Agricultural R&D Lags from a Dual Perspective

Authors:

Presenting Author:
Xiaojia Yao
University of Wyoming
Department of Agricultural and
Applied Economics
xyao@uwyo.edu

Co-Author:
Matt Andersen
University of Wyoming
Department of Agricultural and
Applied Economics
mander60@uwyo.edu

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1. Introduction

This paper examines the role of public agricultural research and development (*R&D*) in the process of knowledge production and productivity growth in U.S. agriculture from a new perspective. Specifically, we estimate knowledge production functions using a dual measure of productivity. The authors have not seen a dual measure of productivity applied in this context, and the results provide some valuable insights into the process of knowledge production and productivity growth in U.S. agriculture. The primary objective is to identify a preferred research lag specification for estimating knowledge production functions from a dual approach, and compare the results with some recent literature examining research lag specifications for U.S. agriculture.

The paper begins with a discussion of some relevant literature describing the theoretical relationship between primal and dual measures of productivity growth and the conditions under which these measures are equivalent. We examine measures of productivity growth for U.S. agriculture for the nation and the 48 contiguous states that were obtained from a primal and dual approach, and some important differences in the measures are presented and discussed. Next, we expand on recently published research by Alston, Andersen, James, and Pardey (2010), in which the authors conduct a grid search of different research lag distributions for the purpose of estimating knowledge production functions.[1] We replicate some of their analysis using a dual approach, and our results support a main finding of their research. Namely, research lags are substantially longer than previously considered by other studies on this topic. Furthermore, the dual approach in this paper indicates a very similar research lag distribution as a primal approach

[1] For the remainder of this paper the Alston, Andersen, James, and Pardey (2010) study will be referred to as the AAJP study.

providing additional important evidence about how *R&D* expenditures translate into productivity improvements over time.

2. Dual Measures of Productivity

In this section we formalize the relationship between primal and dual measures of productivity and provide a brief review of some important literature on this topic. A measure of productivity can be calculated as a residual from a production function or alternatively as a residual from a dual cost function. Similarly, an index of productivity can be calculated as the ratio of an index of the quantity of aggregate output to an index of the quantity of aggregate input, or alternatively as the ratio of an index of the price of aggregate input to an index of the price of aggregate output. The primal and dual indexes are equal under very restrictive economic conditions. Additionally, many of the factors that affect measures of productivity, such as macroeconomic influences related to the business cycle, or technology shocks, may affect the primal and dual measures of productivity differentially.

Increases in productivity have the effect of shifting the supply function for outputs. The outward shift may be parallel or pivotal, and the magnitude of the resulting output price effect depends on the elasticity of demand. The more inelastic the demand, the greater the resulting price decrease from an outward shift in the supply function. Changes in technology also affect prices in factor markets, and the aggregate effect depends on such things as the elasticity of demand for inputs and the substitutability among inputs. In the case of U.S. agriculture, price distortions from subsidies and other government programs may dampen or amplify the price effects of productivity changes in output and input markets. The United States is also a major exporter and importer of agricultural products so international markets also affect the domestic prices of agricultural products and the quantities produced. These factors should be kept in mind when interpreting dual measures of productivity, which are perhaps even more sensitive to market distortions than primal measures.

The basic duality relationship for multi-factor productivity indexes was outlined by Siegel (1961). Jorgenson and Griliches (1967) formalized the relationship between the primal and dual measures of *MFP*. Hulten (1986) showed that under perfect competition the change in *MFP* can be calculated using data on input and output prices. Antle-Capalbo (1988) showed that the primal and dual rates of technological change are the same if and only if there are constant returns to scale in production. Roeger (1995) examined differences in primal and dual measures of productivity for the U.S. manufacturing sector and concluded that these measures are similar once imperfect competition was incorporated in the analysis. In what follows we use a similar framework to one established by Jorgenson and Griliches (1967). Assuming perfect competition, exogenous prices, and constant returns to scale in production, a fundamental identity for each period is that the value of output is equal to the value of input:

$$p_1q_1 + p_2q_2 + ... + p_mq_m = w_1x_1 + w_2x_2 + ... + w_nx_n \tag{1}$$

where there are m outputs and n inputs, q_i is the quantity of the i^{th} output; x_j is the quantity of the j^{th} input; p_i is the price of the i^{th} output; and w_j is the price of the j^{th} input, respectively.

A measure of multi-factor productivity growth is obtained by differentiating equation (1) with respect to time and dividing both sides by the corresponding total value. The result is an identity equation (2) between a weighted average of the sum of the rates of growth of output prices and quantities and a weighted average of the sum of rates of growth of input prices and quantities:

$$\sum_{i=1}^{m} u_i \left[\frac{\dot{p}_i}{p_i} + \frac{\dot{q}_i}{q_i} \right] = \sum_{j=1}^{n} v_j \left[\frac{\dot{w}_j}{w_j} + \frac{\dot{x}_j}{x_j} \right] \tag{2}$$

The weights u_i and v_j are given by the relative shares of the value of the i^{th} output in the value of total output, and the value of the j^{th} input in the value of total input:

$$u_i = \frac{p_i q_i}{\sum_{i=1}^{m} p_i q_i}; \; v_j = \frac{w_j x_j}{\sum_{j=1}^{n} w_j x_j} \tag{3}$$

$$u_i \geq 0, \; i = 1 \ldots m; \;\; v_j \geq 0, \; j = 1 \ldots n; \;\; \sum_{i=1}^{m} u_i = \sum_{j=1}^{n} v_j = 1.$$

