ACCOUNTING FOR BADS IN THE MEASUREMENT OF PRODUCTIVITY GROWTH: A Cost Indirect Malmquist Productivity Measure and its Application to U.S Agriculture[*]

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Abstract: This paper starts with the basic premise that the conventional measures of productivity growth, which ignore joint production of good and bad outputs, are biased. We then construct an alternative productivity growth measure using activity analysis. An application to U.S. agriculture demonstrates its usefulness. More specifically, we show that the Törnqvist index of productivity is biased upward when production of undesirable outputs or "bads" is increasing. Conversely, this same measure of productivity is biased downward when externalities in production are decreasing.

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1. Introduction

Concerns about environmental degradation have prompted government agencies to adopt measures that would internalize externalities in production. The measures taken, ranging from command and control policies such as regulation to more market oriented policies such as issuing tradable pollution permits, were aimed at preventing the use of the environment as a medium whereby undesirable outputs or "bads" could be freely disposed. These developments, in turn, have required that models of producer behavior be extended to accommodate joint production of good and bad outputs. Early innovators were Shephard (1970) and Shephard and Färe (1974).

More recently, the focus has shifted towards measuring the cost of reduced disposability and the environmental performance of producers.[1] A recent study by Ball *et al*. (2000) points out that measures of productivity growth that ignore joint production of good and bad outputs and the restrictions on disposability of bad outputs will overstate the "social benefits" of production. They call for a revised measure of productivity growth that captures the cost associated with environmental externalities. This issue has been addressed within a "production" framework with the development of the Malmquist-Luenberger productivity index (see Chung, Färe and Grosskopf, 1997; Ball, Färe, Grosskopf and Nehring, 1999). The objective of the present study is to derive an alternative measure of productivity growth within a "cost" framework, which we term the Cost Indirect Malmquist Productivity (CIMP) index. We then demonstrate its usefulness in an application to U.S. agriculture. We believe that our CIMP measure represents an attractive alternative to the Malmquist-Luenberger index of productivity growth, since it uses price information as well as information on quantities of inputs and outputs. Moreover, using this index, we can approximate conventional measures of productivity growth such as the Törnqvist index and, therefore, provide a benchmark which can be used to assess the bias associated with ignoring joint production of good and bad outputs when there are restrictions on disposability of "bads."

In constructing our CIMP index, we rely on activity analysis which conveniently allows us to model joint production of good and bad outputs, thereby putting due emphasis on the characteristics of production with negative externalities. The basic building blocks of our approach are as follows. First, we explicitly account for joint production of goods and bads. Second, we allow our technology to reflect restrictions on the disposability of bads. This implies that the reduction of bad outputs is possible either by reducing the production of good outputs given a fixed level of inputs (where some inputs must be diverted from the production of goods to the reduction of bads) or by increasing input use (again to reduce bad outputs) while maintaining the same level of production of good outputs. Notice that in either case the reduction of bad outputs is achieved by increased cost to the producer, since the environment ceases to be a free factor of production with a positive marginal benefit to the producer.[2] Finally, we assume that some bads are always produced when good outputs are produced, thereby ruling out production of good outputs with no environmentally detrimental impacts.

The paper unfolds as follows. Section 2 presents the basic features of the methodology and introduces the CIMP index and its decomposition. In Section 3, we apply the proposed index to a state-by-year panel recently made available by the U.S. Department of Agriculture's (USDA) Economic Research Service. Section 4 concludes.

2. The Theoretical Underpinnings

In this section, we discuss how joint production of good and bad outputs can be modeled. We begin with some notation. Let us denote good outputs by $y = (y_1,...,y_M) \in R_+^M$ and bad outputs by $b = (b_1,...,b_I) \in R_+^I$. These outputs (y,b) are produced from inputs $x = (x_1,...,x_N) \in R_+^N$ using technology

$$T = \{(x, y) : x \text{ can produce } (y,b)\}. \quad (1)$$

Technology T may be equivalently represented by the output set $P(x)$ or by the input set $L(y,b)$; that is,

$$(x, y, b) \in T \Leftrightarrow (y,b) \in P(x) \Leftrightarrow x \in L(y,b). \tag{2}$$

The particular properties associated with joint production of good and bad outputs are best modeled in terms of output sets. The cost function is best modeled in terms of input sets. Given (2), however, there is no difficulty in using the appropriate representation of technology for joint production and cost.

The output set $P(x)$ consists of all vectors (y,b) that can be produced by the input vector x. The restrictions imposed on $P(x)$ include:

P.1 $P(0) = \{0,0\}$.

P.2 $P(x)$ is compact for each $x \in R_{+}^{N}$.

P.3 $P(x) \supseteq P(x^{'}), x \geq x^{'}$

Property P.1 says that zero inputs yield zero outputs. Property P.2 essentially says that only finite output can be produced given finite inputs. Finally, property P.3 imposes free disposability of inputs.

Restrictions associated with joint production of good and bad outputs include:

P.4 $(y,b) \in P(x)$ and $0 \leq \theta \leq 1$ imply $(\theta y, \theta b) \in P(x)$ [3]

P.5 $(y,b) \in P(x)$ and $y^{'} \leq y$ imply $(y^{'}, b) \in P(x)$.

P.6 $(y,b) \in P(x)$ and $b = 0$ then $y = 0$.

