2012

Rates of return to public agricultural research in 48 US states

Alejandro Plastina
International Cotton Advisory Committee, alejandro@icac.org

Lilyan E. Fulginiti
University of Nebraska-Lincoln, lfulginiti1@unl.edu

Published in *Journal of Productivity Analysis* 37 (2012), pp. 95–113; doi: 10.1007/s11123-011-0252-0

Published online November 18, 2011.

Rates of return to public agricultural research in 48 US states

Alejandro Plastina

International Cotton Advisory Committee (ICAC), 1629 K St, NW, Suite 702, Washington, DC 20006, USA;
Corresponding author, email alejandro@icac.org

Lilyan Fulginiti

University of Nebraska–Lincoln, 307C Filley Hall, Lincoln, NE 68583, USA; email lfulginiti@unl.edu

Abstract
The internal rate of return to public investment in agricultural R&D is estimated for each of the continental US states. Theoretically, our contribution provides a way of obtaining the returns to a local public good using Rothbart's concept of virtual prices. Empirically, a stochastic cost function that includes own knowledge capital stock as well as spillover capital stock variables is estimated. Stochastic spatial dependency among states generated by knowledge spillovers is used to define the "appropriate" jurisdictions. We estimate an average own-state rate of 17% and a social rate of 29% that compare well to the 9 and 12% average returns of the S&P500 and NASDAQ composite indexes during the same period.

Keywords: Internal rates of return, Public R&D, Spillins, Spillovers, Local public goods, Appropriate jurisdiction, Spatial

1. Introduction

Several studies report significant returns to public investments in agricultural research and development (R&D) in the United States by regions, commodities or at the national level.[1] The existence of significant regional knowledge spillovers has led authors to conclude that public agricultural R&D should be coordinated at regional or national levels. However, little evidence is available on the returns to agricultural R&D by state and, therefore, little guidance exists on where to invest taxpayers' dollars to maximize agricultural productivity.

The present study intends to contribute to the debate by providing an assessment of the benefits from public investment in agricultural R&D for each continental US state, acknowledging in theory and empirics their local public goods nature. This is the first study to endogenously recover the impact of public investments in agricultural R&D for each of the 48 continental US states while accounting for structural and stochastic dependency among the states due to knowledge spillovers.[2] The assessment is conducted in terms of the Internal Rate of Return[3] (IRR): the greater is the IRR for one state, ceteris paribus, the more socially desirable it is to invest in public agricultural R&D in that state. Any responsible policy discussion about the disposition of public funds should be based on knowledge of the returns to such investment. We provide the estimates of the IRR to public investments in agricultural R&D for each US state hoping in this way to contribute to the policy debate.

1. For a review of the economic impacts of agricultural R&D at sectoral and aggregate levels both for the US and other countries, see Evenson (2001), Alston et al. (2000), Alston (2002), Huffman and Evenson (2006).
2. Khanna et al. (1994) analyzed the optimal allocation of public monies to agricultural R&D in the same 48 US states considered in the present study with a joint production model of public and state-specific benefits. Spillovers were defined as contemporary expenditures on R&D in neighboring states, and state expenditures on R&D were endogenous to their formulation.
3. The IRR is the rate of return that equals the discounted stream of benefits from an investment with its initial cost.

In addition, we contribute to the literature by providing a general theory and a way of measuring the returns to a local public good using the concept of virtual prices.[4] In assessing the benefits of public agricultural R&D, it is crucial to recognize its local public goods nature. Since there is no market for trading public goods, no market assessment of the value of public goods is readily available, and their value must be recovered endogenously. In addition, a local public good needs a definition of its 'appropriate' jurisdiction. While some research results are fully usable only by the jurisdiction that the research was intended for some are also usable by other jurisdictions, giving rise to knowledge spillovers.[5] Therefore, the major challenges for the researcher are: to estimate the returns to this public good and to do so by attributing the benefits from an investment in R&D to the 'appropriate' jurisdiction. Latimer and Paarlberg (1965) and Evenson (1967) have early indicated the potential distortion in the estimates of the contribution of public R&D to the agricultural sector due to the presence of spillovers.[6] It is in this sense that the researcher must define the jurisdiction under analysis. In this study, the benefits from an investment in R&D are estimated from the impacts of such investment on the production structure for two different levels of aggregation: the state where the investment was undertaken (the own state benefits), and the state and other states in its 'jurisdiction' (the social benefits).[7]

The researcher then must address the problems in estimation of the benefits of R&D, not only for the own state, but for all other states affected by the existence of spillover effects across them. Most of the studies on the effects of R&D are ad-hoc. They include primal and dual approaches in which a variable representing the stock of own state R&D is included in a production function, cost function or on a two step regression of a productivity index to capture the own state benefits. Some studies add an ad-hoc spill-in variable to capture the social benefits and to avoid the structural dependence problem among states due to the local public goods nature of the investment. But it is possible that knowledge generated in one state might benefit other states beyond the geographical limits imposed ad-hoc by researchers when defining the spill-in stocks. If this is the case, the residuals of the estimating model will contain relevant information and will be correlated among geographical units, generating cross-sectional stochastic dependence.

A distinctive feature of this article is that the aggregate technology is represented by a stochastic variable cost function with knowledge capital stock (research) variables and a stochastic spatial error structure. The own-state stock of public R&D enters this function as a fixed input of production. A spill-in variable is also explicitly incorporated into the model to account for structural dependency among "similar" states due to knowledge spill-ins. Following Fulginiti and Perrin (1993) and Onofri and Fulginiti (2008) and using the derivative property of the cost function we recover the virtual prices for own-state public R&D and spill-in knowledge stocks. Parameters of such a model are then used in the calculation of IRRs. These IRRs then will include own state plus spill-in impacts of the R&D investment. In addition to incorporating knowledge stock spill-ins in the structure of the cost function, we allow in estimation for the existence of stochastic spatial dependency in the error term to adjust the estimates by the extent of propagation across states not captured structurally. A model with spatial autocorrelation (SAR) in the error structure is estimated with US state-level annual data for the period 1949–1991 (Craig et al. 2002) using generalized spatial three stage least squares (Keleijian and Prucha 2004). The resulting estimates from the spatial model are compared to the estimates from a non-spatial model to assess the impact of stochastic spatial dependency on estimated IRRs. We expect that failing to correct for stochastic spatial dependency induced by knowledge spillovers would affect the definition of the appropriate jurisdiction and the magnitude of returns to R&D.

The estimates of the IRR to public agricultural R&D are positive and significant for all states. The average own state IRR for the nation is estimated, in the spatial model, at 17%, while the average social IRR is estimated at 29%. In the non-spatial model these estimates are 12 and 14% higher, respectively. The returns estimated are fairly high, even though correcting for stochastic spill-ins in public agricultural research has resulted in lower IRRs.

The paper is organized as follows. In the next section the economic model used to capture the virtual prices of a local public good is presented. It is shown then how

4. A virtual price, introduced originally in demand theory by Rothbart (1941), is the price at which the consumer/producer, acting as a price taker, will choose to consume a specified bundle.

5. As mentioned by a reviewer, there are many examples of knowledge spillovers, like formula-based public research committed to, for example, Michigan's experiment station to study poultry diseases intended to benefit local poultry producers that benefit producers in Delaware, North Carolina, and other poultry producing states as well.

6. White and Havlicek (1979) showed that failure to take into account geographical spillovers from US regional agricultural research inflated the estimated rate of return to R&D in the Southern region by more than 25%.

7. Huffman et al. (2002) estimated the own state IRR to public expenditures on agricultural R&D for the "representative" Midwestern state to be 11% per annum, and a social rate of return of 43% per annum. Yee et al. (2002) estimated the social rate of return to public agricultural research to be about 3.5–6.7 times the own state rate of return for the "representative" state in each of the seven regions defined in their study. Huffman and Evenson (2006) estimated regional social IRRs to range from 49 to 62%.

these virtual prices are incorporated into the calculation of the own state and the social IRRs and how the "appropriate jurisdictions" are determined. The data used and the estimation procedure are described next, followed by a description of the results. A summary of the findings and their relevance is provided in the concluding section.

2. The model

The unit of analysis, determined by the level of aggregation of the available data, is the state. We assume that each state produces an aggregate output, y, using variable inputs $x = x_1,\ldots,x_N$, fixed private inputs $v = v_1,\ldots,v_M$, and fixed public inputs $V = V_1,\ldots,V_Q$. The vector of prices of the variable inputs is denoted by $w = w_1,\ldots,w_N$, with $w \cdot x = \sum_{n=1}^{N} w_n x_n$. Let $y = f(x, v, V)$ be the production function satisfying monotonicity and weak essentiality in x. Let $B(y, v, V) = \{x: f(x, v, V) \geq y\}$ be the closed, non-empty and convex restricted input requirement set to produce output y. Then, a well-defined non-negative short-run variable cost function $c(w, y, v, V)$ exists which is non-decreasing, concave, continuous and positively linearly homogeneous in w, and non-decreasing in y (Chambers 1988):

$$c(w,y,v,V) = \min_{x \geq 0}\{w \cdot x : x \in B(y,v,V)\} \tag{1}$$

Furthermore, if $c(w, y, v, V)$ is differentiable in w, it also satisfies Shephard's lemma in w:

$$x = \nabla_w c(w,y,v,V) \tag{2}$$

where x is the vector of cost-minimizing variable input demands, homogeneous of degree zero in w and with symmetric and negative semi-definite matrix $_w x = \nabla_{ww} c(w, y, v, V)$. If $c(w, y, v, V)$ is differentiable in v and V, Shephard's lemma can be applied to fixed factors. For convenience, $c(w, y, v, V)$ is assumed twice continuously differentiable in all its arguments. The monetary value placed by producers on marginal units of private fixed factors v, hereon referred to as the shadow value or virtual price Z_v, is represented by the amount of variable cost saved in the production of y due to the availability of an extra unit of v:

$$Z_v = -\nabla_v c(w,y,v,V) \tag{3}$$

In the short-run, Z_v can be positive or negative, depending on the level of the private fixed factor with respect to its long-run optimum and on its disposability assumption. If the level of the private fixed factor is below its long-run optimum, the variable cost function is expected to be decreasing in v (i.e., $Z_v > 0$) since the set of feasible combinations of (x, v, V) increases when an extra unit of v is available for production, so that new cost-minimizing opportunities (previously unavailable) are opened up (Chambers 1988, p. 102).[8] If the private fixed factor is above its long-run optimum and it is freely disposable (i.e., it does not cost anything in terms of output or other inputs to get rid of the extra units above the optimal level), then the variable cost function is expected to be independent of v (i.e., $Z_v = 0$). However, if the private fixed factor is above its long-run optimum but it is not freely disposable (i.e., it is costly to dispose off the extra units), its shadow value is expected to take a negative sign (i.e., $Z_v < 0$), indicating that an extra unit of the private fixed factor might actually increase short-run variable costs. Since we make no *a priori* assumption about the free disposability of private fixed inputs or their level with respect to their long-run optimum, we do not expect any particular sign for Z_v.