The growth in a Divisia index of the quantity of total output may be defined in terms of the weighted average of the rates of growth of the individual outputs from (2); denoting the index of the quantity of output by Q, the rate of change of this index is,

$$\frac{\dot{Q}}{Q} = \sum_{i=1}^{m} u_i \frac{\dot{q}_i}{q_i} \,. \tag{4}$$

A Divisia index of the quantity of total input, X, has a rate of change equal to,

$$\frac{\dot{X}}{X} = \sum_{j=1}^{n} v_j \frac{\dot{x}_j}{x_j} \,. \tag{5}$$

The corresponding Divisia price indexes for total output, P, and total input, W, have respective rates of growth:

$$\frac{\dot{P}}{P} = \sum_{i=1}^{m} u_i \frac{\dot{p}_i}{p_i} \qquad (6)$$

$$\frac{\dot{W}}{W} = \sum_{j=1}^{n} v_j \frac{\dot{w}_j}{w_j} \quad . \qquad (7)$$

The rate of change of the primal measure of multi-factor productivity (MFP_p) may be expressed as:

$$\frac{M\dot{F}P_p}{MFP_p} = \frac{\dot{Q}}{Q} - \frac{\dot{X}}{X} \, . \qquad (8)$$

And the rate of change of the dual measure of productivity (MFP_d) may be expressed as:

$$\frac{M\dot{F}P_d}{MFP_d} = \frac{\dot{W}}{W} - \frac{\dot{P}}{P} \qquad (9)$$

Equations (8) and (9) are two definitions of multi-factor productivity growth which are dual to each other and equivalent by equation (2). In general, any index of multi-factor productivity can be computed either from indexes of the quantity of total output and total input or from the corresponding price indexes. Assuming perfectly competitive input and output markets, exogenous prices, a lack of any price distortions, no factor hoarding, constant return to scale in production, and long run equilibrium, these measures are theoretically equivalent.

$$MFP_p = \frac{Q}{X} = \frac{W}{P} = MFP_d \, . \qquad (10)$$

3. Data Analysis

The data used in this paper are from the International Science and Technology Practice and Policy (InSTePP) Center at the University of Minnesota, the same as those used in the AAJP study. The productivity data include Fisher Ideal Indexes of the prices and quantities of agricultural outputs and inputs in U.S. agriculture for the nation and the 48 contiguous states for the years 1949-2002. The price and quantity indexes were used to form the primal and dual indexes of *MFP* for comparison in this paper. Additional details about these data can be found in Pardey et al (2009). Data on public investments in agricultural *R&D* are also from InSTePP, and include a long time series of State and Federal investments on research and extension at State Agricultural Experiment Stations (SAES), as well as federal intramural research. Specific details about the data, including data sources and construction methods are available in AAJP.

In Figure 1 Graph (a) we show the indexes of the price of aggregate input and output in U.S. agriculture, 1949-2002. The price of inputs increased dramatically in this period, with the price of aggregate input almost 8 times higher in 2002 than 1949. The increase in the price of aggregate output was less dramatic in the same period, with the 2002 level approximately 2.5 times higher than the 1949 level. Figure 1 Graph (b) shows the indexes of the quantity of aggregate output and input, showing that aggregate output was approximately 2.5 times higher in 2002 than 1949, and aggregate inputs were slightly lower in 2002 as compared to 1949. The ratio of the series in Graph (a) and Graph (b) are the dual and primal indexes of *MFP* respectively, and both series are shown in Figure 1 Graph (c).

[Figure 1: *Production and Productivity Trends in U.S. Agriculture, 1949-2002*]

The simple correlation between the primal and dual *MFP* indexes is equal to 0.977, which is remarkable given the many factors that are affecting each series. The dual *MFP* index is generally higher than the primal except for a few years where there were major downward fluctuations in the dual index. This is true during the turbulent economic period of the 1970s, where there was large downward shock in dual *MFP* from 1971-1973. Also note the divergence between the series that started in the mid-1990s and continues thru 2002. The dual *MFP* index increases rapidly in this period while the increase in the primal *MFP* index is less rapid, and possibly less than increases experienced in previous periods indicating a possible productivity slowdown.

Table 1 shows the annual average growth rates 1949-2002 of the indexes of input and output prices and quantities, as well as the primal and dual indexes of *MFP* for 48 states, 7 regions, and the nation as a whole.

[Table 1: *Average Growth Rates of Input and Output Prices and Quantities and Primal and Dual MFP, 1949-2002*]

Nationally, the price of aggregate inputs increased at an annual rate of 3.85 percent per year and the price of aggregate output grew at a rate of 1.63 percent per year, resulting in a national estimate of dual *MFP* growth of 2.21 percent per year from 1949 to 2002. Over the same period the aggregate quantity of output increased by 1.68 percent per year, while the aggregate quantity of input decreased slightly by 0.11 percent per year, and the primal *MFP* index grew by 1.78 percent per year. The difference between a 2.21 percent annual percentage growth rate and a 1.78 percent rate is substantial over a 54 year time span, so the primal and dual measures of *MFP* are quite different when considering annual averages.

In terms of the primal measures of productivity growth the Southeast (2.09% per year), Northern Plains (1.89% per year), and Southern Plains (1.88% per year) regions recorded the highest rates; the Northeast (1.64% per year), Central (1.61% per year), and Mountain (1.59% per year) regions the lowest. In terms of the dual measures, the Southern Plains (2.65% per year) recorded the highest productivity growth followed by the Northern Plains (2.47% per year) and Central Regions (2.31% per year); the Northeast (1.95% per year) and Pacific (1.56% per year) regions recorded the lowest.

Although the long-run trend shows that agricultural productivity growth has been sustained over the past several decades, there is significant year-to-year fluctuation in productivity due to weather, policy interventions, general economic conditions, and other factors. Figure 2 shows the primal and dual measures of productivity growth 1949-2002.