Property P.4 is weak disposability of good and bad outputs. It says that for a given input vector, proportional contractions of good and bad outputs are feasible. Property P.5 merely says that good outputs can be freely disposed. Property P.6 is referred to as null-jointness.[4] It says that for a given input vector, if bad output is zero, then so too must be good output. In other words, if one wishes to produce good output, some bad output will also be produced. There is no fire without smoke.

An example of an output set $P(x)$ that satisfies properties P.4-P.6 is illustrated in Figure 1. We note that for each (y,b) in $P(x)$, proportional contractions of any feasible output pair are feasible. Also, the good output y is freely disposable. Finally, the good and bad outputs are null-joint. If $b=0$, then $y=0$ whenever (y,b) is in $P(x)$.

Next we formulate an activity analysis problem that satisfies the properties discussed above. We assume that there are K observations on inputs and outputs, where k indexes firms (or states):

$$\left\{\left(x^k, y^k, b^k\right): k = 1,\ldots,K\right\}. \tag{3}$$

The piecewise linear output set associated with (3) is (see Färe, Grosskopf and Lovell, 1994):

$$\begin{aligned} P(x) = \{(y,b): \quad & \sum_{k=1}^{K} z_k y_{km} \geq y_m, \quad && m = 1,\ldots,M, \\ & \sum_{k=1}^{K} z_k b_{ki} = b_i, && i = 1,\ldots,I, \\ & \sum_{k=1}^{K} z_k x_{kn} \leq x_n, && n = 1,\ldots,N, \\ & z_k \geq 0, && k = 1,\ldots,K\}, \end{aligned} \tag{4}$$

where the z_k are intensity variables which serve to form the technology from convex combinations of the data.

The technology represented in (4) satisfies P.1-P.3.[5] It also satisfies constant returns to scale; that is:

$$P(\lambda x) = \lambda P(x), \lambda > 0. \tag{5}$$

The first inequality in (4) implies that good outputs are freely disposable. Since the intensity variables $z^k, k = 1,...,K,$ are nonnegative and the bad output constraint is a strict equality, one can show that (4) satisfies weak disposability of outputs.

Null-jointness requires that

$$\sum_{k=1}^{K} b_{ki} > 0,\ i = 1,...,I, \tag{6}$$

$$\sum_{i=1}^{I} b_{ki} > 0,\ i = 1,...,K\ . \tag{7}$$

The first inequality says that each bad output is produced by some firm k, while the second inequality states that each firm k produces some bad output. Now if (6) and (7) hold and if $b_i = 0, i = 1,...,I,$ then each intensity variable in (4) will be zero, thus all good outputs must be zero. These two restrictions can, therefore, be used to determine whether a particular data set satisfies null-jointness of good and bad outputs. In our application we omit observations that violate null-jointness.

We now turn our attention to the dual cost function for a technology that produces both good and bad outputs. So far, we have relied on the output set $P(x)$ in defining the technology and its properties. Since this set is "inverse" to the input set $L(y,b)$, the input set inherits its properties from $P(x)$.[6] Here we focus on properties P.4-P.6 and the equivalent properties of the input set $L(y,b)$. These are, respectively:

L.4 $L(y,b) \subseteq L(\theta y, \theta b), 0 \leq \theta \leq 1;$

L.5 $L(y,b) \subseteq L(y^{'}, b), y^{'} \leq y;$

L.6 $x \in L(y,b)$ and $b = 0 \Rightarrow y = 0.$

Notice that property L.6 implies that if $b = 0$ and $y > 0$, then $L(y,b)$ is empty; it is not possible to produce positive good output and zero bad output.

We denote the vector of input prices by $w = (w_1,...,w_N) \in R_+^N$. The dual cost function is now defined by

$$C(y,b,w) = \inf\{wx : x \in L(y,b)\}. \tag{8}$$

The cost function defined by (8) will satisfy the following properties with respect to prices w:

C.1 $C(y,b,w)$ is nonnegative and non-decreasing in w;
C.2 $C(y,b,w)$ is homogeneous of degree one in w;
C.3 $C(y,b,w)$ is concave in w and continuous for strictly positive prices.

The cost function also satisfies the following properties with respect to outputs (y,b):

C.4 $C(y,b,w) \geq C(\theta y, \theta b, w), 0 \leq \theta \leq 1;$
C.5 $C(y,b,w) \geq C(y,b,w), y^{'} \leq y;$
C.6 $C(y,b,w) = +\infty$ if $b = 0$ and $y > 0$.

Properties C.4-C.6 follow directly from P.4-P.6 or equivalently L.4-L.6, given the observation that $L(y,b) = \emptyset$ for $b = 0$ and $y > 0$.

Before we define our productivity index, we introduce the cost indirect output distance function[7]

$$ID_o(w/c, y, b) = \inf\{\theta : C(\frac{y}{\theta}, \frac{b}{\theta}, w) \leq c\}. \tag{9}$$

This function expands outputs (y,b) as much as feasible given input prices w and target cost c. Under constant returns to scale, we have

$$C(\lambda y, \lambda b, w) = \lambda C(y,b,w), \lambda > 0$$

and (10)

$$ID_0(\lambda w, y, b) = \lambda ID_0(w, y, b).$$

The cost indirect distance function under constant returns to scale becomes

$$ID_o(w/c, y, b) = C(y,b,w)/c = C(y,b,w/c), \tag{11}$$

where the last equality follows since the cost function is homogeneous of degree one in input prices.[8]

