under a range of assumed reinvestment rates.

7. Recent developments and future research

Maybe the biggest recent development in the estimation of knowledge productivity functions is the use of Bayesian models to attempt to address uncertainties related to the knowledge formation process and the sources driving agricultural productivity. Two recent studies using this methodology are Qin and Buccola (2017) and Baldos *et al.* (2018). The latter of these studies investigates the robustness of various assumptions that have been made about the knowledge formation process including the shape and the length of the research lag distribution. Bayesian models are not without controversy however, and their application to studies of the returns to agricultural research has yet to withstand the acid test of time and widespread acceptance among practitioners.

Future studies of the relationship between R&D spending and agricultural productivity will need to address some current trends in agriculture, such as the recent number of mergers and acquisitions in many agricultural input industries such as seed producers and agrichemical companies. This consolidation is changing the structure of the markets in which they operate, as well as the agricultural R&D that they conduct. This could have substantial effects on the private funding of agricultural R&D, the types of research projects selected and the distribution of benefits over time. Some additional relevant topics for investigation include the factors driving technology adoption and diffusion, intellectual property rights issues and the increasing need for maintenance research to keep agricultural productivity from faltering. In the United States, another recent trend worth noting is the reduction in public spending on agricultural R&D in general, and a shifting of the focus of research spending from farm productivity enhancing to other growing areas of research such as environmental degradation or nutrition. Given the very long time frames involved, the effects of these changes on agricultural productivity and the return-to-research have yet to be fully realised and should remain a focus of future studies. The literature has provided ample evidence that the economic return to public investments in agricultural R&D is large, but it remains to be determined how these benefits are distributed among producers and consumers, or among highly developed counties and less developed countries.[7] This information is important for the evaluation of investments in terms of choosing reinvestment rates, as well as to respond to the moral obligations of food security.

[7] Some evidence on the distribution of benefits from R&D can be found in Freebairn *et al.* (1982) and Alston and Scobie (1983).

8. Conclusion

Perhaps too much emphasis has been placed on the technical aspects of econometric estimation in models of the returns-to-research. Much has been learned from these studies, but it is apparent that future improvement and refinement of these models will come from refocusing on the basic ingredients of the model—the raw data, the data construction methods, and the guiding economic theory. The sophistication of the econometric estimation procedures is sufficient for these models provided we have access to accurate detailed data, employ the appropriate economic data construction methods and avoid other common specification errors.

It is important to note that the variables used to estimate knowledge productivity functions are commonly nonstationary and become stationary after first-differencing. This means a linear combination of the variables could form a stationary time series, which allows for consistent estimation of research elasticities using an OLS procedure. Additional econometric problems related to the structure of the error terms can be handled with the use of the appropriate estimator, such as the PCSE and the FGLS estimators described above.

A final important decision must be made about the calculation of a financial return to the R&D investments, and the most important distinction relates to if they are public of private investments. Historically, the most widely reported measure of financial return to public agricultural R&D is an IRR, but recent research points to the MIRR as a superior measure. If the investments are private, then either an IRR or a BC is recommended, and if they are public, then a MIRR or a BC is recommended. When an IRR is used to evaluate public agricultural R&D, the resulting estimated return has been gigantic, usually exceeding 50 per cent per annum. A corresponding MIRR with appropriate assumptions about the cost of debt capital and the reinvestment rate will be much lower, on the order of one-half to one-quarter of the IRR.

The raw data, the important economic assumptions regarding data construction, the econometric estimation methods and the financial calculations – each potentially impact the estimated return to investments in R&D. It is the responsibility of the economic researcher to get these correct so that we are reporting results that are consistent with empirical observations, historical facts, and current realities. Finally, agricultural economists may debate the size of the benefit, but they generally agree that the economic return to public investment in agricultural R&D is large.

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