[Figure 2: *Growth Rates of the Primal and Dual Indexes of MFP, 1949-2002*]

Note that beginning in the early 1970s and continuing to the mid-1990s, both measures of *MFP* growth exhibited increased volatility. This can be partly explained by a number of specific events, such as the global energy crises of 1973 and 1979, serious droughts in 1983, 1988 and 1995, and an agricultural policy intervention in 1983 called the Payment-In-Kind, or PIK program. Table 2 shows the annual average growth rates of the primal and dual indexes for various sub-periods.

[Table 2: *Annual Average Growth Rates by Period*]

The figures in Table 2 indicate the large differences between the primal and dual indexes of *MFP* in terms of annual averages. Overall, the dual measures indicate higher levels of productivity growth but there are some interesting exceptions. For example, during the 1970-

1980 period the primal index of *MFP* indicated strong productivity growth of 2.51 percent per year, but the dual index indicated weak growth of only 1.05 percent per year. The opposite result holds for 1990-2002, where the primal index indicates weak productivity growth of 1.10 percent per year, and the dual index indicates strong growth of 2.21 percent per year.

4. Alternative Research Lag Distributions

The primarily concern of this paper relates to the dynamics linking research investment, knowledge stocks, and productivity; however, the relationship between public investments in agricultural *R&D* and the productivity enhancing benefits they produce is complicated. This is because of the large spillovers that public investments in *R&D* generate across entities and over time, and difficulties in properly attributing productivity enhancements to the various sources investing in agricultural research, commonly called the attribution problem (Alston 2002). The bottom line is that many different sources of research affect agricultural production, research takes a long time to affect production, and then it affects production for a very long time.

Constructing measures of knowledge stocks requires two primary tasks: deciding on the appropriate lag structure for accumulating past investments and deciding how to include the effect of spillover research from the outside. Both the shape as well as the length of the distribution is important. Many different lag structures for estimating knowledge stocks have been considered in the literature, including geometric, gamma, and trapezoidal distributions to name a few. In a recent study of U.S. agriculture Huffman and Evenson (2006) used a trapezoidal distribution to sum *R&D* expenditures. A gamma distribution has been utilized in studies by Alston, Craig, and Pardey (1998) and Alston, Pardey, and Carter (1994). These studies indicate a long lag between research investments and the measurable productivity enhancing benefits, so we consider a lag distribution with a maximum length of 50 years.

The gamma distribution has several favorable characteristics: 1) all lag weights determined by the function are non-negative; 2) the shape implied is relatively smooth; 3) the gamma distribution is unimodal; 4) the distribution can be skewed to give more weight to more recent or more distant lags; and 5) the distribution can be characterized by only two parameters, δ and λ. The gamma distribution weights that are used to calculate knowledge stocks are defined as in AAJP:

$$b_k = \frac{(k-g+1)^{\left(\frac{\delta}{1-\delta}\right)} \lambda^{k-g}}{\sum_{k=0}^{L} \left[(k-g+1)^{\left(\frac{\delta}{1-\delta}\right)} \lambda^{k-g} \right]}; \text{ for } L > k > g; \text{ otherwise } b_k = 0; \sum_{k=0}^{L} b_k = 1. \tag{11}$$

Where L is the lag length, g is the gestation period, and δ and λ are the parameters that define the shape of the gamma distribution.

Figure 3 shows an (8 *x* 8) grid of feasible gamma distributions with different values for parameters δ and λ and the gestation lag set to zero. Each parameter ranges from 0.6 to 0.95 in increments of 0.05, resulting in eight different values for each parameter. The resulting grid of 64 distributions includes a wide variety of possible shapes as can be seen in Figure 3. Each graph in Figure 3 indicates the peak year of the distribution as well as the number of years it takes 50 percent (C_{50}) and 75 percent (C_{75}) of the impact of spending to accumulate. The location of the peak year shows how many years it takes for a given investment to have the largest impact on the current stock of knowledge. It is important to note that the 64 distributions considered in this study (Figure 3) effectively allows the consideration of no gestation or an extremely long gestation, as well as distributions with all the weight given in the first few years and essentially none in the later and vice versa. We want to determine which distribution is best at explaining the behavior of the primal and dual measures of *MFP*.

[Figure 3: *Gamma Distribution Parameters and Shapes Used in Estimation*]

5. Econometric Analysis

In order to measure the contribution of research and development to economic growth, we specify the following general form:

$$MFP_{i,t} = f(SK_{i,t}, SS_{i,t}, Z_{i,t}) \tag{12}$$

We use the panel data on productivity for 48 contiguous states over the period 1949-2002, and panel data on U.S. public agricultural research stocks for the same period. This results in a panel data set with $N \times T = 48 \times 54 = 2{,}592$ observations. The model is focused on the productivity–enhancing effects of public *R&D* spending, implicitly setting aside spillover influences from private agricultural research, international agricultural *R&D*, and non-agricultural *R&D*.[2]

The variables in the model include:

- $MFP_{i,t}$ is a Fisher ideal index of multi-factor agricultural productivity in state i in year t, constructed using the dual price indexes.

[2] Knowledge production functions are inherently susceptible to specification errors because of the attribution problems discussed in this paper, the lack of available data, as well as our ability to capture all the sources affecting current productivity.

- $SK_{i,t}$ is the own-state stock of knowledge in state i in year t from own-state government spending on agricultural research, and extension, in real dollars.
- $SS_{i,t}$ is the state-specific spillover stock of knowledge in state i in year t from other-state government spending on agricultural research, and extension, and federal spillover research, in real dollars.
- $Z_{i,t}$ represents the effects of weather and other uncontrolled factors.