Now, suppose we have observations for time periods t and $t+1$. Then following Färe, Grosskopf, and Lovell (1992), the Cost Indirect Malmquist Productivity (CIMP) index is defined as

$$CIMP_t^{t+1} = \left[\frac{ID_o^t((w/c)^{t+1}, y^{t+1}, b^{t+1})}{ID_o^t((w/c)^t, y^t, b^t)} \frac{ID_o^{t+1}((w/c)^{t+1}, y^{t+1}, b^{t+1})}{ID_o^{t+1}((w/c)^t, y^t, b^t)} \right]^{1/2} \tag{12}$$

which under constant returns to scale equals[9]

$$CIMP_t^{t+1} = \left[\frac{C^t(y^{t+1}, b^{t+1}, w^{t+1})}{C^t(y^t, b^t, w^t)} \frac{C^{t+1}(y^{t+1}, b^{t+1}, w^{t+1})}{C^{t+1}(y^t, b^t, w^t)} \right]^{1/2} \frac{c^t}{c^{t+1}}. \tag{13}$$

In the empirical application we take the target cost c^t and c^{t+1} to be observed cost; that is,

$$c^t = \sum_{n=1}^{N} w_n^t x_n^t \text{ and } c^{t+1} = \sum_{n=1}^{N} w_n^{t+1} x_n^{t+1} . \tag{14}$$

Like other Malmquist productivity indexes, this index can be decomposed into an efficiency change and a technical change component.[10] The efficiency change component is

$$EFFCH_t^{t+1} = \frac{C^{t+1}(y^{t+1}, b^{t+1}, w^{t+1}) / c^{t+1}}{C^t(y^t, b^t, w^t) / c^t}, \tag{15}$$

and the technical change component is

$$TECH_t^{t+1} = \left[\frac{C^t(y^{t+1}, b^{t+1}, w^{t+1})}{C^{t+1}(y^{t+1}, b^{t+1}, w^{t+1})} \frac{C^t(y^t, b^t, w^t)}{C^{t+1}(y^t, b^t, w^t)} \right]^{1/2}. \tag{16}$$

The product of the two component measures equals the productivity index

$$CIMP_t^{t+1} = EFFCH_t^{t+1} \cdot TECH_t^{t+1}. \tag{17}$$

We note that the efficiency change component is the ratio of two Farrell (1957) measures of cost efficiency. The indirect Malmquist index (12) contains mixed period cost functions $C^t(y^{t+1}, b^{t+1}, w^{t+1})$ and $C^{t+1}(y^t, b^t, w^t)$. For some observations, the corresponding input sets $L^{t+1}(y^t, b^t)$ or $L^t(y^{t+1}, b^{t+1})$ may be empty, implying that the value of the cost function is infinity. Under such conditions, the Malmquist index is undefined. In the empirical section this is indicated by "infeasible solutions."

Now, suppose we have observations for firm $k, k = 1,...,K$, at time period $t, t = 1,...,T$. For a given observation k' at period t the minimum cost can be computed as

$$C^t(y^{k',t}, b^{k',t}, w^{k',t}) = \min \sum_{n=1}^{N} w_{k'n}^t x_n^t \text{ s.t } (x_1^t,..., x_n^t) \in L^t(y^{k',t}, b^{k',t}). \tag{18}$$

Since the output and input sets are inversely related, we may use the output set (4) and the cost function (16) to formulate the following linear programming problem:

$$\begin{aligned} C^t(y^{k',t}, b^{k',t}, w^{k',t}) &= \min \sum_{n=1}^{N} w_{k'n}^t x_n^t \\ &\text{s.t.} \\ &\sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{k'm}^t \qquad m = 1,..., M \\ &\sum_{k=1}^{K} z_k^t b_{ki}^t = b_{k'i}^t \qquad i = 1,..., I \\ &\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t \qquad n = 1,..., N \\ &z_k^t \geq 0 \qquad k = 1,..., K. \end{aligned} \tag{19}$$

Note that all observations on prices and quantities in (19) are from period t. In the mixed period problem, with technology from period t and prices and quantities from period $t+1$, the cost minimization problem becomes:

$$\begin{aligned} C^t(y^{k',t+1}, b^{k',t+1}, w^{k',t+1}) &= \min \sum_{n=1}^{N} w_{k'n}^{t+1} x_n^{t+1} \\ &\text{s.t} \\ &\sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{k'm}^{t+1} \qquad m = 1,..., M \\ &\sum_{k=1}^{K} z_k^t b_{ki}^t = b_{k'i}^{t+1} \qquad i = 1,..., I \\ &\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^{t+1} \qquad n = 1,..., N \\ &z_k^t \geq 0 \qquad k = 1,..., K. \end{aligned} \tag{20}$$

We now turn to an empirical application.

3. Measurement of Productivity Growth in U.S. Agriculture

We use the index number procedure derived in the previous section to measure productivity growth in the U.S. farm sector. Our data consist of a state-by-year panel containing price and quantity indexes for two "good" outputs (crops and livestock) and four inputs (capital, land, labor, and materials).[11] A unique feature of our data series is that it also contains a number of "bad" outputs, which is crucial for our analysis of productivity growth. The bad outputs are measures of risk to human health from exposure to agricultural pesticides in drinking water. Our assessment of risk is based on the extent to which the concentration of a specific pesticide exceeds a water quality threshold. The first of two bad outputs is the risk from exposure to pesticide runoff (*i.e.*, surface water contamination). The second is the risk from pesticides leaching into groundwater.[12]

In our empirical analysis, we include only forty-six of forty-eight states. This is because of our requirement that the technology satisfy null-jointness. For two states Nevada and Rhode Island, we observe zero production of bad outputs for some years. This does not imply that there was zero environmental risk. Rather, the pesticide concentration in some years did not exceed the water quality threshold. Since the shares of these states in sectorwide production and in total pesticides consumption are small, omitting these states should have little effect on our results.