The monetary value placed by producers on marginal units of public factors V, hereon referred to as the shadow value or virtual price Z_V, is represented by the amount of variable cost saved in the production of y due to the availability of an extra unit of V:

$$Z_V = -\nabla_V c(w,y,v,V) \tag{4}$$

Similar to the shadow values of private fixed factors, the shadow values of public factors can be positive or negative, depending on their free disposability. While some public inputs might be freely disposable, (e.g. public roads that producers might choose not to use), some others are not (e.g. pollution). Since we make no *a priori* assumption about the free disposability of public inputs, we do not expect any particular sign for Z_V. If $Z_V \geq 0$, an extra unit of the public factor generates short-run savings to agricultural producers; while if $Z_V < 0$ it might actually increase short-run variable costs.[9]

Local public goods are provided to satisfy the needs of a certain group of economic agents in a specific jurisdiction. In particular, local public knowledge on agricultural sciences generated for a specific state i, G_i, is developed to satisfy the needs of producers in that state. Therefore, it is completely usable by local producers and is incorporated as a public fixed input of production in the present model. However, that same knowl-

8. In primal space, $Z_v \geq 0$ implies that the marginal product of an extra unit of the private fixed factor v is positive when the marginal cost of producing an extra unit of output is positive; i.e., $Z_v = -\partial\ell^*/\partial v = (\partial\ell^*/\partial y)(\partial y/\partial v) \geq 0 \Leftrightarrow (\partial y/\partial v) \geq 0$, where ℓ^* is the Lagrange function corresponding to Equation (1) evaluated at the optimal x values, $(\partial\ell^*/\partial y)$ is the reciprocal marginal cost of an extra unit of output, and $(\partial y/\partial v)$ is the marginal product of the private fixed factor v.

9. Since the second order gradients of the variable cost with respect to private and public fixed inputs — $\nabla_{vv}c(\cdot)$, $\nabla_{vV}c(\cdot)$, and $\nabla_{VV}c(\cdot)$ — characterize the rate of change of their shadow values, and no assumption was made on the sign of their shadow values, no assumption is made on the rates of change.

edge might also be used by producers in other states after some adjustments to (different) local conditions. The stock of knowledge spill-outs from state i to state j ($i \neq$ i), S_{ji}, is the share of the stock of knowledge generated in state i, G_i, usable by producers in state j:

$$S_{ji} = \alpha_{ji} G_i, \tag{5}$$

where α_{ji} represents the degree of usability of knowledge from state i in state j, and $0 \leq \alpha_{ji} < 1$. Therefore, the aggregate stock of spill-ins from neighboring states (indexed by j) to state i is defined as:

$$S_i = \sum_{j \neq i} S_{ij} = \sum_{j \neq i} \alpha_{ij} G_j, \tag{6}$$

and the vector of the stocks of public fixed inputs available to producers in state i is:

$$V' = \{G_i, S_i\} \tag{7}$$

The shadow value of the own state stock of public R&D in state i, Z_{Gi}, can now be expressed as:

$$Z_{Gi} = -\nabla_{Gi} c(w, y, v, G_i, S_i) \tag{8}$$

and the shadow value of the stock of public R&D from a neighboring state j, Z_{Sij}, as:

$$Z_{Sij} = -\nabla_{Gj} c(w, y, v, G_i, S_i) = -\alpha_{ij} \nabla_{Si} c(w, y, v, G_i, S_i) \tag{9}$$

where the second equality holds by construction of the stock of knowledge spill-outs from state j to state i (Equation 5). These two concepts, obtained from the theoretical model, are used below in the calculation of the own state and the social IRRs of public investments.

The internal rate of return to public outlays in agricultural R&D is the discount rate that makes the discounted stream of benefits during m periods stemming from an increase in public investments in R&D in a given state i at time t_0, equal to its initial cost. The initial cost is the extra investment at time t_0, conventionally represented in discrete terms in the corporate finance literature as a negative amount, $\Delta R_{i,t_0} < 0$. In the present analysis, the stream of benefits for the state that conducted the R&D activities, state i, are the reductions in the cost of agricultural production in successive periods ($-\Delta c_{i,t}$) derived from the increased stock of publicly available knowledge ($\Delta G_{i,t}$) generated by the investment in R&D in t_0. Therefore, the own state internal rate of return is the rate r that solves the following program:

$$0 = \Delta R_{i,t_0} - \sum_{q=1}^{m} \frac{\Delta c_{i,t_0+q}}{\Delta G_{i,t_0+q}} \frac{\Delta G_{i,t_0+q}}{(1+r)^q} \tag{10}$$

Note that $-\Delta c_{i,t}/\Delta G_{i,t}$ corresponds to the concept of Z_{Gi}, as defined in Equation (8). Therefore, Equation (10) can be re-expressed as:

$$0 = \Delta R_{i,t_0} + \sum_{q=1}^{m} Z_{Gi,t_0+q} \frac{\Delta G_{i,t_0+q}}{(1+r)^q} \tag{11}$$

and a necessary condition for r to exist is that the shadow value of G_i be positive for at least one period, i.e., $Z_{Gi,t0+q} > 0$ for some $q > 0$. However, as long as the knowledge generated by one state i is free and usable by producers in other j states, the concept of total benefits from an increase in public investments in R&D in state i at time t_0 might be expanded to also include the spillovers of that investment, i.e. the reductions in the cost of agricultural production in the other j states. The *social* internal rate of return is the rate r_1 that solves the following program:

$$\begin{aligned} 0 = \Delta R_{i,t_0} &- \sum_{q=1}^{m} \frac{\Delta c_{i,t_0+q}}{\Delta G_{i,t_0+q}} \frac{\Delta G_{i,t_0+q}}{(1+r_1)^q} \\ &- \sum_{j \neq i} \sum_{q=1}^{m} \frac{\Delta c_{j,t_0+q}}{\Delta S_{j,t_0+q}} \frac{\Delta S_{j,t_0+q}}{\Delta G_{i,t_0+q}} \frac{\Delta G_{i,t_0+q}}{(1+r_1)^q} \end{aligned} \tag{12}$$

Note that $-\Delta c_{j,t}\ \Delta S_{j,t}/\Delta S_{j,t}\ \Delta G_{i,t}$ corresponds to the concept of the shadow value to state j of an increase in the stock of knowledge in state i, Z_{Sji} as defined in Equation (9). Equation (12) can be re-expressed in terms of virtual prices as:

$$\begin{aligned} 0 = \Delta R_{i,t_0} &+ \sum_{q=1}^{m} Z_{Gi,t_o+q} \frac{\Delta G_{i,t_o+q}}{(1+r_1)^q} \\ &+ \sum_{j \neq i} \sum_{q=1}^{m} Z_{Sji,t_o+q} \frac{\Delta G_{k,t_o+q}}{(1+r_1)^q} \end{aligned} \tag{13}$$

The variable G_i is constructed as a weighted sum of previous expenditures on public agricultural R&D in state i (R_i), with the weights following an inverted V-pattern.[10]

$$G_{i,t} = \sum_{a=1}^{U} \varpi_{t-a} R_{i,t-a} \tag{14}$$

Given that the α_{ij}'s are not observable, the variable S_i is constructed as the direct sum of the stocks of G_j's conducted in other states ($j \neq i$):[11]

$$S_{i,t} = \sum_{j \neq i} G_{j,t} \tag{15}$$

and the imperfect usability nature of knowledge generated in other states is incorporated structurally into the analysis through interaction terms (rather than S being treated as another fixed input like G or T) in the variable

10. A complete description on construction of G_i is given in the following section.

11. A complete description of S_i is given in the following section.

cost chosen. The following translog cost function is hypothesized to be stable over the period 1949–1991:

$$\begin{aligned}\ln c_i = & \sum_{n=M,L,K}\sum_{j=1}^{48}\delta_{n,j}\ln w_{n,i}DUM_j + \sum_{h=y,T,G}\delta_h \ln h_i \\ & + \sum_{n=M,L,K}\sum_{h=y,T,G}\beta_{nh}\ln w_{n,i}\ln h_i \\ & + \frac{1}{2}\sum_{n=M,L,K}\sum_{m=M,L,K}\beta_{nm}\ln w_{n,i}\ln w_{m,i} \\ & + \frac{1}{2}\sum_{h=y,T,G}\sum_{k=y,T,G}\beta_{hk}\ln h_i \ln k_i \\ & + \ln S_i\left(\sum_{h=y,T,G}\beta_{hS}\ln h_i + \sum_{n=M,L,K}\beta_{nS}\ln w_{n,i}\right)\end{aligned} \tag{16}$$

where i indexes states ($i = 1, 2, \ldots, 48$). In this study, labor (L), purchased inputs (M), and capital (K) are treated as variable inputs, while land (T) is considered a private fixed input. Note that the stock of spill-ins is treated differently than the own-state stock of R&D: while G is fully usable by the state and is treated similarly to the private fixed factor T, S is only partially usable and enters the variable cost through interaction terms.

In addition, since agricultural production is sensitive to the geoclimatic characteristics (soil type, humidity, etc.) of the area in which it is conducted, farms in different locations might use different technologies of production, this being another source of structural spatial heterogeneity across states (Anselin 1998). This translog function incorporates fixed state effects, represented by the dummy variables DUM_j that capture, structurally, the unobservable characteristics of each state that influence local agricultural production. Note that these parameters are interacted with input prices in their levels to allow for fixed effects in the derived input demands. In addition to the inclusion of terms in the specification of the cost function to capture structural differences and interactions across states, this study allows stochastic spatial interaction with the purpose of using information that might not be captured structurally.

For each state i, the three private input share equations ($n = M, K, L$), the virtual share of the private fixed input T, and the virtual shares of the public fixed inputs G and S implied by (16) are derived using Shephard's lemma, respectively, as (i subscripts omitted for simplicity of exposition):

$$\begin{aligned}SH_n &= \frac{\partial \ln c}{\partial \ln w_n} = \frac{w_n n}{c} \\ &= \sum_j \delta_{n,j}DUM_j + \sum_{m=M,L,K}\beta_{nm}\ln w_m + \sum_{h=y,T,G,S}\beta_{nh}\ln h\end{aligned} \tag{17}$$

$$\begin{aligned}\varepsilon_{c,T} &= -\frac{\partial \ln c}{\partial \ln T} = \frac{Z_T T}{c} \\ &= -\left[\delta_T + \sum_{n=L,K,M}\beta_{nT}\ln w_n + \sum_{h=y,T,G}\beta_{hT}\ln h + \beta_{TS}\ln S\right]\end{aligned} \tag{18}$$

$$\begin{aligned}\varepsilon_{c,G} &= -\frac{\partial \ln c}{\partial \ln G} = \frac{Z_G G}{c} \\ &= -\left[\delta_G + \sum_{n=L,K,M}\beta_{nG}\ln w_n + \sum_{h=y,T,G}\beta_{hG}\ln h + \beta_{GS}\ln S\right]\end{aligned} \tag{19}$$

$$\varepsilon_{c,S} = -\frac{\partial \ln c}{\partial \ln S} = \frac{Z_S S}{c} = -\left[\sum_{n=L,K,M}\beta_{nS}\ln w_n + \sum_{h=y,T,G}\beta_{hS}\ln h\right] \tag{20}$$

Equations (18), (19), and (20) are, respectively, the elasticity of cost with respect to land, the elasticity of cost with respect to the own state stock of public agricultural R&D, and the elasticity of cost with respect to the stock of spill-ins from public agricultural R&D conducted in neighboring states. These elasticities can be either positive or negative, depending on the free disposability of the fixed inputs and their levels with respect to their long-run optimum.

In order to estimate the *own state* IRR to public expenditures on agricultural R&D, (11) can be conveniently expressed as the discounted sum of the shadow values of G_i over time weighted by the research expenditure weights used to construct the stocks of public agricultural R&D from Equation (14)

$$\begin{aligned}0 &= 1 + \sum_{q=1}^{m} Z_{Gi,t_0+q}\frac{\Delta G_{i,t_0+q}}{\Delta R_{i,t_0}}\frac{1}{(1+r)^q} \\ &= 1 + \sum_{q=1}^{m}\frac{\varpi_{t_0+q}Z_{Gi,t_0+q}}{(1+r)^q} = 1 + \sum_{q=1}^{m}\frac{B_{i,t_0+q}}{(1+r)^q}\end{aligned} \tag{21}$$

where $B_{i,t} = \varpi_t ZG_{i,t}$ is a direct measure of the own state monetary benefits at t from an extra dollar invested in public agricultural R&D at t_0. We use Equation (19) with $\varpi_{t_0} = 0$ to evaluate Equation (21) and obtain the own state IRR to investment in public agricultural R&D in each of the 48 states.