In our estimation we also include a variable to proxy the effect of weather on growing conditions, denoted $Z_{i,t}$. This is the same measure as was utilized in AAJP – a state-specific index of range and pasture conditions on September 1 of each year published by the Economics, Statistics, and Market Information System. It is not immediately apparent how the growing conditions index will affect the 'dual' regressions in this paper but it was included to make the results directly comparable with the AAJP study.[3]

The base model in this regression process is a linear model. We also estimate the model with all of the variables in natural logs. Given linear aggregation of the elements of the knowledge stocks the linear model can be represented as:

$$MFP_{i,t} = \beta_i + \beta_k SK_{i,t} + \beta_s SS_{i,t} + \beta_z Z_{i,t} + u_{i,t} \tag{13}$$

The final specification has two knowledge stock variables; one is the sum of own-state research and extension, and the other the sum of spillovers from research and extension in other states, as well as spillovers from federal research. The regressions also include a state-specific weather index, $Z_{i,t}$, and state-specific intercept terms (a fixed-effects model). We also assume

[3] We also estimated the preferred specifications with and without the growing conditions index to check if this had a significant impact on the other estimated coefficients in the model and there was not a significant impact.

that the error terms are *i.i.d*. random variables – independent and identically distributed across states and years.[4]

The analysis proceeds by first calculating 64 sets of knowledge stocks based on the 64 gamma distributions in Figure 3 and an assumed lag length of 50 years. The goal is to examine the best lag structure to represent the relationship between *R&D* expenditures, knowledge production, and the resulting productivity enhancing benefits by estimating the knowledge production functions under the different lag specifications and choosing the specification that produces the smallest Sum-of-Squared Errors (SSE). The resulting distribution is the best among all the distributions at explaining the behavior of *MFP*.

We focused on four primary models in the analysis, using either the primal or dual index of *MFP* as the independent variable in the regression, and all of the variables specified in either levels or natural logs. We estimated 64 specifications of each of the four models according to our grid of lag distributions, choosing the specification with lowest SSE for each model. All parameter estimates are 'fixed-effects' panel data estimates obtained from STATA. The general results of the regressions were that the knowledge stocks were very significant in most of the regressions using a primal measure of *MFP* in levels and logs, and the same was true for the regressions using a dual measure of *MFP* in logs. For most of the regressions using the dual measure of *MFP* in levels, the own-state research stock variable was insignificant. These patterns are also represented by the top ranked of the 64 specifications for each of the 4 models presented in Table 3, where Panel (a) shows the top ranked model estimates using the primal measure of *MFP* and Panel (b) the dual.

[4] We performed Hausman's specification test for random or fixed effects, indicating rejection of the null hypothesis that the difference in the random-effects and fixed-effects coefficients is not systematic; therefore the fixed effects estimator is the consistent estimator. Panel data issues such as heteroscedasticity and autocorrelation within the states, as well as contemporaneous correlation and heteroscedasticity between states was not modeled in this paper.

[Table 3: *Estimation Results for Top Ranked Primal and Dual Models*]

In the case of the linear dual model, the highest-ranked model corresponded to λ = 0.95 and δ = 0.60, implying a peak lag at year 28. In the case of the logarithmic dual model, the top ranked model corresponded to λ = 0.75 and δ = 0.90 and a peak lag at year 30. The double log model is the preferred model among the dual models because the estimated elasticities have the correct signs and size and the estimated coefficients are statistically significantly different from zero at the 1 percent level of significance. Furthermore, the model has a high *R*-square at 0.90 indicating the model explains 90 percent of the behavior of dual *MFP*. The weather index was insignificant so the same double log model was re-estimated without the weather index, and the coefficient estimates on the knowledge stocks were basically unchanged; therefore, the presence of the weather index is not biasing the other estimates.

Some interesting points can be drawn from a comparison of the primal and dual results. First, in terms of the double log specifications, primal model specification 51 minimized the SSE, and in the dual model specification 52 minimized SSE. The shape of the research lag distribution is similar in the primal and dual results but the peak lag year is later in the dual model (peak year 24 in the primal and 30 in the dual). This provides more evidence that it takes a long time for a given research investment to have a measurable economic benefit, and also suggests that the price effects that result from investments in *R&D* make take even longer to materialize than changes in the relationship between the quantities of inputs and outputs that are embodied in primal measures of productivity.

Second, the magnitudes of the elasticities in the dual log model seem reasonable and are actually very similar to the elasticity estimates in the linear primal model. The logarithmic dual model indicates a ten percent increase in the own-state knowledge stock results in approximately a 1 percent increase in *MFP*, and a ten percent increase in the stock of spillover knowledge results in an approximately 5 percent increase in *MFP*. The primal model in logs indicates a different relative contribution of own-state and spillover research. In this model a ten percent increase in own-state research stock results in a 3.22 percent increase in *MFP*, and a ten percent increase in spillover stock results in a 2.35 percent increase in *MFP*. By comparison, we can see that *MFP* becomes more sensitive to the spillover investment using the price index approach.

The results indicated in Table 3 for the preferred specification of the logarithmic dual model are also robust to the other top five specifications of this model ranked by the lowest SSE as can be seen in Table 4. The elasticity estimates are very similar for the listed specifications and all are statistically significantly different from zero at the 1 percent level of significance. The other top ranked specifications of the logarithmic dual model indicate lengthy peak lag effects at 34, 37, 44, 24, and 27 years for models 2 - 6 respectively.

[Table 4: *Summary of Results for the 50-Year Lag Dual Model in Logs, Top-Ranked Models*]

6. Conclusion

Some important conclusions that can be drawn from this paper are that public investments in agricultural *R&D* take a long time to affect production but eventually affect production for many years. This study suggests a peak affect 30 years after a given investment. The dual index of productivity examined in this paper is highly correlated to the primal index, but also differs substantially in terms of annual averages for the entire period under examination as well as various sub-periods. The dual index indicated strong productivity growth 1990-2002 (2.21 %) where the primal index indicated a productivity slowdown (1.10%) compared to long run levels. Generally, the dual index of *MFP* indicates a higher level of productivity growth than the primal index.