We begin by computing the CIMP index including only good outputs. Since conventional measures of productivity growth such as the Törnqvist productivity index ignore joint production of good and bad outputs, this serves two purposes. First, it provides an approximation to the Törnqvist index. It also provides a benchmark which can be used to assess the bias associated with ignoring "bads." We report the average annual rates of change in the CIMP index and its decomposition into technical change and change in efficiency in Table 1 for each of the forty-six states in our sample. Recall that values greater than unity indicate an improvement in productivity performance, while values less than unity indicate deterioration. Remarkably, every state exhibits a positive and generally substantial average annual rate of productivity growth. Moreover, our results suggest that technical change dominates efficiency change as a source of productivity growth.

We also include in Table 1 the average growth rates based on the Törnqvist index. These two indexes not only produce very similar estimates of productivity growth, but also similar rankings of productivity performance. In fact, the Spearman rank correlation coefficient between these two series is 0.86.

Before reporting productivity growth rates that account for the detrimental effects on water quality, we provide a brief overview of the trends in production of the bad outputs. Figure 2 plots the time paths of both pesticide leaching and runoff for the period 1960-96 for the aggregate farm sector. We observe an upward trend in both pesticide leaching and runoff between 1960 and 1974. The two series trend downward between 1976 and 1984. This reduction in risk from the exposure to pesticides was coincident with passage of the Federal Environmental Pest Control Act (FEPCA) of 1972, which significantly increased authority to regulate pesticides. The FEPCA allowed registration of a pesticide only if it did not cause unreasonable adverse effects to human health or the environment. It also required an examination of the safety of all previously registered pesticides using new health and environmental protection criteria. Pesticides with risks that exceeded those criteria were subject to cancellation. After 1984, pesticide leaching resumed an upward trend, while pesticide runoff continued to decline.

In Table 2, we report average annual rates of growth in pesticide leaching and runoff for each state for the complete 1960-96 period and for two subperiods—1960-74 and 1974-96. Our choice of subperiods delineates the era of regulatory scrutiny of pesticides.

During the 1960-74 period, all forty-six states exhibited increases in pesticide leaching. Although the growth rates slowed dramatically during the 1974-96 period, few states actually reduced pesticide leaching. In fact, the level of pesticide leaching in 1996 exceeded that in 1960 in every state. As for pesticide runoff, the positive growth rates observed during the 1960-74 period were largely negative during the subsequent time period. Thirty-six of forty-six states reduced pesticide runoff between 1974 and 1996. Twenty-five states achieved reductions from 1960 levels.

Finally, in Figures 3 and 4, we portray the regional incidence of pesticide leaching and runoff in 1996.[13] A quick glance at the figures reveals that pesticide contamination of surface water is the more pervasive problem.

This brings us to the main theme of this paper, the measurement of productivity when there are externalities in production. We report in Table 3 average annual productivity growth rates for each state for the same time periods indentified in Table 2. For comparison purposes, we also include the productivity growth rates from Table 1. First, note that the inclusion of bad outputs in the measurement of productivity growth has a marked impact on the rank order of state growth rates. The rank correlation coefficient between the model that accounts for the production of bads (CIMP with bads) and the Törnqvist index of productivity growth is 0.39.[14] Recall that the rank correlation between the CIMP index including only good outputs and the Törnqvist index of productivity growth was 0.86.

Consider the subperiod 1960 to 1974. The risk from exposure to pesticides was generally increasing over this period. Therefore, we would expect that a measure of productivity that explicitly accounts for joint production of goods and bads would exhibit slower growth than conventional measures which ignore bads. A comparison of productivity growth rates in Table 3 reveals that for twenty-six states (AR, AZ, CA, CO, CT, IA, ID, IL, KY, LA, MA, ME, MN, MO, MT, NC, ND, NH, NM, NY, OH, PA, SC, VT, WA, and WY) the CIMP index with bads increases more slowly than does the CIMP index without bads.[15] In all but seven of these states (AR, CT, LA, MT, NM, SC, and WA), productivity growth was slower than that suggested by the Törnqvist index. In nine states (AL, DE, FL, GA, MD, NC, SC, VA, and WV) where the CIMP index with bads increases more rapidly, we observe reductions in pesticide runoff. However, in ten states (IN, KS, MI, MS, NE, OK, SD, TN, TX, and WI), we observe seemingly contradictory results. Our CIMP index including bads increases more rapidly, notwithstanding increases in both pesticide leaching and runoff.

Turning our attention to the 1974-96 period, we see that thirty-six states achieved reductions in pesticide runoff. However, in eighteen of the thirty-six states, pesticide leaching continued its upward trend. Our CIMP index including bads points to slower productivity growth in ten of these states (GA, IA, IL, IN, MO, MS, NC, NE, OK, and SC). Nineteen states reduced pesticide leaching during this period. Relatively rapid productivity growth was indicated for thirteen of the nineteen states (AL, CT, FL, ID, MA, MN, NH, NJ, NY PA, SD, TX, and WV). Seventeen states achieved reductions in both pesticide leaching and runoff. Our CIMP index grew more rapidly than either of the two alternative measures in eleven of these states (AL, CT, FL, ID, MA, MN, NH, NY, SD, TX, and WV). For two states (KY and LA) where both leaching and runoff increased, slower productivity growth was indicated. Still, for a number of states, we obtain empirical results that appear to be in conflict with our theoretical model. We attribute this to our focus on average growth rates over a number of years rather than on actual year-to-year changes in the series.