Similarly, using Equations (13), (14), and (15), the *social* IRR r_1 can be expressed as:

$$\begin{aligned}-1 &= \sum_{q=0}^{m}\frac{\varpi_{t_0+q}Z_{Gi,t_0+q}}{(1+r_1)^q} + \sum_{j\neq i}\sum_{q=0}^{m}\frac{\varpi_{t_0+q}Z_{Sji,t_0+q}}{(1+r_1)^q} \\ &= \sum_{q=0}^{m}\frac{\varpi_{t_0+q}\left(Z_{Gi,t_0+q} + \sum_{j\neq i}Z_{Sji,t_0+q}\right)}{(1+r_1)^q} \\ &= \sum_{q=0}^{m}\frac{\varpi_{t_0+q}F_{i,t_0+q}}{(1+r_1)^q} = \sum_{q=0}^{m}\frac{B^*_{i,t_0+q}}{(1+r_1)^q}\end{aligned} \tag{22}$$

where $F_{i,t}$ is the social shadow value of G_i at time t; and $B^*_{i,t} = \varpi_t F_{i,t}$ measures social monetary benefits at time t from an extra dollar invested in public agricultural R&D in state i at t_0. We use Equations (19) and (20) to estimate r_1.

If $Z_{Si} \geq 0$ then $r_1 \geq r$, indicating that the total benefits of R&D are at least as big as the benefits that accrue only to the state where the expenses were incurred.

3. Data

The agricultural production variables for all 48 states for the period 1949–1991 are from Craig et al. (2002).[12] According to Acquaye et al. (2003) this data set "was developed with a view in particular to measuring the effects of public agricultural R&D on productivity" and it included Fisher Ideal quantity indexes for the flows of agricultural output, labor, purchased inputs, capital and land, expenditures on land, labor, purchased inputs and capital, and the value of total agricultural output for each state (see "Appendix 1"). The variable cost in this study is the sum of expenditures on labor, purchased inputs and capital for farm production in constant 1949 dollars.[13] In order to reflect the differences in the relative sizes of the agricultural sector across states, we multiplied quantity indexes for land and output by their respective expenditures in 1949.[14]

The own-state R&D stock G was constructed as a 31-years weighted average of gross public expenditures on agricultural R&D at state level in constant US dollars, according to (14).[15] As in McCunn and Huffman (2000), the reason for using political rather than geoclimatic borders is our focus on public funding, which is based on political borders. The weights ϖ_t are constructed by transforming Chavas and Cox's (1992) estimated marginal effects of public research expenditures on US agricultural productivity, CC_t, to add up to one:

$$\varpi_{t_0+i} = \frac{CC_{t_0+i}}{\sum_{i=1}^{31} CC_{t_0+i}} \tag{23}$$

The weights follow an inverted-V distribution of the lags of the effects of R&D on productivity through time implying a gestation period of 7 years, followed by an 8 years period of increasing effects at a low rate, and another 8 years period of increasing effects at a higher rate, reaching a maximum in year twenty-three, and declining to zero from there onwards by year thirty-one.[16] These estimates are appealing because they were obtained using non-parametric methods, avoiding strong distributional assumptions required in parametric estimation.[17] Gross

12. This data set is available at http://www.apec.umn.edu/faculty/ppardey/data.html , and was used in Acquaye et al. (2003). This data set has been revised and extended over 1949–2002 (Pardey et al. 2007), but was not publicly available. Comparing the descriptive statistics of the newer series from Table 1 in Andersen et al. (2007) to the older series, capital seems to have been revised downwards (the mean, the minimum and the maximum values are about 5% lower in the newer data set than in the older one, while the standard deviation is only 1.5% higher). The output series also seems to have suffered significant revision: the minimum value is 24% lower and the standard deviation is 19% higher in the newer data set, while the mean is only 1.6% higher. We did not use the 1960–1993 data set from O'Donnel et al. (1999) because it was revised and modified after 1993. Alternatively we could have used the data developed by ERS (1998) to obtain indexes of productivity by state for 1960–1996 or the revised version used in Ball et al. (2001). But the state-level expenditures on agricultural inputs used in the construction of their quantity indexes needed for our estimation were not available to us.

13. We obtained the series of expenditures in purchased inputs, capital and labor in constant 1949 dollars by multiplying the Fisher Ideal input quantity indexes (1949 = 100) by the expenditures in each input in 1949. Following standard indexing procedures when quantity indexes take the value of 100 in 1949 the expenditures in that year are used as proxies for prices. According to Acquaye et al. (2003), data for labor comprise 30 farm operator classes (five age and six education characteristics), family labor, and hired labor. Data for purchased inputs involve pesticides, fertilizers, fuel, seed, feed, repairs, machine hire, and miscellaneous expenses. Capital involves buildings and structures, automobiles (units not for personal use), trucks, pickers and balers, mowers and conditioners, tractors, combines, dairy cattle, breeder pigs, sheep and cows, and chickens (not broilers).

14. Land comprises cropland, irrigated cropland, and grassland, pasture, range and grazed forest. Agricultural output aggregates field crops, fruits and nuts, vegetables and livestock.

15. Evenson (1989), Huffman and Evenson (1989, 1992, 1993, 2001), and Khanna et al. (1994) have constructed and used R&D stocks for US states but these data sets have not been made public. We proceed to build our own for the purpose of this study. The mean of G in our study closely resembles the mean of Huffman and Evenson's "public agricultural research capital for an originating state": \$1.73 million in 1949 dollars or \$10.1 million in 1986 dollars. The mean of S in our study is lower than the mean of Huffman and Evenson's "public agricultural research capital spillin": \$7.65 million versus \$8.86 million in 1949 dollars, or \$44.7 million versus \$51.8 million in 1986 dollars. We were unable to compare the distribution of our variables to theirs. This is true for variables G and S in our study.

16. Different studies adopt different weight structures: inverted-V form (Evenson 1967), second order polynomial (Knutson and Tweeten 1979) or trapezoidal (Huffman and Evenson 1989).

17. We realize that the marginal effects of public agricultural research expenditure on agricultural productivity might be endogenous to each state and are likely to differ among states. But given that no publicly available study estimates the marginal effects for each state, we use a set of estimated marginal effects at the national aggregate to compute the R&D stocks. While some early studies used 10- or 20-years lags (Evenson 1967; Knutson and Tweeten 1979; White and Havlicek 1979), more recent studies suggest that in order to properly capture the benefits of investment in research on agricultural production, lags of at least 30 years must be used in the construction of the stocks (Pardey and Craig 1989; Schimmelpfennig and Thirtle 1994; Alston et al. 1998; Alston and Pardey 2001).

public expenditures include all USDA appropriations, CSREES administered funds, state appropriations, and other federal and non-federal funds for State Agricultural Experiment Stations (SAES) and 1890 Institutions.[18] Data on total public agricultural R&D expenditures at the state level in current US dollars were obtained from the Current Research Information System Database (CRIS) for the period 1970–1991. Given the long lags assumed to construct the stock, data is needed for earlier periods and for the years 1919–1969, we have data only for agricultural R&D expenditures at SAES. These were collected, in current dollars, from several USDA reports. These series were used to construct a proxy for total agricultural R&D expenditures at the state level for the years 1919–1969 using the average ratio of total to SAES agricultural R&D expenditures in 1970–1980 and extrapolating to 1919.[19] An agricultural R&D price index was constructed for the period 1919–1999 from Huffman and Evenson (1993)and USDA data, which was used to express the expenditure series in constant 1949 dollars.[20]

The spill-in variable *S* is constructed as the sum of the stocks of public agricultural R&D of the states that share common borders or vertices with the state under analysis, indexed by *j* and *i*, respectively, in Equation (6). Similar geographical proximity criteria to construct spillover variables have previously been used by Khanna et al. (1994), Huffman et al. (2002), and Yee et al. (2002) to reflect similarities in climatic conditions, production conditions, input–output mixes, etc., among the states under analysis. In the present study, *S* captures the effects of structural spill-ins from R&D conducted in neighboring states. For example, *S* for Nebraska consists of the sum of the stocks of R&D in Wyoming, South Dakota, Iowa, Missouri, Kansas and Colorado.[21]

4. Estimation and results

This section is organized as follows. Two versions of the model consisting of the cost function and the capital and purchased inputs shares, Equations (16) and (17), are estimated maintaining symmetry and linear homogeneity in prices. Model 1 assumes that the spill-in variable *S* captures all relevant knowledge spillovers across states, i.e. it models *structural* spatial dependency. To test for the existence of stochastic effects of knowledge spillovers beyond the structural effects captured by *S*, a modified version of the Keleijian and Robinson (1992) test is performed on the residuals of Model 1. This test provides an assessment of the extent of the propagation of spillovers not captured by the variable S, and of the impact of any event that affects adjacent states and is not captured in the structure of the model. It indicates the necessity to acknowledge and model *stochastic* spatial dependency. Model 2 is estimated using three-stage generalized spatial least squares (3SGSLS) to correct for the stochastic effects. Results from Model 2 are then compared to those from Model 1 to assess the effect of failing to account for stochastic dependency among states. The best model is selected on the basis of the McElroy System R^2 and the Akaike Information Criterion (AIC) for each equation.[22]

The variable cost and the purchased inputs and capital shares in Model 1 are estimated using iterative seemingly unrelated least squares (ITSUR in version SAS 9.1). The share of labor has been dropped from the estimation to avoid singularity of the estimation matrix and its parameters recovered using the set of restrictions imposed. One hundred and seventy-four parameters are estimated with 6,192 observations (three stacked equations and 43 years for each of the 48 states.)

The model fits the data reasonably well, with a system R^2 of 0.896 and adjusted R^2 for each estimating equation greater than 0.8. These parameters conform to symmetry and homogeneity as these properties have been imposed in estimation. The Hessian is negative semi-definite at the mean of the data for each state implying concavity of the cost in prices at the mean of the data. The cost function is non-decreasing in output as the marginal cost evaluated at the mean of the data is positive for all states. Parameter estimates are reported in "Appendix 2".

Given that our main objective is the estimation of returns to local public inputs and the calculation of the implied IRR for public R&D investments we focus on these estimates. The effects of public inputs on the demand for private variable inputs are computed from

18. USDA appropriations for the Forest Service, the McIntire-Stennis Act from the CSREES Administered Funds, and all funds for Forestry Schools are excluded. USDA's intramural research is not included in the current analysis, since it is not possible to assign benefits to particular states, and the focus of this study is to estimate the IRR to agricultural R&D conducted at the state level. Extension is also excluded from the current analysis due to lack of data.

19. A similar methodology has been applied by Khanna et al. (1994) and Yee et al. (2002).

20. The concept of deflated total public agricultural R&D expenditures in this study resembles that of total public expenditures on agricultural research used by Khanna et al. (1994). The main difference is that forestry funds are excluded from the present study. We have not been able to do a numerical comparison as their data is not publicly available.

21. We also experimented with another pattern of technological similarity across states by applying cluster analysis techniques to the states' agricultural output-mix, and the results were highly dependent on the method used (single linkage, average linkage or centroid) and the criteria used to define the optimal number of clusters (hierarchical tree diagram, pseudo *F* statistic or pseudo Hotteling's T^2 test statistic).

22. The McElroy System R^2 is a weighted average of the R^2 for each equation in the system, and is bounded to the 0–1 interval (Greene 2003, p. 345).