The shape of the research lag distribution identified in this paper was similar in the primal and dual analysis, with both methods indicating a slow progression of the effect of public investments on *MFP* (both indicating negligible research lag weights for 10 years after a given investment). In the dual model research was still affecting *MFP* 50 years after a given investment.

Public investments in *R&D* have substantial and measurable benefits in terms of enhancing our ability to produce agricultural goods given scarce resources.   Measuring those benefits is typically focused on the technological relationship between quantities of inputs used in production and the resulting outputs. But public investments in *R&D* also change relative prices of inputs and outputs in predictable ways that can also be used to track productivity changes and the benefits to *R&D*.   Ultimately, these investments are critical to insuring strong productivity growth in agriculture in the future, but this research suggests that we will have to be extremely patient in waiting for the full impact of the rewards.

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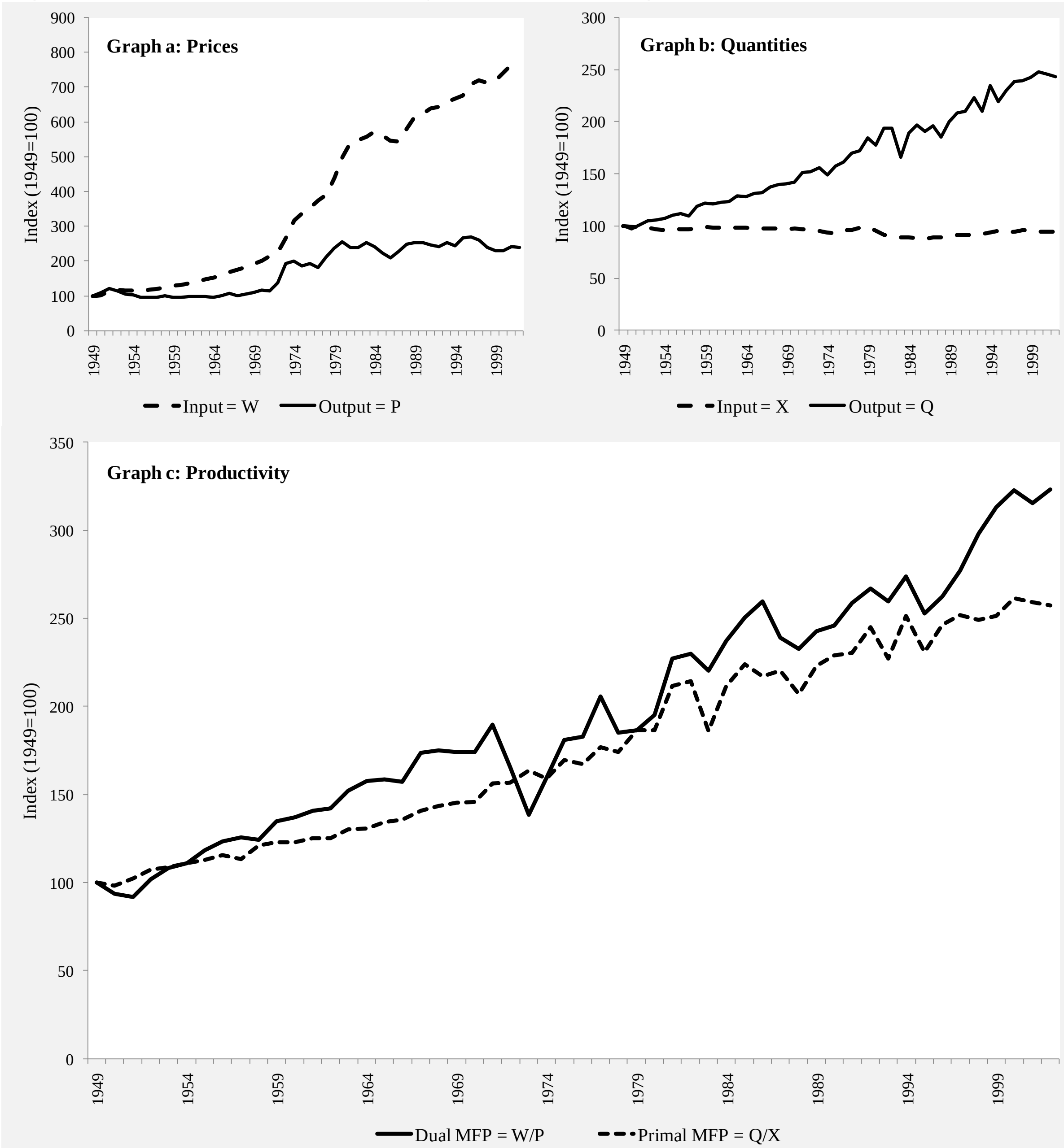
Figure 1: Production and Productivity Trends in U.S. Agriculture, 1949-2002