To test this hypothesis, we examine the time paths of production of bads and the alternative measures of productivity for selected states. Figure 5 plot the annual indexes of pesticide leaching and runoff for Iowa for the complete period 1960 to 1996. We observe that pesticide leaching increased sharply from 1960 to 1978. The increase in pesticide runoff was less pronounced. Both series declined after 1978. If our concern is the measurement of productivity growth over the 1960-78 period, we would expect conventional measures such as the Törnqvist index to exhibit faster growth than our CIMP index. Conversely, if our focus is the 1978-96 period when the production of bads was declining, we would expect the Törnqvist index to exhibit slower rates of productivity growth.

Our findings are consistent with expectations. Figure 6 shows a dramatic slowdown in productivity growth between 1960 and 1978 based on our CIMP index. The Törnqvist index suggests strong productivity growth over this period. Our CIMP index increased more rapidly over the 1978-96 period, reflecting the decline in both pesticide leaching and runoff.

The indicators of environmental risk for Illinois are presented in Figure 7. The risk from pesticide runoff is increasing over the 1960-79 period and from pesticide leaching over the 1960-80 period. There are no discernable trends in either leaching or runoff after 1980. Again, when the risks from pesticide leaching and runoff are increasing, we see from Figure 8 that our CIMP index including bads increases more slowly than the alternatives. However, when the level of risk is constant (as is the case for the period 1980 to 1996), the three measures of productivity growth are quite similar.

Finally, Figure 9 plots the time paths of both pesticide leaching and runoff for Nebraska for the 1960-96 period. We see no discernable trend in pesticide runoff over the entire thirty-seven year period. However, the trend line for pesticide leaching is unmistakably upward sloping. Consider the subperiod from 1968 to 1978 when the risk from pesticide leaching is increasing most rapidly. We see from Figure 10 that our CIMP index including bads increases more slowly. Also note that during the period 1978 to 1986 when both leaching and runoff trended downward, our CIMP index points to more rapid productivity growth. Finally, during the subperiod 1988 to 1996 when production of both bads are increasing, our CIMP index including bads provides a lower bound on our estimates of productivity growth.

We now turn to a discussion of the productivity performance of the aggregate farm sector. Recall that the time series of bads for the aggregate farm sector are presented in Figure 2. In Figure 11, we plot the annual indexes of productivity.[16] Note that ignoring bads when their production is increasing, as is the case during the 1960-72 period, results in an overstatement of productivity growth. In fact, our CIMP index including bads shows negative productivity growth over the 1960-72 period, while its counterpart points to gains in productivity. Ignoring the reductions in bads during the 1972-84 period results in an understatement of productivity growth. Finally, when the two series move in opposite directions, as in the 1984-96 period, our CIMP index including bads points to stronger growth in productivity than do either of the two alternative measures.

4. Summary and Conclusions

This paper suggests a procedure for measuring productivity growth in the presence of production externalities. The absence of price data for these undesirable or "bad" outputs is a limiting factor in measuring productivity growth using conventional growth accounting and index number approaches. Our procedure allows us to model joint production of good and bads without requiring data on (shadow) prices of the bad outputs.

An application using a state-by-year panel demonstrates its usefulness. More specifically, we show that conventional measures of productivity growth such as the Törnqvist index are biased upward when the production of bads is increasing. Conversely, when the environmental risks associated with production are decreasing, these same measures understate the social benefits of production and, hence, productivity growth.

Endnotes

[1] See, for example, Färe, Grosskopf, Lovell, and Pasurka (1989), Färe, Grosskopf, and Pasurka (1986; 1989), Färe, Grosskopf, and Tyteca (1996), Tyteca (1996; 1997), and Zaim and Taskin (2000).

[2] This property, which is referred as weak disposability of bads in the nonparametric production frontier literature, is also adopted by studies that utilize parametric approaches. In parametric models this is a derivative property which implies that the partial derivative of total cost with respect to a bad output is negative (see e.g., Ball, Felthoven, Nehring and Morrison (2000)).

[3] Shephard (1970) introduced the notion of weak disposability of outputs.

[4] Shephard and Färe (1974) introduced this property.

[5] See Färe and Grosskopf (1996) for details.

[6] For a general discussion of the properties of $L(y,b)$ and $P(x)$, see Shephard (1970) or Färe (1988).

[7] This function is due to Shephard (1974), see also Färe and Grosskopf (1994).

[8] See Färe and Grosskopf (1994, p.42) for a proof.

[9] Färe and Grosskopf (1996, p.54) show that the direct Malmquist index must be computed relative to a reference technology satisfying constant returns to scale in order

for it to have an average product interpretation as a measure of total factor productivity. Thus here we also use constant returns to scale technology as a reference.

[10] See Färe, Grosskopf, Lindgren, and Roos (1992).

[11] Construction of the data is described in detail in Ball, Butault, and Nehring (2000).

[12] For details on the construction of the bad outputs, see Kellogg, Nehring, Grube, Goss and Plotkin (2000).

[13] We would like to thank Robert Kellogg for producing these maps.