Equations (19) and (20).[23] The effects of G and S on purchased inputs and labor are statistically significant for all states, but their effects on capital are not. An increase in G or in S generates an increase in the demand for purchased inputs and a decrease in the demand for labor, suggesting that technical change induced by public agricultural R&D has been biased towards the use of purchased inputs and against the use of labor in all states.[24]

The most important estimates for our purpose are the estimates of the shadow prices for public inputs G and S as they enter directly the calculation of the IRRs. The shadow price of the *own state* stock of public agricultural R&D as defined in Equations (4) and (19) is evaluated at the sample mean of all variables and for each state and it is reported in the second column of Table 1. $\bar{Z}_G$ measures the amount of cost savings in the production of output at constant 1949 dollars stemming from the public provision of an extra unit of G. Alternatively, $\bar{Z}_G$ measures producers' willingness to pay for an extra unit of stock of public local agricultural R&D. For example, the shadow value of G for Nebraska is, at the mean, $414.69, indicating that a $1 increase in the stock of public agricultural R&D in Nebraska in a given year generated annual cost savings to agricultural producers of, on average, $414.69. The estimates of $\bar{Z}_G$ are statistically significant and positive for all states but California, Maine, and Maryland. As shown below, the fact that $\bar{Z}_G$ is not statistically different from zero for California, Maine, and Maryland is driven by the inability of Model 1 to incorporate the effects of stochastic spatial dependency, resulting in estimates with wide confidence intervals.[25]

Note, however, that in the present study a $1 increase in the stock of public agricultural R&D in a given year requires a $1 investment in public agricultural R&D activities during the previous 31 years. Therefore, the own state annual average monetary benefit from investing an extra dollar in public agricultural R&D in t_0, is

$$\bar{B} = \sum_{i=1}^{31} B_{t_0+i} \Big/ 31 \tag{24}$$

where B refers to *own state* benefits as defined in Equation (21), and is a more intuitive measure of the benefits from R&D investments in agriculture (second column of Table 1). The 31-years annual average benefits vary from $0.63 for New York to $23.28 for Missouri for every $1 invested (constant 1949 dollars), and the national simple average amounts to $7.63 with a standard deviation among states of $5.43. The national weighted average of the *own state* benefits, with the weights being each state's average share in total output, amounts to $8.22 and is significant at the 1% level. It must be emphasized, however, that given the distribution assumed in constructing the research stock variable, the impacts are assumed to be higher in the distant future than in the years immediately following the investment.

The average social shadow value of G,

$$\bar{F} = \sum_{i=1}^{31} F_{t_0+i} \Big/ 31 \tag{25}$$

where F is the *social* shadow value of research stocks defined in Equation (22), and the average social monetary benefits from an extra dollar invested in agricultural R&D in t_0,

$$\bar{B}^* = \sum_{i=1}^{31} B^*_{t_0+i} \Big/ 31 \tag{26}$$

where B^* refers to *social* benefits as defined in Equation (22), are reported for each state in the last two columns of Table 1. Except for Maine, all estimates of $\bar{F}$ are positive and significantly different from zero. As expected, $\bar{F}$ is greater than $\bar{Z}_G$, implying a positive shadow value for research spillovers, $\overline{\sum_{j\neq i} Z_{Sji}}$. The implied annual average social benefits from R&D, in 1949 dollars, range from $3.79 (Rhode Island) to $90.09 (Missouri). The simple national average is $34.29 with a standard deviation across states of $20.78. The national weighted average of the *social* benefits, with the weights being each state's average shares in total output, amounts to $40.44 and is significant at the 1% level.

The estimated average marginal IRR from own state investment in public agricultural R&D, $\hat{r}$, is obtained by plugging the estimate of $\bar{Z}_G$ from Table 1 into Equation (21) and solving for r. Similarly, the estimated average marginal IRR from social investments in public agricultural R&D, $\hat{r}_1$, is obtained by plugging the estimate of $\bar{F}$ from Table 1 into Equation (22) and solving for r_1. Ninety-five percent confidence intervals for $\hat{r}$ and $\hat{r}_1$ for each state are obtained by plugging the corresponding shadow values plus/minus two standard errors in Equations (21) and (22), respectively (Table 2 and Figures 1 and 2). The simple average *own state* IRR for the nation is 26.9%, with a standard deviation of 8.91% across states. The weighted average *own state* IRR for the nation is 27.4%, and the 95% confidence interval is [26.2; 29.5%]. The highest *own state* IRR is 39% and cor-

23. Since private R&D expenditures are embodied in purchased inputs and capital, these effects should account, at least theoretically, for the interaction of public and private research. Our estimates also indicate that, at the mean of the data, land is a substitute for purchased inputs and capital, and a complement for labor in all states.

24. Price elasticities evaluated at the mean of the data for each state indicate that own-price elasticities are negative, as expected. Cross-price elasticities for all inputs evaluated at the mean are positive, indicating that labor, purchased materials and capital are substitutes in production. Marginal cost elasticities evaluated at the mean of the data show 26 states with increasing returns to scale and 22 states with decreasing returns to scale.

25. The coefficients of variation are 107, 242 and 51% for California, Maine and Maryland respectively. Coefficient of variation = standard error/|mean|.

Table 1. Own state and social shadow values (Z, F) and benefits (B, B^*) from agricultural R&D, no stochastic spatial dependency (Model 1, constant 1949 dollars)

State	$\bar{Z}_G$	$\bar{B}$	$\bar{F}$	$\bar{B}^*$
AL	226.42 (9.11)	7.30 (0.082)	759.57 (18.76)	24.5 (0.170)
AR	608.53 (27.48)	19.63 (0.249)	1,987.12 (49.99)	64.1 (0.452)
AZ	126.93 (5.08)	4.09 (0.046)	1,021.54 (33.09)	32.95 (0.299)
CA	−15.9 (16.95)	n/a	367.04 (19.40)	11.84 (0.176)
CO	214.5 (9.86)	6.92 (0.089)	1,747.31 (58.14)	56.36 (0.526)
CT	66.2 (4.77)	2.14 (0.043)	239.98 (11.49)	7.74 (0.104)
DE	193.1 (15.39)	6.23 (0.139)	386.26 (19.19)	12.46 (0.174)
FL	27.7 (6.81)	0.89 (0.062)	280.25 (13.14)	9.04 (0.119)
GA	173.03 (10.51)	5.58 (0.095)	882.39 (28.29)	28.46 (0.256)
IA	430.66 (28.19)	13.89 (0.255)	1,903.17 (64.29)	61.39 (0.582)
ID	275.95 (12.16)	8.90 (0.110)	1,204.72 (34.82)	38.86 (0.315)
IL	171.61 (13.23)	5.54 (0.120)	1,815.68 (59.57)	58.57 (0.539)
IN	275.7 (13.57)	8.89 (0.123)	1,179.57 (30.00)	38.05 (0.271)
KS	410.22 (23.86)	13.23 (0.216)	1,434.58 (44.22)	46.28 (0.400)
KY	311.79 (14.78)	10.06 (0.134)	1,906.61 (53.69)	61.5 (0.486)
LA	51.7 (5.42)	1.67 (0.049)	809.63 (24.97)	26.12 (0.226)
MA	118.5 (7.4)	3.82 (0.067)	315.37 (19.41)	10.17 (0.176)
MD	−5.14 (2.64)	n/a	374.39 (25.13)	12.08 (0.227)
ME	−9.82 (23.74)	n/a	−29.03 (25.41)	n/a
MI	298.21 (12.5)	9.62 (0.113)	1,552.31 (42.67)	50.07 (0.386)
MN	359.97 (23.12)	11.61 (0.209)	1,525.61 (51.36)	49.21 (0.465)
MO	675.1 (32.11)	21.78 (0.291)	2,792.67 (83.15)	90.09 (0.752)
MS	96.96 (7.5)	3.13 (0.068)	793.26 (24.36)	25.59 (0.220)
MT	148.62 (9.38)	4.79 (0.085)	891.18 (35.1)	28.75 (0.318)
NC	266.31 (16.07)	8.59 (0.145)	834.11 (27.11)	26.91 (0.245)
ND	128.96 (8.36)	4.16 (0.076)	811.07 (35.2)	26.16 (0.318)
NE	414.69 (22.71)	13.38 (0.205)	2,112.61 (79.8)	68.15 (0.722)
NH	105.79 (16.04)	3.41 (0.145)	255.01 (21.51)	8.23 (0.195)
NJ	65.93 (4.68)	2.13 (0.042)	296.8 (15.91)	9.57 (0.144)
NM	302.95 (14.2)	9.77 (0.128)	1,447.21 (38.23)	46.68 (0.346)
NV	172.85 (12.68)	5.58 (0.115)	1,076.17 (32.54)	34.72 (0.294)
NY	19.4 (6.97)	0.63 (0.063)	369.16 (26.59)	11.91 (0.241)
OH	241.41 (11.88)	7.79 (0.107)	1,196.53 (32.36)	38.60 (0.293)
OK	249.73 (9.25)	8.06 (0.084)	1,846.47 (66)	59.56 (0.597)
OR	130.88 (12.61)	4.22 (0.114)	859.55 (25.62)	27.73 (0.232)
PA	214.87 (11.47)	6.93 (0.104)	642.32 (25.75)	20.72 (0.233)
RI	32.83 (4.48)	1.06 (0.041)	117.54 (7.34)	3.79 (0.066)
SC	92.81 (7.99)	2.99 (0.072)	385.78 (15.08)	12.44 (0.136)
SD	721.77 (36.73)	23.28 (0.332)	2,275.57 (63.4)	73.41 (0.574)
TN	510.12 (21.14)	16.46 (0.191)	1,936.01 (48.88)	62.45 (0.442)
TX	113.32 (20.09)	3.66 (0.182)	764.04 (28.48)	24.65 (0.258)
UT	116.51 (12.18)	3.76 (0.110)	1,021.92 (35.42)	32.97 (0.320)
VA	343.09 (13.28)	11.07 (0.120)	938.1 (22.95)	30.26 (0.208)
VT	421.46 (24.33)	13.60 (0.220)	564.29 (25.78)	18.20 (0.233)
WA	44.95 (11.28)	1.45 (0.102)	408.34 (15.15)	13.17 (0.137)
WI	290.79 (13.65)	9.38 (0.123)	1,301.38 (35.79)	41.98 (0.324)
WV	210.93 (11.10)	6.80 (0.100)	829.04 (24.83)	26.74 (0.225)
WY	171.29 (12.15)	5.53 (0.110)	1,501.56 (56.36)	48.44 (0.510)
Simple national average	221.13	7.63	1,040.25	34.29
Simple national SD	173.72	5.43	656.54	20.78
Weighted national average	254.73 (16.85)	8.22 (0.15)	1,253.72 (41.10)	40.44 (0.37)

Approximated standard errors in parentheses; approximated standard errors obtained by the Delta method (Greene 2003).
n/a = not available

Table 2. Own state (r) and social (r_1) IRRs (in percentage), no stochastic spatial effects (Model 1), 95% confidence intervals in square brackets