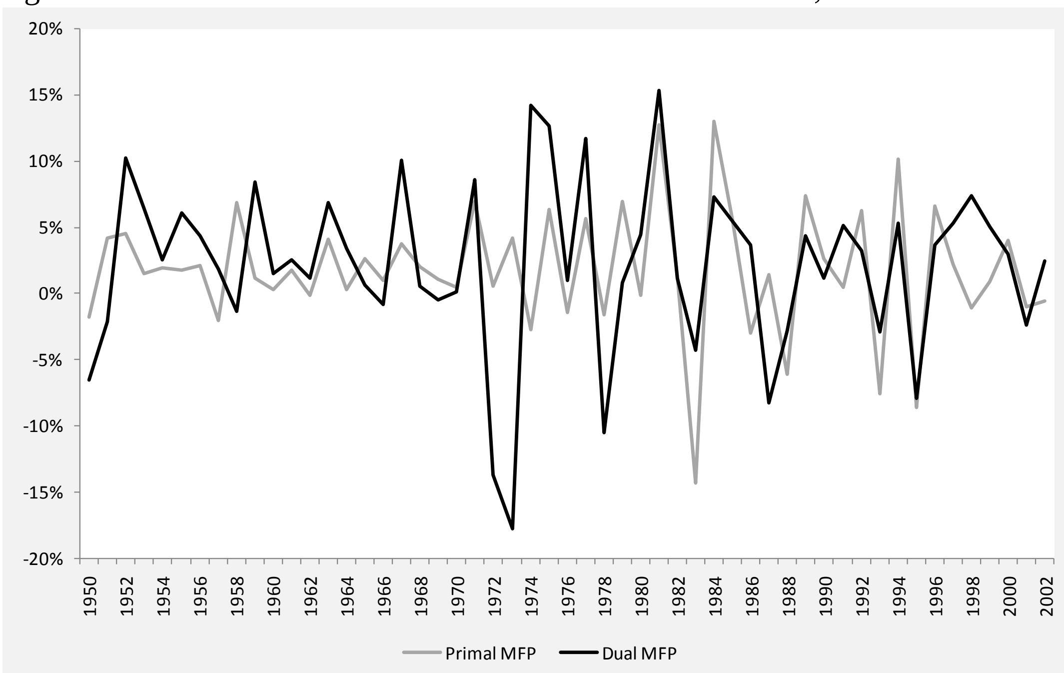


Source: InSTePP production accounts.

Table 1: Average Growth Rates of Input and Output Prices and Quantities and Primal and Dual *MFP*, 1949-2002

	Input Price	Output Price	Dual *MFP*	Input Quantity	Output Quantity	Primal *MFP*
	Average Annual Growth Rate, 1949-2002					
United States	**3.85**	**1.63**	**2.21**	**-0.11**	**1.68**	**1.78**
Pacific	**3.61**	**2.06**	**1.56**	**0.82**	**2.64**	**1.82**
California	3.59	2.11	1.48	0.97	2.74	1.77
Oregon	3.70	1.81	1.90	0.37	2.03	1.65
Washington	3.66	2.00	1.66	0.62	2.55	1.93
Mountain	**3.84**	**1.87**	**1.97**	**0.45**	**2.04**	**1.59**
Arizona	3.92	2.41	1.51	0.94	2.43	1.48
Colorado	3.58	1.82	1.76	0.54	1.90	1.35
Idaho	3.99	1.81	2.19	0.68	2.82	2.14
Montana	3.81	1.85	1.97	0.26	1.31	1.04
Nevada	5.04	2.17	2.87	0.21	1.09	0.88
New Mexico	3.81	1.61	2.19	0.59	2.36	1.77
Utah	3.64	1.70	1.94	-0.08	1.43	1.51
Wyoming	3.57	2.05	1.52	0.09	0.93	0.84
N Plains	**3.85**	**1.44**	**2.41**	**0.16**	**2.05**	**1.89**
Kansas	3.72	1.44	2.28	0.23	1.90	1.67
Nebraska	3.81	1.41	2.40	0.42	2.35	1.94
North Dakota	4.09	1.38	2.71	-0.18	1.94	2.12
South Dakota	3.89	1.65	2.24	-0.07	1.70	1.77
S Plains	**4.05**	**1.41**	**2.65**	**-0.12**	**1.76**	**1.88**
Arkansas	3.93	1.13	2.80	-0.02	2.87	2.89
Louisiana	4.10	1.29	2.81	-0.78	1.26	2.04
Mississippi	4.05	1.31	2.73	-0.97	1.99	2.95
Oklahoma	3.95	1.76	2.19	-0.04	1.29	1.33
Texas	3.72	1.48	2.24	0.20	1.53	1.32
Central	**3.87**	**1.49**	**2.37**	**-0.27**	**1.34**	**1.61**
Illinois	3.86	1.38	2.48	-0.27	1.27	1.54
Indiana	3.76	1.38	2.39	-0.34	1.21	1.56
Iowa	3.73	1.35	2.38	-0.03	1.65	1.68
Michigan	4.02	1.70	2.32	-0.59	1.20	1.79
Minnesota	3.98	1.47	2.51	-0.10	1.89	1.99
Missouri	3.99	1.43	2.56	-0.23	0.96	1.19
Ohio	3.87	1.52	2.35	-0.58	0.83	1.40
Wisconsin	3.81	1.97	1.84	-0.40	1.00	1.40
Southeast	**3.87**	**1.73**	**2.14**	**-0.41**	**1.68**	**2.09**
Alabama	3.95	1.63	2.32	-0.59	1.86	2.45
Florida	4.16	2.00	2.16	1.18	2.90	1.72
Georgia	3.81	1.20	2.61	-0.09	2.63	2.71
Kentucky	4.09	2.04	2.05	-0.46	0.41	0.87
North Carolina	4.05	1.74	2.32	-0.44	2.04	2.48
South Carolina	4.24	1.66	2.58	-1.38	0.94	2.32
Tennessee	4.10	1.77	2.33	-0.63	0.65	1.28
Virginia	3.97	1.76	2.21	-0.58	0.78	1.36
West Virginia	4.18	1.44	2.74	-1.60	-0.15	1.44
Northeast	**3.66**	**1.71**	**1.95**	**-0.84**	**0.80**	**1.64**
Connecticut	3.52	1.75	1.77	-1.39	0.00	1.39
Delaware	3.28	0.90	2.39	0.45	2.78	2.33
Maine	3.52	1.27	2.25	-1.37	0.31	1.67
Maryland	3.65	1.44	2.21	-0.30	1.69	1.99
Massachusetts	3.72	1.87	1.85	-1.99	-0.62	1.37
New Hampshire	3.66	1.79	1.88	-1.88	-0.42	1.46
New Jersey	3.59	2.04	1.55	-1.25	-0.22	1.03
New York	3.66	1.95	1.72	-0.99	0.31	1.30
Pennsylvania	3.80	1.63	2.17	-0.53	1.30	1.83
Rhode Island	3.73	2.04	1.69	-1.84	-0.39	1.45
Vermont	3.60	2.14	1.46	-0.87	0.57	1.44

Figure 2: Growth Rates of the Primal and Dual Indexes of *MFP*, 1949-2002



Source: Author's calculations using data from InSTePP production accounts. Annual growth rates calculated as the first difference of the natural logs the variables.