[14] The Spearman correlation coefficient between CIMP-with bads and CIMP-without bads is 0.32.

[15] Note that for two states, NJ and UT no computations of CIMP with bads could be made due to infeasible solutions for the period 1960-1974.

[16] In order to aggregate productivity growth across states at a particular year, the appropriate approach should be one which accounts for the relative importance of each state in each year. Towards this objective, for both the CIMP indexes (i.e., with bads and without bads) we computed the weighted geometric mean of productivity growth across individual states, weights being chosen as the optimum cost share of each state (in total costs) in a particular year. These optimal shares of each state are computed from the solution of our linear programming problems. For the Törnqvist index conventional methods of aggregation are employed (see Ball et. al. (1999)).

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Table 1. Cost Indirect Malmquist Productivity (CIMP) and Törnqvist Indexes, 1960-96

STATE	CIMP	EFFICIENCY CHANGE	TECHNICAL CHANGE	TORNQVIST
AL	1.0267	1.0034	1.0232	1.0188
AR	1.0360	1.0096	1.0262	1.0252
AZ	1.0071	0.9813	1.0263	1.0143
CA	1.0241	0.9980	1.0262	1.0176
CO	1.0219	0.9951	1.0269	1.0141
CT	1.0346	1.0102	1.0241	1.0285
DE	1.0336	1.0078	1.0256	1.0196
FL	1.0287	1.0000	1.0287	1.0214
GA	1.0382	1.0113	1.0266	1.0257
IA	1.0210	0.9964	1.0247	1.0168
ID	1.0321	1.0026	1.0294	1.0237
IL	1.0247	0.9952	1.0297	1.0168
IN	1.0265	0.9974	1.0292	1.0200
KS	1.0213	0.9945	1.0269	1.0135
KY	1.0269	0.9991	1.0278	1.0244
LA	1.0368	1.0084	1.0282	1.0288
MA	1.0291	1.0048	1.0242	1.0217
MD	1.0258	1.0025	1.0233	1.0200
ME	1.0240	0.9997	1.0242	1.0200
MI	1.0312	1.0037	1.0274	1.0264
MN	1.0192	0.9952	1.0241	1.0182
MO	1.0184	0.9944	1.0242	1.0176
MS	1.0375	1.0081	1.0291	1.0269
MT	1.0150	0.9866	1.0289	1.0144
NC	1.0393	1.0108	1.0282	1.0275
ND	1.0295	1.0007	1.0288	1.0233
NE	1.0265	0.9983	1.0282	1.0197
NH	1.0261	1.0004	1.0257	1.0207
NJ	1.0260	1.0000	1.0260	1.0174
NM	1.0257	0.9998	1.0258	1.0216
NY	1.0171	0.9932	1.0241	1.0153
OH	1.0233	0.9946	1.0288	1.0183
OK	1.0155	0.9896	1.0261	1.0099
OR	1.0243	0.9961	1.0283	1.0204
PA	1.0263	1.0010	1.0253	1.0225
SC	1.0374	1.0082	1.0289	1.0247
SD	1.0209	0.9980	1.0230	1.0191
TN	1.0199	0.9956	1.0244	1.0195
TX	1.0175	0.9930	1.0246	1.0136
UT	1.0151	0.9896	1.0258	1.0180
VA	1.0255	1.0005	1.0249	1.0217
VT	1.0282	1.0030	1.0251	1.0190
WA	1.0334	1.0017	1.0316	1.0237
WI	1.0109	0.9892	1.0219	1.0142
WV	1.0151	0.9919	1.0234	1.0187
WY	1.0103	0.9828	1.0280	1.0094