State	$\hat{r}$	$\hat{r}_1$	State	$\hat{r}$	$\hat{r}_1$	State	$\hat{r}$	$\hat{r}_1$
AL	30.08 [29.5; 30.6]	39.41 [39.0; 39.8]	MD	n/a [n/a,n/a]	33.78 [32.7; 34.7]	OR	26.29 [24.9; 27.5]	40.45 [39.9; 40.9]
AR	37.58 [36.8; 38.3]	48.05 [47.6; 48.5]	ME	n/a [n/a; 18.5]	n/a [n/a; 15.3]	PA	29.7 [28.9; 30.4]	38.02 [37.3; 38.7]
AZ	26.08 [25.5; 26.6]	41.94 [41.4; 42.5]	MI	32.07 [31.4; 32.7]	45.71 [45.2; 46.2]	RI	17.65 [15.8; 19.1]	25.57 [24.7; 26.4]
CA	n/a [n/a; 14.2]	33.63 [32.8; 34.4]	MN	33.48 [32.4; 34.4]	45.54 [44.9; 46.2]	SC	24.03 [22.8; 25.1]	34 [33.4; 34.6]
CO	29.69 [29.0; 30.3]	46.82 [46.2; 47.4]	MO	38.43 [37.6; 39.2]	51.43 [50.8; 52.0]	SD	38.98 [38.1; 39.8]	49.37 [48.8; 49.9]
CT	21.88 [20.9; 22.7]	30.49 [29.8; 31.2]	MS	24.31 [23.2; 25.2]	39.77 [39.2; 40.3]	TN	36.17 [35.5; 36.8]	47.8 [47.3; 48.3]
DE	28.95 [27.7; 30.0]	34.01 [33.2; 34.7]	MT	27.14 [26.2; 28.0]	40.76 [40.1; 41.4]	TX	25.33 [22.5; 27.4]	39.46 [38.8; 40.1]
FL	16.67 [12.9; 19.0]	31.62 [30.9; 32.3]	NC	31.25 [30.3; 32.1]	40.2 [39.6; 40.7]	UT	25.51 [24.0; 26.8]	41.94 [41.3; 42.5]
GA	28.19 [27.3; 29.0]	40.67 [40.1; 41.2]	ND	26.19 [25.3; 27.0]	39.96 [39.2; 40.7]	VA	33.12 [32.5; 33.7]	41.2 [40.8; 41.6]
IA	34.85 [33.8; 35.8]	47.63 [47.0; 48.3]	NE	34.56 [33.7; 35.4]	48.64 [47.9; 49.4]	VT	34.68 [33.7; 35.5]	36.98 [36.2; 37.7]
ID	31.5 [30.8; 32.1]	43.39 [42.9; 43.9]	NH	24.88 [22.6; 26.6]	30.93 [29.6; 32.1]	WA	19.51 [15.5; 22.0]	34.44 [33.9; 35]
IL	28.13 [27.0; 29.1]	47.18 [46.5; 47.8]	NJ	21.86 [20.9; 22.7]	32.04 [31.2; 32.8]	WI	31.89 [31.2; 32.6]	44.09 [43.6; 44.6]
IN	31.5 [30.7; 32.2]	43.21 [42.7; 43.6]	NM	32.19 [31.5; 32.9]	45.06 [44.6; 45.5]	WV	29.57 [28.8; 30.3]	40.14 [39.6; 40.6]
KS	34.47 [33.5; 35.3]	44.98 [44.4; 45.5]	NV	28.18 [27.1; 29.1]	42.39 [41.8; 42.9]	WY	28.12 [27.1; 29.0]	45.4 [44.7; 46.1]
KY	32.4 [31.7; 33.1]	47.65 [47.1; 48.2]	NY	14.66 [8.0; 17.7]	33.67 [32.5; 34.7]	SNA*	28.65 [25.7; 28.5]	39.84 [39.2; 40.8]
LA	20.36 [18.9; 21.5]	39.94 [39.4; 40.5]	OH	30.54 [29.8; 31.2]	43.33 [42.8; 43.8]	WNA*	27.37 [26.2; 29.5]	42.33 [41.7; 43.0]
MA	25.62 [24.7; 26.4]	32.49 [31.5; 33.4]	OK	30.78 [30.2; 31.3]	47.34 [46.6; 48.0]			

n/a IRR can not be calculated since the corresponding shadow value is negative, SNA simple national average, WNA weighted national average.
* The bounds of the confidence interval for the National Average are calculated as the average of the respective bounds for all states.

responds to South Dakota. The simple average *social* IRR for the nation is 40%, with a standard deviation of 8.38%. The weighted average *social* IRR for the nation is 42.3%, and the 95% confidence interval is [41.7; 43.0%]. The highest *social* IRR is 51% and corresponds to Missouri. In all states but Maine the *social* IRR is significantly higher than the *own state* IRR, as indicated by the non-overlapping confidence intervals reported beside the IRR estimates in Table 2.

A modified version of the Keleijian and Robinson (KR) test for spatial autocorrelation in systems of equations, from Cohen and Morrison Paul (2007) is used on the errors of Model 1 to test for *stochastic spatial dependence* across states. The KR test provides an estimate of the number of significant spatial lags in each equation. It is a large sample test based on the generalized method of moments (GMM) and it does not require the model to be linear, the disturbance terms to be normal, or the pattern of spatial correlation to be specified. The KR test requires an *a priori* choice of the neighboring states that might be spatially correlated, but it does not require knowledge of the spatial weights. A geographical pattern of proximity among states is proposed as the driving force for spatial autocorrelation in the error structure. For each state, the US map is divided in concentric "rings" with the state under analysis as its center, the states that share a common border or intercept with the center as the first "ring" of neighboring states; the states that are detached from the center but share common borders or intercepts with the first "ring" as the second "ring" of neighboring states; and so on and so forth.[26] In this geographical partitioning of the space, states are expected to be more closely related to immediate neighboring states than those farther away. The results from the KR test suggest that there exists *stochastic spatial dependency* among states that are as much as four states apart from one another. This would be consistent with knowledge spillovers flowing widely across states and

26. For example, Wyoming, South Dakota, Iowa, Missouri, Kansas and Colorado belong to the first "ring" of neighboring states for Nebraska; while New Mexico, Arizona, Utah, Idaho, Montana, North Dakota, Minnesota, Wisconsin, Illinois, Kentucky, Tennessee, Arkansas and Oklahoma form its second "ring" of neighboring states; Texas, California, Nevada, Oregon, Washington, Michigan, Indiana, Ohio, West Virginia, Virginia, North Carolina, Louisiana, Mississippi, Alabama and Georgia form its third "ring" of neighboring states.

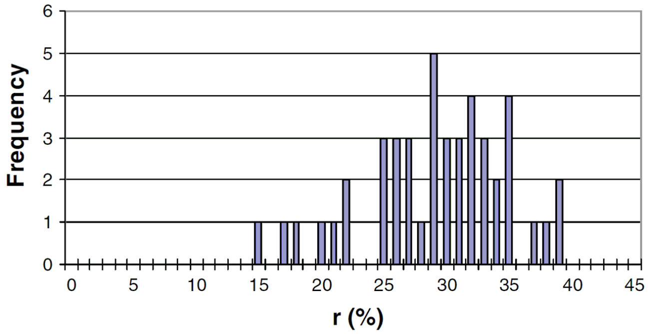

Figure 1. Histogram of the *own state* IRR's, ($\hat{r}$)—Model 1

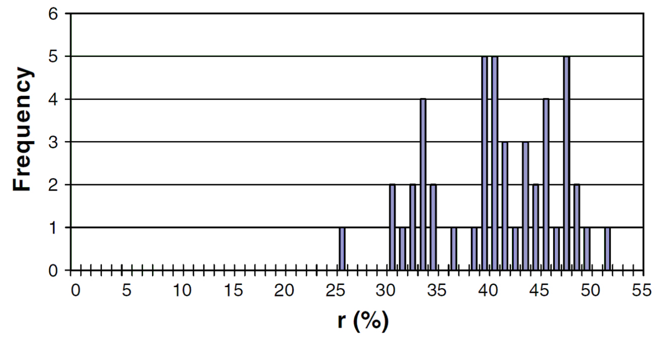

Figure 2. Histogram of the *social* IRR's, ($\hat{r}_1$)—Model 1

generating the spatial lag structures.[27] The variable cost function, ln c, and the capital share, SH_k, support a spatial lag length of 5, while the share of purchased inputs, SH_M, has a spatial lag of length 4.

To incorporate the effects of *stochastic spatial dependency* in the estimation of the benefits from public agricultural R&D, Model 2 is estimated using the GS3SLS procedure proposed by Keleijian and Prucha (2004). The first stage corresponds to the estimation of Model 1. In the second stage, the residuals from Model 1 and the lag structure suggested by the KR test are used to estimate the spatial autocorrelation parameters for each estimating equation using GMM. The estimates of the spatial autocorrelation parameters (Table 3), which are all bounded to the unit circle, are used to perform a Cochrane-Orcutt-type transformation on the observed variables, in a similar fashion to the standard procedure to correct for serial autocorrelation in time series. In the third stage, Model 2 determined by Equations (16) and (17) is re-estimated on the transformed variables with symmetry and linear homogeneity in prices maintained.[28]

The share of labor has been dropped from the estimation to avoid singularity as in estimation of Model 1. One hundred and seventy-four parameters are estimated with 6,192 observations (three stacked equations and 43 years for each of the 48 states) in Model 2. The system R^2 for Model 2 ($R^2 = 0.911$) is higher than the one from Model 1, and the AICs are lower for each estimating equation. Model 2 provides a better fit to the transformed data than Model 1 does to the untransformed data. The estimated parameters conform to symmetry and homogeneity as these properties have been imposed in the estimation. The Hessian is negative semi-definite at the mean of the data for each state implying concavity of the cost in prices at the mean of the data. The cost function is non-decreasing in output as the marginal cost evaluated at the mean of the data is positive for all states.[29] The estimates from Model 2 and the associated goodness of fit measures are reported in "Appendix 3".

The effects of G and S on the demand for variable inputs (measured as the elasticities of demand with respect to the fixed public inputs) are all significant in Model 2. An increase in G or S generates an increase in the demand for purchased inputs and capital, and a decrease in the demand for labor, suggesting that technical change induced by public agricultural R&D has been biased towards the use of purchased inputs and capital and against labor.[30, 31]

The *own state* shadow value of G, $\bar{Z}_G$, and the *own state* monetary benefits from an extra dollar invested in R&D in t_0, $\bar{B}$, are evaluated at the mean and reported for each state in the first two columns of Table 4. The estimates of $\bar{Z}_G$ are statistically significant and positive for all states.[32] $\bar{B}$ ranges from \$0.05 in Oregon to \$2.63 in

27. We cannot discard the possibility of other variables not included in the model structure, like weather for example, adding to this dependency. In any case IRRs should be corrected if spatial dependency is present no matter what the source.

28. Plastina and Fulginiti (2007) provide a more detailed description of the GMM estimator of the spatial lags, along with descriptive statistics, elasticity estimates and concavity results by states not included here due to space limitations.

29. The marginal cost elasticities evaluated at the mean of the variables indicate increasing returns to scale for all states, satisfying one of the necessary conditions for endogenous growth (Onofri and Fulginiti). A second condition, namely that of non-negative returns to public inputs, is also satisfied as the estimates of the shadows for public R&D in Table 4 show.

30. Land is a substitute for purchased inputs and capital, and a complement of labor.

31. For all states, the own-price elasticities are negative, as expected, and the cross-price elasticities for all inputs are positive, indicating that labor, purchased materials and capital are substitutes.

32. The coefficients of variation for California, and Maine are now significantly lower than in Model 1 (55, and 18%, respectively), while the coefficient of variation for Maryland is higher (77%).

Table 3. Estimates of the spatial autocorrelation parameters

Equation	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5
$\ln c$	0.265554	0.493288	0.196007	−0.37656	0.180117
SH_K	0.634002	−0.14269	0.22608	0.063719	0.010952
SH_M	0.587572	−0.05815	0.353718	−0.19113	

Standard errors for estimates in Table 3 are not reported because the significance of the spatial effects has been determined through the KR test, as a previous step to the estimation of the ρ's using GMM.

Maine and the simple national average is \$0.94, while the weighted national average is \$1.02 and is statistically significant at the 1% level (constant 1949 dollars). The estimates of own state benefits are now significantly lower than the own state benefits obtained in Model 1.