Table 2: Annual Average Growth Rates by Period

	Primal	**Dual**
Sub-periods	*average annual percentage change*	
1949-1960	2.04	2.91
1960-1970	1.68	2.34
1970-1980	2.51	1.05
1980-1990	1.79	2.48
1990-2002	1.10	2.21
1949-1990	2.01	2.19
1949-2002	1.78	2.21

Figure 3: Gamma Distribution Parameters and Shapes Used in Estimation

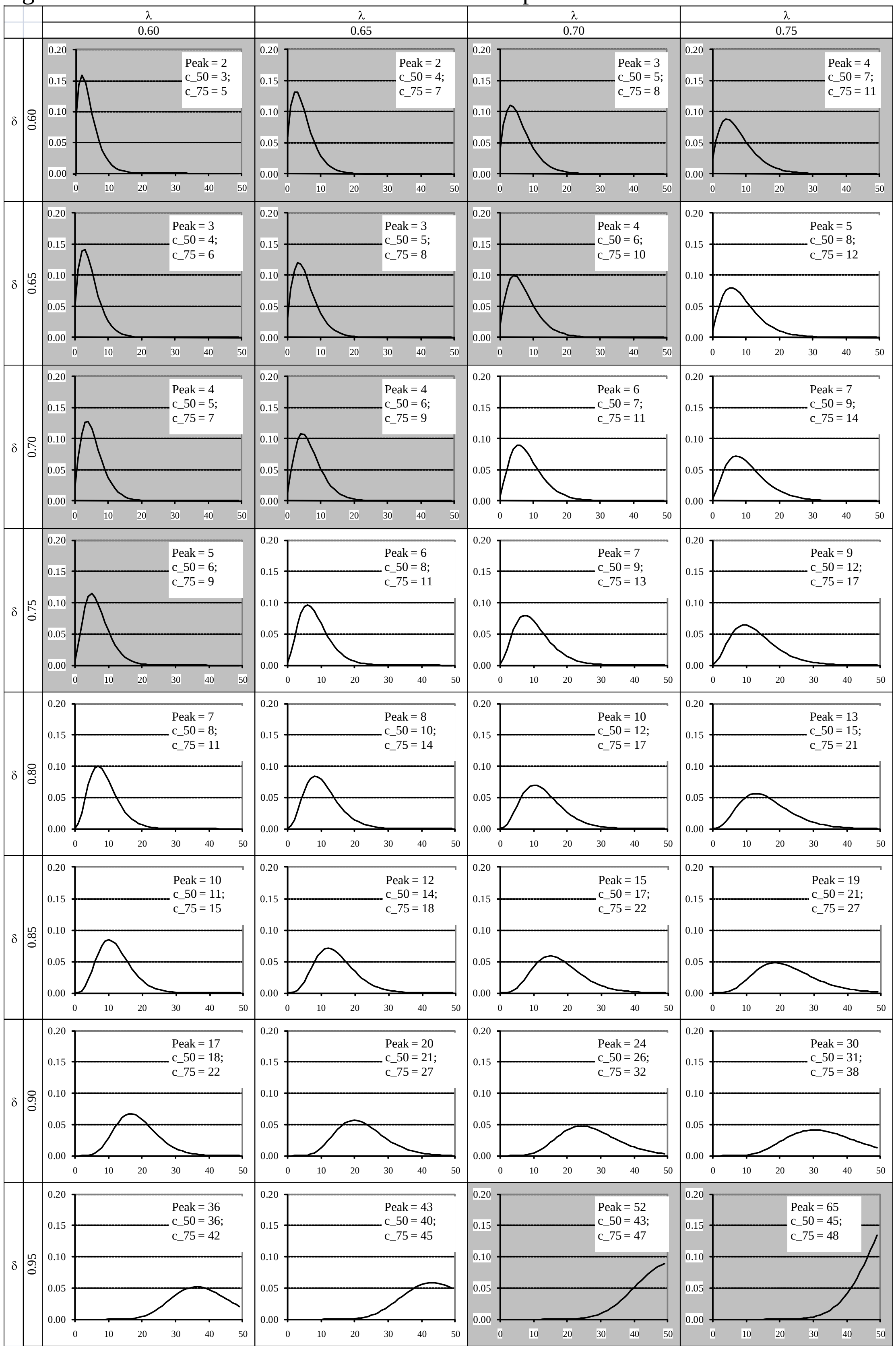
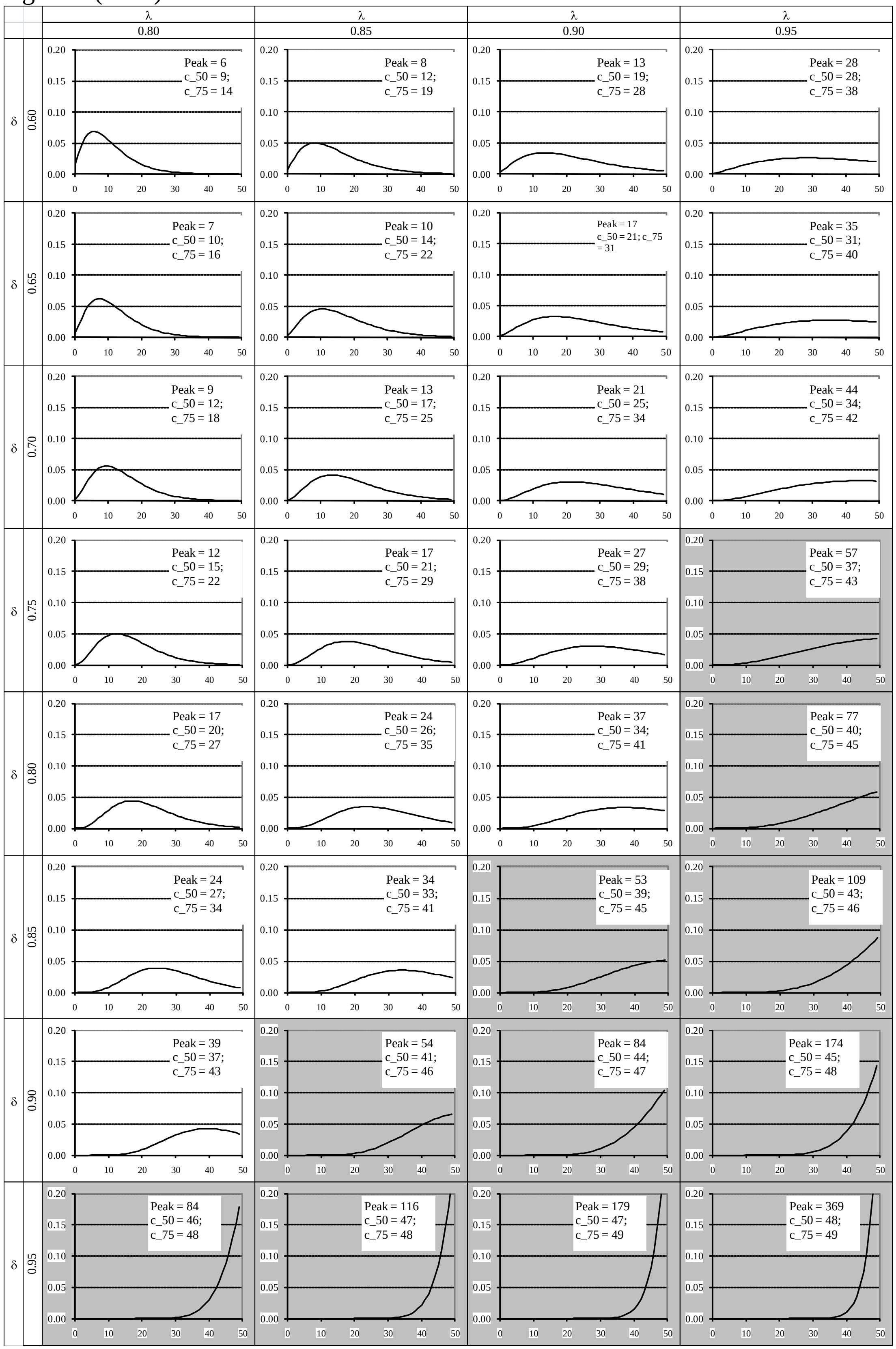