Table 2. Production of “Bads:” Pesticide Leaching and Runoff

STATE	Average annual growth rates Leaching			Average annual growth rates Runoff		
	1960-1974	1974-1996	1960-1996	1960-1974	1974-1996	1960-1996
AL	0.1893	-0.0230	0.0596	-0.0491	-0.0257	-0.0348
AR	0.2477	0.0536	0.1291	0.1083	0.0008	0.0426
AZ	0.3689	0.1396	0.2299	0.0754	-0.0863	-0.0234
CA	0.0248	0.0285	0.0270	0.0166	0.0326	0.0264
CO	0.0650	0.0193	0.0371	0.1729	-0.0873	0.0139
CT	0.3437	-0.0231	0.1196	0.1063	-0.0322	0.0216
DE	0.2161	-0.0097	0.0781	-0.1025	-0.0160	-0.0496
FL	0.2336	-0.0165	0.0807	-0.1730	-0.0245	-0.0822
GA	0.1669	0.0342	0.0858	-0.1500	-0.0106	-0.0648
IA	0.3730	0.0002	0.1452	0.0366	-0.0434	-0.0123
ID	0.1061	-0.0122	0.0338	0.0843	-0.0765	-0.0140
IL	0.2020	0.0167	0.0887	-0.0211	-0.0359	-0.0301
IN	0.3292	0.0052	0.1312	0.0560	-0.0649	-0.0179
KS	0.2511	0.0148	0.1067	0.0582	-0.0383	-0.0008
KY	0.2063	0.0227	0.0941	-0.0151	0.0092	-0.0002
LA	0.2269	0.0689	0.1303	0.0798	0.0272	0.0476
MA	0.3406	-0.0270	0.1160	0.1358	-0.0056	0.0494
MD	0.2476	0.0010	0.0969	-0.1028	0.0208	-0.0273
ME	0.4849	-0.2771	0.2299	0.1005	-0.0466	0.0106
MI	0.2518	-0.0182	0.0868	0.0747	-0.0099	0.0230
MN	0.3456	-0.0310	0.1155	0.1013	-0.0263	0.0233
MO	0.2320	0.0129	0.0981	0.0103	-0.1104	-0.0634
MS	0.2554	0.0250	0.1146	0.0664	-0.0068	0.0217
MT	0.0288	0.0186	0.0225	0.1487	-0.1034	-0.0053
NC	0.3073	0.0436	0.1462	-0.0931	-0.0725	-0.0805
ND	0.3569	-0.1326	0.0578	0.0411	-0.0378	-0.0071
NE	0.2877	0.0160	0.1217	0.0542	-0.0229	0.0071
NH	0.3654	-0.1520	0.0610	0.2777	-0.0027	0.1127
NJ	0.2883	-0.0267	0.0958	0.0629	0.0352	0.0460
NM	0.2566	0.0013	0.1006	0.1147	-0.0923	-0.0118
NY	0.4502	-0.0129	0.1672	0.3276	-0.0060	0.1237
OH	0.3560	-0.0341	0.1176	0.0073	-0.0687	-0.0392
OK	0.1725	0.0637	0.1060	0.0569	-0.0696	-0.0204
OR	0.1375	0.0769	0.1004	-0.0091	0.0117	0.0036
PA	0.3362	-0.0187	0.1193	0.1168	0.0225	0.0592
SC	0.2528	0.0134	0.1065	-0.1082	-0.0460	-0.0702
SD	0.1664	-0.0567	0.0301	0.0764	-0.0358	0.0078
TN	0.1745	0.0076	0.0725	0.0114	-0.0123	-0.0031
TX	0.2214	-0.0010	0.0855	0.0719	-0.0467	-0.0005
UT	0.0990	0.0589	0.0754	0.1426	-0.0571	0.0206
VA	0.3436	0.0000	0.1336	-0.0948	-0.0468	-0.0655
VT	0.3048	0.0195	0.1305	0.2811	0.0135	0.1176
WA	0.1147	0.0924	0.1010	0.0404	0.0010	0.0163
WI	0.3505	-0.0302	0.1178	0.3231	-0.0017	0.1246
WV	0.1588	-0.0345	0.0407	-0.0718	-0.0070	-0.0322
WY	0.1944	0.0758	0.1219	0.1380	-0.1174	-0.0181

Table3. Cost Indirect Malmquist Productivity (CIMP) Indexes Including and Excluding "Bads"