The *social* shadow value of public agricultural R&D, $\bar{F}$, and the social monetary benefits from an extra dollar invested in R&D in t_0, $\bar{B}^*$, are evaluated at the mean and reported for each state in the last two columns of Table 4. All social shadows are non-negative and significantly different from zero. Social shadows are higher than own state shadow values for public agricultural R&D stocks (estimates of $\bar{F}$ are greater than $\bar{Z}_G$), implying a positive shadow value for spillouts, $\overline{\sum_{j\neq i} Z_{Sji}}$. Social benefits, $\bar{B}^*$, range from \$0.33 in Rhode Island to \$18.46 in Missouri, with a simple national average of \$6.39 (constant 1949 dollars) and a weighted national average of \$7.98, significant at the 1% level. As mentioned before, benefits from the investment have a higher impact in the distant future than in the years immediately following the investment in R&D.

The estimated own state ($\hat{r}$) and social ($\hat{r}_1$) IRRs consistent with Model 2 for each state are reported in Table 5 and Figures 3–6, along with their 95% confidence intervals. The highest average own state IRR corresponds to Maine and equals 23.18%, while the lowest corresponds to Oregon and equals 2%. The simple average *own state* IRR for the nation is 16% with a standard deviation across states of 4.51%. The weighted average *own state* IRR for the nation is 16.5%, with a 95% confidence interval ranging from 8.6 to 19.8%. In all states but California, Maryland and Maine (states where the own state IRR could not be estimated in Model 1), the *own state* IRR from Model 2 is significantly lower than that from Model 1.[33]

These estimates are consistent with the estimates of returns to investments in public agricultural R&D and extension by Lu et al. (1979) (25%), White and Havlicek (7–36%), Evenson (11–45%), Oehmke (1996) (11.6%), and Alston, Craig and Pardey (7–31%). However, they are significantly lower than the rates estimated in most other studies. Evenson (2001) reports IRRs to aggregate public sector agricultural research (not including extension) from several studies ranging from 25 to 212%.

The *social* IRRs from Model 2 range from 11.26% in Rhode Island to 37.09% in Missouri. The simple national average is 27% and its standard deviation across states is 6.56%. The weighted national average is 29.3%, and the 95% confidence interval is [26.5; 31.1%]. The social IRRs are lower in Model 2 than in Model 1 for all states except for Maine (state for which the social IRR could not be calculated in Model 1). These are significant differences as indicated by the non-overlapping confidence intervals. The social IRRs obtained from Model 1 are, on average, 14% higher than the ones estimated with Model 2.

Our estimates of the *social* IRRs, once correction has been made for stochastic spatial dependency, even though impressive relative to market returns of private investments, are significantly lower than those calculated by Evenson (1989), Huffman and Evenson (1993, 2006), and Yee et al. (2002). These authors estimate rates between 49 and 600%.

Huffman et al. (2002) obtain estimates for the Midwestern states. For comparison purposes we calculate a simple average and a weighted average of our estimates for the states of Minnesota, Iowa, Illinois, Missouri, and Indiana. The simple and weighted average own state IRRs for the Midwestern states, 18 and 17.32%[34] respectively, are higher than the 11% in their study. Our simple and weighted *social* IRR for the Midwestern states are approximately 33%[35]—figures that are lower than the "significantly higher than 40%" reported in their paper.[36]

Although the analysis of the patterns of these rates across states is not the objective of this paper, we note here some interesting relationships. The ten states with lower spillover effects are concentrated in the Northeast of the country, and include Rhode Island, Maine, Connecticut, Delaware Vermont, Massachusetts, New Jersey, New Hampshire, Pennsylvania, and New York. These states' average own IRRs is 16%, equal to the average for all states but their spillovers are very low, with an average rate of 0.8%. This result is consistent with the percep-

33. Mean difference of 12.8% and a standard deviation of 4.6%.

34. The 95% confidence interval is [5.98; 21.14%].

35. The 95% confidence interval is [31.21; 34.91%].

36. Our estimate of the average elasticity of variable cost with respect to the stock of public R&D in these states is −5%, lower than the −87% estimated in their study.

Table 4. Own state and social shadow values ($\bar{Z}_G$, $\bar{F}$) and benefits ($\bar{B}$,$\bar{B}$*) from agricultural R&D, with stochastic spatial effects (Model 2, constant 1949 dollars)

State	$\bar{Z}_G$	$\bar{B}$	$\bar{F}$	$\bar{B}$*
AL	34.9 (5.78)	1.13 (0.052)	123.7 (15.79)	3.99 (0.143)
AR	51.0 (17.07)	1.65 (0.154)	317.0 (40.70)	10.23 (0.368)
AZ	11.6 (3.16)	0.38 (0.029)	198.4 (24.39)	6.4 (0.221)
CA	17.1 (9.41)	0.55 (0.085)	94.4 (12.34)	3.04 (0.112)
CO	21.1 (6.40)	0.68 (0.058)	385.9 (43.37)	12.45 (0.392)
CT	14.4 (2.63)	0.47 (0.024)	12.9 (8.41)	0.42 (0.076)
DE	33.2 (8.90)	1.07 (0.081)	29.9 (12.86)	0.97 (0.116)
FL	22.0 (3.64)	0.71 (0.033)	64.8 (8.56)	2.09 (0.077)
GA	31.5 (6.39)	1.02 (0.058)	159.1 (21.18)	5.13 (0.192)
IA	37.1 (18.19)	1.2 (0.165)	390.4 (46.32)	12.59 (0.419)
ID	31.7 (7.51)	1.02 (0.068)	226.3 (26.90)	7.3 (0.243)
IL	12.3 (8.61)	0.4 (0.078)	358.3 (44.04)	11.56 (0.398)
IN	29.4 (9.13)	0.95 (0.083)	183.1 (24.95)	5.91 (0.226)
KS	62.3 (14.88)	2.01 (0.135)	313.0 (33.41)	10.1 (0.302)
KY	14.3 (9.72)	0.46 (0.088)	350.9 (42.92)	11.32 (0.388)
LA	5.5 (3.25)	0.18 (0.029)	157.3 (19.09)	5.07 (0.173)
MA	22.4 (4.13)	0.72 (0.037)	21.6 (13.30)	0.7 (0.12)
MD	1.9 (1.42)	0.06 (0.013)	55.0 (15.76)	1.78 (0.143)
ME	81.4 (14.80)	2.63 (0.134)	72.0 (15.52)	2.32 (0.14)
MI	30.0 (8.27)	0.97 (0.075)	243.9 (34.21)	7.87 (0.31)
MN	52.2 (14.40)	1.68 (0.13)	313.7 (36.78)	10.12 (0.333)
MO	51.7 (20.58)	1.67 (0.186)	572.3 (63.53)	18.46 (0.575)
MS	17.6 (4.60)	0.57 (0.042)	174.3 (18.59)	5.62 (0.168)
MT	30.0 (5.88)	0.97 (0.053)	231.6 (25.33)	7.47 (0.229)
NC	55.5 (9.75)	1.79 (0.088)	175.1 (19.58)	5.65 (0.177)
ND	30.3 (5.19)	0.98 (0.047)	214.2 (24.12)	6.91 (0.218)
NE	52.4 (14.32)	1.69 (0.13)	525.6 (56.47)	16.96 (0.511)
NH	49.9 (9.32)	1.61 (0.084)	80.6 (13.73)	2.6 (0.124)
NJ	13.0 (2.63)	0.42 (0.024)	16.8 (11.33)	0.54 (0.103)
NM	23.8 (8.07)	0.77 (0.073)	240.0 (30.81)	7.74 (0.279)
NV	6.3 (6.96)	0.2 (0.063)	172.7 (24.64)	5.57 (0.223)
NY	8.6 (3.78)	0.28 (0.034)	20.7 (17.32)	0.67 (0.157)
OH	31.7 (7.86)	1.02 (0.071)	185.9 (26.30)	6.0 (0.238)
OK	30.1 (6.23)	0.97 (0.056)	444.6 (47.68)	14.34 (0.431)
OR	1.6 (7.67)	0.05 (0.069)	143.4 (20.04)	4.63 (0.181)
PA	20.3 (7.56)	0.65 (0.068)	34.1 (19.68)	1.1 (0.178)
RI	12.7 (2.56)	0.41 (0.023)	10.4 (4.96)	0.33 (0.045)
SC	35.9 (4.51)	1.16 (0.041)	96.0 (10.45)	3.1 (0.095)
SD	70.8 (21.84)	2.28 (0.198)	420.0 (49.68)	13.55 (0.449)
TN	34.8 (13.23)	1.12 (0.12)	342.2 (40.86)	11.04 (0.37)
TX	24.2 (11.91)	0.78 (0.108)	168.5 (20.00)	5.44 (0.181)
UT	10.4 (7.20)	0.33 (0.065)	228.5 (26.57)	7.37 (0.24)
VA	34.2 (8.31)	1.1 (0.075)	122.6 (19.00)	3.96 (0.172)
VT	65.1 (13.25)	2.1 (0.12)	58.9 (16.08)	1.9 (0.145)
WA	20.2 (6.84)	0.65 (0.062)	98.6 (11.24)	3.18 (0.102)
WI	28.7 (9.29)	0.93 (0.084)	212.3 (28.65)	6.85 (0.259)
WV	13.5 (6.21)	0.44 (0.056)	80.3 (19.50)	2.59 (0.176)
WY	13.6 (7.01)	0.44 (0.063)	359.4 (41.15)	11.59 (0.372)

(continued)

Table 4. *Continued.*

State	$\bar{Z}_G$	$\bar{B}$	$\bar{F}$	$\bar{B}^*$
Simple national average	29.25	0.94	197.95	6.39
Simple national SD	18.64	0.60	141.88	4.58
Weighted national average	31.55 (10.48)	1.02 (0.095)	247.4 (30.52)	7.98 (0.276)

Approximated standard errors in parentheses.

Table 5. Own state ($\hat{r}$) and social ($\hat{r}_1$) IRRs, with stochastic spatial effects (Model 2) 95% confidence intervals in brackets.

State	$\hat{r}$	$\hat{r}_1$	State	$\hat{r}$	$\hat{r}_1$	State	$\hat{r}$	$\hat{r}_1$
AL	18.01 [15.7; 19.7]	25.91 [24.0; 27.4]	MD	2.78 [n/a; 7.2]	20.74 [15.7; 23.6]	OR	1.99 [n/a; 13.9]	26.9 [24.7; 28.6]
AR	20.28 [13.9; 23.5]	32.53 [30.4; 34.3]	ME	23.18 [20.4; 25.2]	22.4 [18.9; 24.7]	PA	14.9 [7.7; 18.1]	17.88 [n/a; 22.5]
AZ	11.88 [7.8; 14.2]	29.14 [27.2; 30.7]	MI	17.12 [12.6; 19.7]	30.61 [28.3; 32.4]	RI	12.33 [9.6; 14.2]	11.26 [n/a; 14.9]
CA	13.97 [n/a; 18.2]	24.13 [22.2; 25.7]	MN	20.42 [15.7; 23.2]	32.45 [30.5; 34.0]	SC	18.18 [16.5; 19.5]	24.24 [22.7; 25.5]
CO	15.13 [10.1; 17.8]	34.01 [32.1; 35.6]	MO	20.36 [11.4; 24.0]	37.09 [35.1; 38.7]	SD	22.3 [16.6; 25.4]	34.66 [32.6; 36.3]
CT	13.04 [10.6; 14.7]	12.42 [n/a; 17.1]	MS	14.12 [10.2; 16.5]	28.24 [26.6; 29.6]	TN	17.99 [10.1; 21.4]	33.1 [31.1; 34.7]
DE	17.73 [13.4; 20.3]	17.12 [6.7; 20.8]	MT	17.12 [14.3; 19.1]	30.24 [28.5; 31.7]	TX	15.89 [n/a; 19.9]	28.01 [26.2; 29.5]
FL	15.36 [13.1; 17.0]	21.75 [19.9; 23.2]	NC	20.79 [18.2; 22.7]	28.27 [26.5; 29.7]	UT	11.27 [n/a; 16.0]	30.14 [28.3; 31.7]
GA	17.41 [14.5; 19.4]	27.61 [25.5; 29.2]	ND	17.19 [14.8; 18.9]	29.68 [27.9; 31.1]	VA	17.89 [14.1; 20.3]	25.85 [23.4; 27.7]
IA	18.38 [n/a; 22.5]	34.1 [32.1; 35.7]	NE	20.44 [15.8; 23.2]	36.41 [34.5; 38.0]	VT	21.77 [18.6; 23.9]	21.16 [16.5; 23.9]
ID	17.45 [13.8; 19.7]	30.07 [28.2; 31.6]	NH	20.15 [17.4; 22.1]	23.12 [20.5; 25.0]	WA	14.89 [8.9; 17.8]	24.42 [22.8; 25.8]
IL	12.19 [n/a; 17.0]	33.44 [31.4; 35.1]	NJ	12.46 [9.7; 14.3]	13.86 [n/a; 18.7]	WI	16.87 [11.1; 19.8]	29.62 [27.4; 31.3]
IN	17.02 [11.7; 19.9]	28.58 [26.4; 30.3]	NM	15.81 [9.7; 18.8]	30.49 [28.4; 32.2]	WV	12.69 [0.5; 16.3]	23.1 [19.0; 25.7]
KS	21.5 [17.6; 24.0]	32.43 [30.7; 33.9]	NV	8.68 [n/a; 14.9]	28.17 [25.9; 29.9]	WY	12.71 [n/a; 16.7]	33.47 [31.5; 35.0]
KY	13 [n/a; 17.8]	33.29 [31.2; 35.0]	NY	10.31 [0.3; 13.7]	15.02 [n/a; 20.8]	SNA*	15.69 [9.7; 18.8]	26.95 [23.1; 29.1]
LA	7.97 [n/a; 12.0]	27.53 [25.7; 29.0]	OH	17.45 [13.6; 19.8]	28.68 [26.4; 30.4]	WNA*	16.54 [8.6; 19.8]	29.31 [26.5; 29.3]
MA	15.46 [12.9; 17.3]	15.26 [n/a; 19.9]	OK	17.15 [14.1; 19.2]	35.1 [33.3; 36.6]			