Figure 3 (cont.)



Source: Alston, Andersen, James, and Pardey (2010).

Notes: In each gamma distribution, c_50 indicates the number of years it takes for 50 percent of the impact of spending to accumulate to the knowledge stock. Similarly, c_75 indicates the number of years it takes for 75 percent of the impact of spending to accumulate.

Table 3: Estimation Results for Top Ranked Primal and Dual Models

Panel (a): Primal *MFP* model with 50 year lag distribution			
Model Results	*Own Research*	*Spillover Research*	*Z*
Linear Model[(a)]			
Elasticities	0.125***	0.530***	0.111***
Standard errors	(0.013)	(0.010)	(0.018)
R-sq = 0.734			
Logarithmic Model[(b)]			
Elasticities	0.322***	0.235***	0.111***
Standard errors	(0.017)	(0.017)	(0.010)
R-sq = 0.876			

Panel (b): Dual *MFP* model with 50 year lag distribution			
Model Results	*Own Research*	*Spillover Research*	*Z*
Linear Model[(c)]			
Elasticities	0.003	0.654***	0.016
Standard errors	(0.008)	(0.010)	(0.016)
R-sq = 0.825			
Logarithmic Model[(d)]			
Elasticities	0.098***	0.492***	0.013
Standard errors	(0.018)	(0.018)	(0.009)
R-sq = 0.900			

Notes: Number of observations is 2,592. Each regression includes state-specific intercept terms so df = 2,592 – 48 – 3 = 2,541. Model (a) has specification = 36, peak lag year = 13, $\lambda = 0.75$, and $\delta = 0.8$, Model (b) has specification 51, peak lag year = 24, $\lambda = 0.7$ and $\delta = 0.9$. Model (c) has specification = 8, peak lag year = 28, $\lambda = 0.95$ and $\delta = 0.6$. Model (d) has specification = 52, peak lag year = 30, $\lambda = 0.75$ and $\delta = 0.9$. Panel (a) estimates obtained from Alston, Andersen, James, and Pardey (2010).

Table 4: Summary of Results for the 50-Year Lag Dual Model in Logs, Top-Ranked Models

Model Details			**Results**			
Logarithmic model rank (ranked by SSE)	1	2	3	4	5	6
Lag Distribution Parameters						
λ	0.75	0.85	0.9	0.95	0.7	0.9
δ	0.9	0.85	0.8	0.7	0.9	0.75
Peak lag year	30	34	37	44	24	27
Implied elasticities						
Own research	0.1	0.1	0.11	0.12	0.11	0.13
Spillover research	0.49	0.48	0.47	0.47	0.53	0.49

Notes: All elasticity estimates are statistically significantly different from zero at the 1% level of significance