n/a: IRR can not be calculated since the corresponding shadow value is negative, SNA simple national average, WNA weighted national average.
* The bounds of the confidence intervals for the National Averages are calculated as the average of the respective bounds for all states.

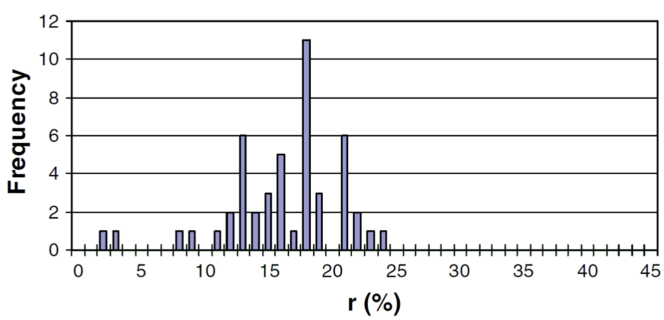

Figure 3. Histogram of the own state IRRs ($\hat{r}$)—Model 2.

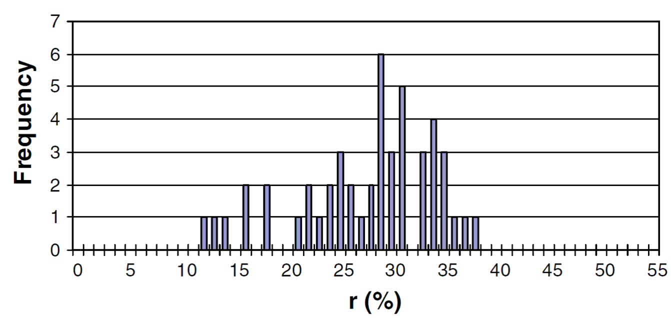

Figure 4. Histogram of the social IRRs ($\hat{r}_1$)—Model 2.

tion that these states produce specialty crops that are not produced in other areas of the country leading to minimal spillovers. The set of states at the opposite side of this spectrum, those with high spillovers are not, except for Illinois, ones thought of as major agricultural producers. This set includes Maryland, Utah, Oklahoma, Colorado, Nevada, Louisiana, Kentucky, Wyoming, Illinois, and Oregon. Presumably these states' public agricultural research is not appropriated fully by each of them but they have important positive effects on other states. These states have below average own IRRs of 10% but important spillover effects of 20%. The states with major agricultural sectors lie in the middle of this distribution. These state's own IRRs and spillover rates are higher than the average, 19 and 13% respectively. They have been able to appropriate their investments as reflected by the decrease in their costs of production plus they have facilitated important productivity improvements in other states, presumably those with similar production characteristics. The explanation of these patterns, though not the objective of this paper, is deserving of additional research and a natural next step to the analysis here.

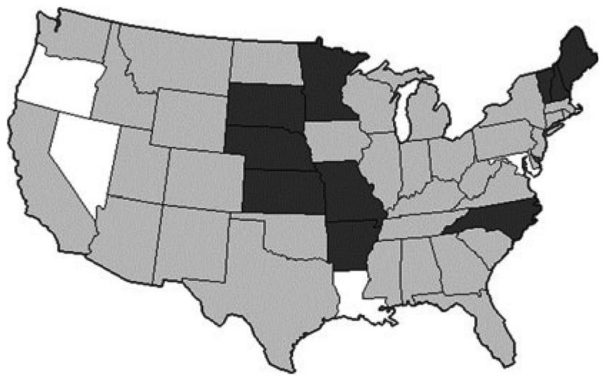

Figure 5. Own state IRRs to public agricultural R&D—Model 2. References: White $r = 0–10\%$; Gray $r = 10–20\%$; Black $r > 20\%$.

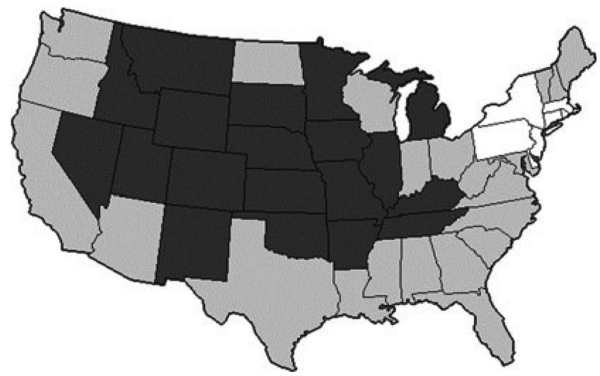

Figure 6. Social IRRs to public agricultural R&D expenditures—Model 2. References: White $r = 10–20\%$; Gray $r = 20–30\%$; Black $r > 30\%$.

5. Conclusions

The present study is an attempt at providing a quantitative assessment of the returns to public agricultural R&D investments in the United States. This is done first by deriving the returns to a local public good from a theoretical model of firm behavior using the concept of virtual prices, then showing how to measure them when no information is available on market rates of return. Our method explicitly acknowledges for the spillover effects of these investments by incorporating them structurally and stochastically in the model and by allowing endogenous derivation of virtual prices, own and social. The objective is to use these estimates in calculating marginal internal rates of return to the use of public monies on R&D investments in agriculture. The study uses a data set of inputs and outputs developed by Craig, Pardey, and Acquaye for specific use in productivity analysis combined with R&D stocks built following Evenson's inverted-V lag structure in a model allowing for spatial stochastic corrections.

The *own state* internal rate of return we estimate is, on average for the nation, 17%. The *social* internal rate of return we estimate is, on average, 29%.

Knowledge spillovers are important in agriculture and an attempt at capturing all information structurally and stochastically should be considered. After adjusting for stochastic spatial effects, the estimated returns to agricultural investments in R&D in the United States are fairly high, but lower than estimates for the Midwest by Huffman et al. (2002).

Although not a primary focus of this analysis, our study has also found that in aggregate US agriculture, technical change induced by public agricultural R&D has been biased towards the use of capital and purchased inputs and against the use of labor. We also found evidence of potential long term impacts of public R&D investments on long run growth of the sector.

A number of important shortcomings of this analysis should be mentioned. First, we know of updated data sets for US agriculture being developed by USDA and by Alston, Pardey, and colleagues. Presumably these would be better to use in the analysis, but the data needed for this analysis is not yet available for public use. Second, given the growing importance of private investments in agricultural R&D, we might err by attributing benefits to public investments that might have been the result of private investments. We hope that the quality adjustments included by Craig, Pardey, and Acquaye in the painstaking job of constructing the output and input indexes are enough to diminish the impact of this potential flaw. We would expect that the appropriable benefits of private research are embodied in the input aggregates used and therefore effectively captured in this study. Similarly, the omission of the extension services, the stock of infrastructure, and of international spillovers as well as USDA's intramural research might also render our estimates upward biased. Third, our analysis is static, and assumes naïve expectation formation in production and decision making, all these compromising our estimates.

All in all, even if we provide estimates of the rate of return to public R&D in agriculture lower than previously suggested, an average return of 29% on public funds is still impressive compared to the 9 and 12% average returns of the S&P500 and NASDAQ composite indexes during the same period.

Acknowledgments — We thank the support provided by the Nebraska Agricultural Experiment Station in the form of a research assistantship for Dr. Plastina during his graduate work at UNL. In particular, we thank Dr. Darrell Nelson, Dean of Agricultural Research and Director of the Nebraska Agricultural Experiment Station (1988–2005), University of Nebraska-Lincoln, for his personal interest and support on this project. In particular his intervention was crucial in obtaining the data on public R&D expenditures. We also thank the support received from the late Dr. Catherine Morrison-Paul.

Appendix 1: Descriptive statistics

Table 6. Descriptive statistics of the variables pooled through time and states.

Variable	Units	N	Mean	SD	Minimum	Maximum
Output quantity	(1949 = 100)	2,064	145.51	55.88	62.65	418.68
Land quantity	(1949 = 100)	2,064	84.56	20.34	23.63	122.88
Labor quantity	(1949 = 100)	2,064	59.49	21.22	16.68	100.99
Capital quantity	(1949 = 100)	2,064	121.47	33.32	40.72	302.30
Purchased inputs quantity	(1949 = 100)	2,064	179.36	85.60	39.08	562.24
Expenditures on land in 1949	$1,000	48	132,515	116,648	2,119	529,117
Expenditures on labor in 1949	$1,000	48	303,343	217,003	11,909	931,771
Expenditures on capital in 1949	$1,000	48	177,403	143,910	8,546	526,525
Expenditures on purchased inputs in 1949	$1,000	48	140,533	115,487	8,641	534,242
Total Value of agricultural output in 1949	$1,000	48	620,240	566,447	21,858	2,399,574

Source: Acquaye et al. (2003)

Table 7. Descriptive statistics of the variables used in the analysis pooled through time and states.

Variable	Units	N	Mean	SD	Minimum	Maximum
w_M	(1949 = 100)	2,064	201	117	94	593
w_L	(1949 = 100)	2,064	446	328	95	1,415
w_K	(1949 = 100)	2,064	207	115	84	483
SH_M	Proportion of the variable cost	2,064	0.3882	0.1182	0.1455	0.8195
SH_L	Proportion of the variable cost	2,064	0.2810	0.0986	0.0623	0.6594
SH_K	Proportion of the variable cost	2,064	0.3307	0.0651	0.1182	0.5300
T	$1,000 (constant 1949 dollars)	2,064	122,989	118,897	587	532,774
y	$1,000 (constant 1949 dollars)	2,064	920,314	905,341	14,694	5,631,427
G	$1,000 (constant 1949 dollars)	2,064	1,729	1,943	99	16,624
S	$1,000 (constant 1949 dollars)	2,064	7,649	5,979	138	31,426
c	$1,000 (constant 1949 dollars)	2,064	664,066	545,272	10,702	3,183,774

Sources G and S are based on author's calculations. All other variables are from Acquaye et al. (2003).

Appendix 2: Model 1, no SAR error structure

Method of estimation: ITSUR.
Parameters in the model: 174.
Linear Restrictions: 55.
Parameters Estimated: 119.
Method: Gauss.
Number of Iterations: 50.
Final Convergence Criteria: CONVERGE = 0.001
Criteria Met.
Observations Processed: 2064.

Equation	DF model	DF error	R^2	Adj. R^2	AIC
ln c	83.11	1,981	0.8084	0.8004	0.24942
SH_M	17.94	2,046	0.9376	0.9371	0.001031
SH_K	17.94	2,046	0.8034	0.8017	0.000985

System R^2: 0.896487

Parameter estimates

Parameter	Estimate	SE	T-value	Parameter	Estimate	SE	T-value
δ_T	1.661054	0.1796	9.25	β_{KY}	−0.03839	0.00509	−7.54
δ_Y	−1.03266	0.2336	−4.42	β_{TY}	0.144139	0.0386	3.73
δ_G	0.439636	0.2601	1.69	β_{MG}	0.009626	0.00415	2.32
β_{MK}	0.067766	0.00568	11.93	β_{LG}	−0.01025	0.00386	−2.65
β_{MT}	−0.01813	0.00601	−3.02	β_{KG}	0.000619	0.00377	0.16
β_{MY}	0.124598	0.00561	22.21	β_{TG}	0.014571	0.0281	0.52
β_{LK}	0.037924	0.00415	9.14	β_{YG}	−0.09133	0.0463	−1.97
β_{LT}	0.068861	0.00575	11.98	β_{GS}	−0.24097	0.021	−11.46
β_{LY}	−0.08621	0.0052	−16.56	β_{ML}	0.081212	0.00325	24.98
β_{LL}	−0.11914	0.00352	−33.87	β_{MS}	0.034992	0.00415	8.43
β_{MM}	−0.14898	0.00501	−29.71	β_{LS}	−0.03773	0.00387	−9.75
β_{KK}	−0.10569	0.00835	−12.66	β_{KS}	0.002742	0.00388	0.71
β_{TT}	−0.19386	0.0293	−6.62	β_{TS}	−0.16861	0.0162	−10.39
β_{YY}	−0.07296	0.0644	−1.13	β_{GG}	0.31271	0.0374	8.35
β_{KT}	−0.05074	0.00559	−9.07	β_{YS}	0.239682	0.0181	13.25

Parameters estimates of dummy variables are not reported but can be obtained from the authors.

Appendix 3: Model 2, with SAR error structure

Method of estimation: ITSUR.
Parameters in the model: 174.
Linear Restrictions: 55.
Parameters Estimated: 119.

Method: Gauss.
Number of Iterations: 41.
Final Convergence Criteria: CONVERGE = 0.001
Criteria Met.
Observations Processed: 2064.

Equation	DF model	DF error	R^2	Adj. R^2	AIC
ln c^*	83.11	1,981	0.9324	0.9296	0.06615
$SH_M{}^*$	17.94	2,046	0.926	0.9254	0.000611
$SH_K{}^*$	17.94	2,046	0.8904	0.8895	0.000418

System R^2: 0.911236
* Transformed variables

Parameter	Estimate	SE	T-value	Parameter	Estimate	SE	T-value
δ_T	1.007875	0.1101	9.15	β_{KY}	−0.05499	0.00384	−14.33
δ_Y	−0.35228	0.1432	−2.46	β_{TY}	−0.07576	0.0204	−3.71
δ_G	−0.40512	0.1617	−2.51	β_{MG}	0.013477	0.00299	4.51
β_{MK}	0.074332	0.00888	8.37	β_{LG}	−0.01807	0.0026	−6.95
β_{MT}	−0.03649	0.00736	−4.96	β_{KG}	0.004589	0.0026	1.77
β_{MY}	0.135337	0.00451	30.02	β_{TG}	0.035987	0.0166	2.17
β_{LK}	0.070494	0.00739	9.54	β_{YG}	−0.04832	0.0268	−1.80
β_{LT}	0.076869	0.00634	12.12	β_{GS}	0.035599	0.0132	2.69
β_{LY}	−0.08035	0.00378	−21.25	β_{ML}	0.058759	0.0058	10.14
β_{LL}	−0.12925	0.0072	−17.95	β_{MS}	0.040074	0.00347	11.54

Parameter	Estimate	SE	T-value	Parameter	Estimate	SE	T-value
β_{MM}	−0.13309	0.00907	−14.68	β_{LS}	−0.03284	0.00329	−9.99
β_{KK}	−0.14483	0.0119	−12.20	β_{KS}	−0.00724	0.00342	−2.12
β_{TT}	0.03303	0.0156	2.12	β_{TS}	−0.05169	0.0096	−5.39
β_{YY}	0.161682	0.0351	4.61	β_{GG}	0.039228	0.0207	1.89
β_{KT}	−0.04038	0.00602	−6.70	β_{YS}	0.020784	0.0104	2.00

The parameters corresponding to dummy variables are not reported but can be obtained from the authors.

References

Acquaye A, Alston J, Pardey P (2003) Post-war productivity patterns in US agriculture: Influences of aggregation procedures in a state-level analysis. Am J Agric Econ 85(1):59–80

Alston J (2002) Spillovers. Aust J Agric Resour Econ 46(3):315–346

Alston, J, Barbara C, Philip P (1998) Dynamics in the creation and depreciation of knowledge and the returns to research. EPDT discussion paper 35, IFPRI, Washington, DC

Alston J, Marra M, Philip P, Wyatt TJ (2000) Research returns redux: a meta-analysis of the returns to agricultural R&D. Aust J Agric Resour Econ 44(2):185–215

Andersen M, Julian A, Philip P (2007). Capital use intensity and productivity biases. University of Minnesota, Department of Applied Economics Staff Paper P07-06, InSTePP Paper 07-02

Anselin L (1998) Spatial econometrics: Methods and models. Kluwer, Dordrecht

Chambers RG (1988) Applied production analysis: A dual approach. Cambridge University Press, New York

Chavas J-P, Cox TL (1992) A nonparametric analysis of the influence of research on agricultural productivity. Am J Agric Econ 74(3):583–591

Cohen JP, Morrison Paul CJ (2007) The impacts of transportation infrastructure on property values: A higher-order spatial econometrics approach. J Reg Sci 47(3):457–478

Craig B, Philip P, Albert A (2002) Data documentation: US agricultural input, output and productivity series 1949–1991. http://www.apec.umn.edu/faculty/ppardey/data.html

Economic Research Service, USDA (1998) Patterns of state productivity growth in the US farm sector. Staff Paper 9804, July

Evenson RE (1967) The contribution of agricultural research to production. J Farm Econ 49(5):1415–1425

Evenson RE (1989) Spillover effects of agricultural research: Evidence from US experience. Am J Agric Econ 71(2):447–452

Evenson RE (2001) Economic impacts of agricultural research and extension. In: Gardner BL, Rausser G, eds., Handbook of agricultural economics, vol 1A. North-Holland, New York, pp 574–628

Fulginiti L, Perrin RK (1993) Theory and measurement of producer response under quotas. Rev Econ Stat 75(1):97–107

Greene WH (2003) Econometric analysis, 5th edn. Prentice Hall, Upper Saddle River

Huffman WE, Evenson RE (1989) Supply and demand functions for multiproduct US cash grain farms: Biases caused by research and other policies. Am J Agric Econ 71(3):761–773

Huffman WE, Evenson RE (1992) Contributions of public and private science and technology to US agricultural productivity. Am J Agric Econ 74(3):751–756

Huffman WE, Evenson RE (1993) Science for agriculture: A long term perspective. Iowa State University Press, Ames

Huffman WE, Evenson RE (2001) Structural and productivity change in US agriculture, 1950–1982. Agric Econ 24:127–147

Huffman WE, Evenson RE (2006) Do formula or competitive grant funds have greater impacts on state agricultural productivity? Am J Agric Econ 88(4):783–798

Huffman WE, Eldon Ball V, Gopinath M, Somwaru A (2002) Public R&D and infrastructure policies: Effects on cost of midwestern agriculture. In: Ball E, Norton G (eds) Agricultural productivity: Measurement and sources of growth. Kluwer, Dordrecht

Keleijian HH, Prucha IR (2004) Estimation of simultaneous systems of spatially interrelated cross sectional equations. J Econ 118:27–50

Keleijian HH, Robinson DP (1992) Spatial autocorrelation: A new computationally simple test with an application to per capita county policy expenditures. Reg Sci Urban Econ 22(3):317–331

Khanna J, Huffman WE, Sandler T (1994) Agricultural research expenditures in the United States: A public goods perspective. Rev Econ Stat 76(2):267–277

Knutson M, Tweeten LG (1979) Toward an optimal rate of growth in agricultural production research and extension. Am J Agric Econ 61(1):70–76

Latimer R, Paarlberg D (1965) Geographic distribution of research costs and benefits. J Farm Econ 47(2):234–241

Lu YC, Philip C, LeRoy Q (1979) Prospects for productivity growth in US agriculture. US Department of Agriculture, Bureau of Economics, Statistics, and Cooperative Service. Agricultural economic report 435

McCunn A, Huffman WG (2000) Convergence in US productivity growth for agriculture: Implications of interstate research spillovers for funding agricultural research. Am J Agric Econ 82(2):370–388

Oehmke JF (1996) The maturity of the US agricultural research system and its impact on productivity. Department of Agricultural Economics, Michigan State University, East Lansing, Michigan. Staff Paper 96-85

Onofri A, Fulginiti L (2008) Public inputs and dynamic producer behavior: Endogenous growth in US agriculture. J Prod Anal 30(1):13–28

Pardey PG, Craig B (1989) Causal relationships between public sector agricultural research expenditures and output. Am J Agric Econ 71(1):9–19

Pardey P, Matt A, Barbara C (2007) Primary data documentation—US agricultural input, output, and productivity series, 1949–2002 (version 4). St Paul: Department of Applied Economics, University of Minnesota, Unpublished 2007

Plastina A, Lilyan F (2007) Rates of return to public agricultural research in 48 US states. Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, July 29–August 1, Portland, OR. Available online at http://purl.umn.edu/9858

Rothbart E (1941) The measurement of change in real income under conditions of rationing. Rev Econ Stud 8:100–107

Schimmelpfennig D, Thirtle C (1994) Cointegration and causality: Exploring the relationship between agricultural R&D and productivity. J Agric Econ 45:220–231

USDA, Agricultural Research Service, Funds for research at state agricultural experiment stations, Washington, D.C., 1960–1973

USDA, Agricultural Research Service, Report on the state agricultural experiment stations, Washington, D.C., 1954–1960

USDA, Office of Experiment Stations, Annual report of the Office of Experiment Stations for the year ended, Washington, D.C., 1904–1911

USDA, Office of Experiment Stations, Report on agricultural experiment stations and cooperative agricultural extension work in the United States for the year ended, Washington, D.C., 1916–1918

USDA, Office of Experiment Stations, Report on the agricultural experiment stations, Washington, D.C., 1926–1953

USDA, Office of Experiment Stations, Report on the work and expenditures of the agricultural experiment stations during the fiscal year ended, Washington, D.C., 1912–1915

USDA, Office of Experiment Stations, Work and expenditures of the agricultural experiment stations, Washington, D.C., 1918–1926

White FC, Havlicek J Jr (1979) Rates of return to agricultural research and extension in the southern region. South J Agric Econ 11:107–111

Yee J, Huffman WE, Aheran M, Newton D (2002) Sources of agricultural productivity growth at the state level, 1960–1993. In: Ball E & Norton G, eds., Agricultural productivity: Measurement, sources of growth. Kluwer, Dordrecht