STATE	CIMP with bads			Infeasible	CIMP without bads			Tornqvist		
	1960-1974	1974-1996	1960-1996	solutions	1960-1974	1974-1996	1960-1996	1960-1974	1974-1996	1960-1996
AL	1.2108	1.0220	1.0968		1.0336	1.0219	1.0267	1.0195	1.0192	1.0188
AR	1.0419	1.0301	1.0350	24	1.0460	1.0289	1.0360	1.0205	1.0236	1.0252
AZ	0.9916	1.0728	1.0247		1.0120	1.0036	1.0071	1.0158	1.0145	1.0143
CA	1.0171	1.0217	1.0212	18	1.0282	1.0212	1.0241	1.0237	1.0137	1.0176
CO	1.0110	1.0320	1.0232		1.0229	1.0212	1.0219	1.0116	1.0126	1.0141
CT	1.0191	1.0526	1.0385		1.0222	1.0435	1.0346	1.0171	1.0340	1.0285
DE	1.2514	1.0078	1.1324	10	1.0384	1.0301	1.0336	1.0315	1.0080	1.0196
FL	1.0460	1.0261	1.0390	16	1.0430	1.0186	1.0287	1.0297	1.0173	1.0214
GA	1.3166	1.0204	1.1493	6	1.0516	1.0287	1.0382	1.0360	1.0233	1.0257
IA	0.5595	0.9706	0.7716		1.0132	1.0267	1.0210	1.0075	1.0165	1.0168
ID	1.0123	1.0358	1.0254	11	1.0330	1.0314	1.0321	1.0237	1.0225	1.0237
IL	0.9947	1.0166	1.0074		1.0261	1.0238	1.0247	1.0041	1.0161	1.0168
IN	1.0277	1.0190	1.0226		1.0244	1.0280	1.0265	1.0093	1.0189	1.0200
KS	1.0250	1.0242	1.0245		1.0207	1.0218	1.0213	1.0122	1.0090	1.0135
KY	1.0193	1.0293	1.0252		1.0226	1.0299	1.0269	1.0284	1.0241	1.0244
LA	1.0375	1.0279	1.0319		1.0430	1.0324	1.0368	1.0298	1.0272	1.0288
MA	0.9982	1.0285	1.0168	2	1.0308	1.0278	1.0291	1.0291	1.0189	1.0217
MD	1.0901	1.0308	1.0551		1.0304	1.0226	1.0258	1.0238	1.0169	1.0200
ME	0.9906	1.0128	1.0013	7	1.0302	1.0195	1.0240	1.0154	1.0160	1.0200
MI	1.0686	1.0156	1.0374		1.0407	1.0245	1.0312	1.0286	1.0230	1.0264
MN	0.9941	1.0456	1.0238		1.0110	1.0250	1.0192	1.0072	1.0162	1.0182
MO	0.9646	1.0163	0.9944		1.0131	1.0222	1.0184	1.0063	1.0164	1.0176
MS	1.0624	1.0172	1.0358		1.0545	1.0255	1.0375	1.0333	1.0199	1.0269
MT	1.0178	1.0088	1.0125		1.0244	1.0084	1.0150	1.0151	1.0134	1.0144
NC	1.0183	1.0315	1.0260		1.0469	1.0340	1.0393	1.0325	1.0237	1.0275
ND	0.8019	0.6046	0.7444	17	1.0373	1.0240	1.0295	1.0185	1.0193	1.0233
NE	1.0326	1.0293	1.0307		1.0217	1.0299	1.0265	1.0082	1.0202	1.0197
NH	1.0194	1.0147	1.0163	7	1.0444	1.0132	1.0261	1.0259	1.0138	1.0207
NJ		1.0344	1.0344	15	1.0156	1.0335	1.0260	1.0128	1.0208	1.0174
NM	1.0291	1.0477	1.0394	2	1.0344	1.0195	1.0257	1.0153	1.0204	1.0216
NY	0.9955	1.0269	1.0154	3	1.0160	1.0179	1.0171	1.0120	1.0156	1.0153
OH	0.8738	1.0112	0.9515		1.0367	1.0138	1.0233	1.0226	1.0187	1.0183
OK	1.0286	1.0021	1.0131		1.0285	1.0063	1.0155	1.0196	1.0031	1.0099
OR	1.2636	1.0361	1.1070	30	1.0421	1.0117	1.0243	1.0375	1.0117	1.0204
PA	1.0128	1.0316	1.0237		1.0214	1.0298	1.0263	1.0197	1.0221	1.0225
SC	1.0267	1.0263	1.0265		1.0489	1.0292	1.0374	1.0251	1.0238	1.0247
SD	1.0119	1.1622	1.0933	2	1.0076	1.0306	1.0209	1.0089	1.0219	1.0191
TN	1.0487	1.0129	1.0277		1.0301	1.0127	1.0199	1.0205	1.0186	1.0195
TX	1.0368	1.0133	1.0230		1.0302	1.0085	1.0175	1.0173	1.0082	1.0136
UT		1.1738	1.1738	35	1.0111	1.0179	1.0151	1.0203	1.0146	1.0180
VA	1.0401	1.0320	1.0353	1	1.0295	1.0226	1.0255	1.0239	1.0212	1.0217
VT	0.9709	1.0229	1.0037	3	1.0465	1.0153	1.0282	1.0262	1.0113	1.0190
WA	1.0426	1.0398	1.0410	9	1.0437	1.0261	1.0334	1.0324	1.0195	1.0237
WI	1.0288	1.0106	1.0181		1.0071	1.0136	1.0109	1.0105	1.0151	1.0142
WV	1.0355	1.0293	1.0319		1.0218	1.0104	1.0151	1.0175	1.0188	1.0187
WY	0.9981	1.0668	1.0330	5	1.0147	1.0071	1.0103	1.0138	1.0085	1.0094

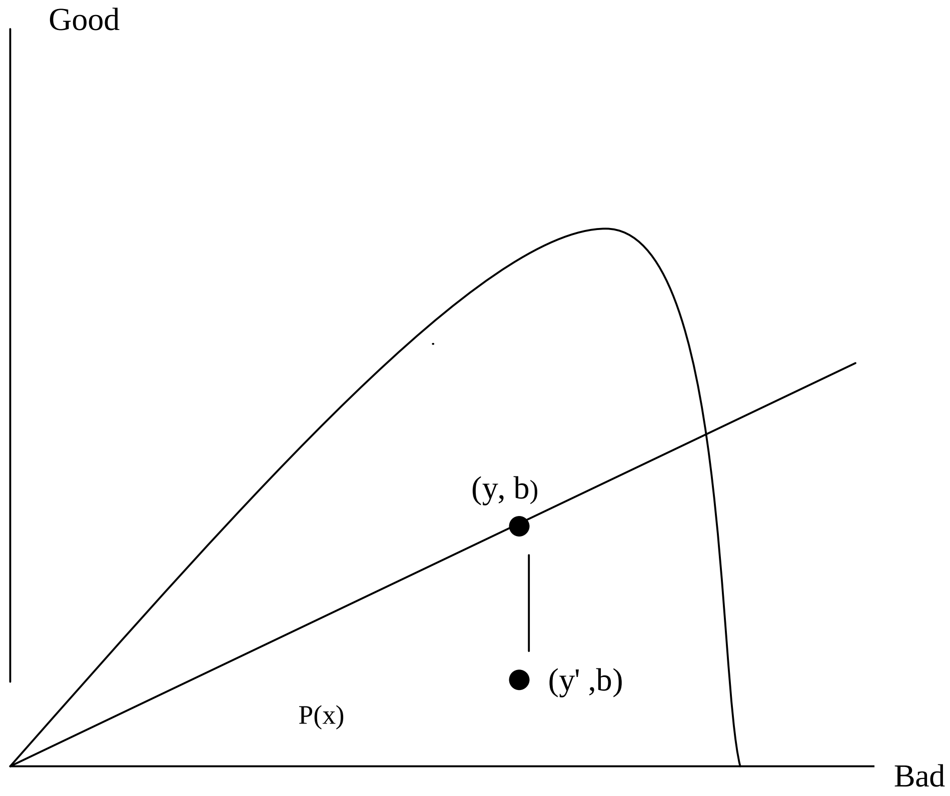

Figure 1. An output set

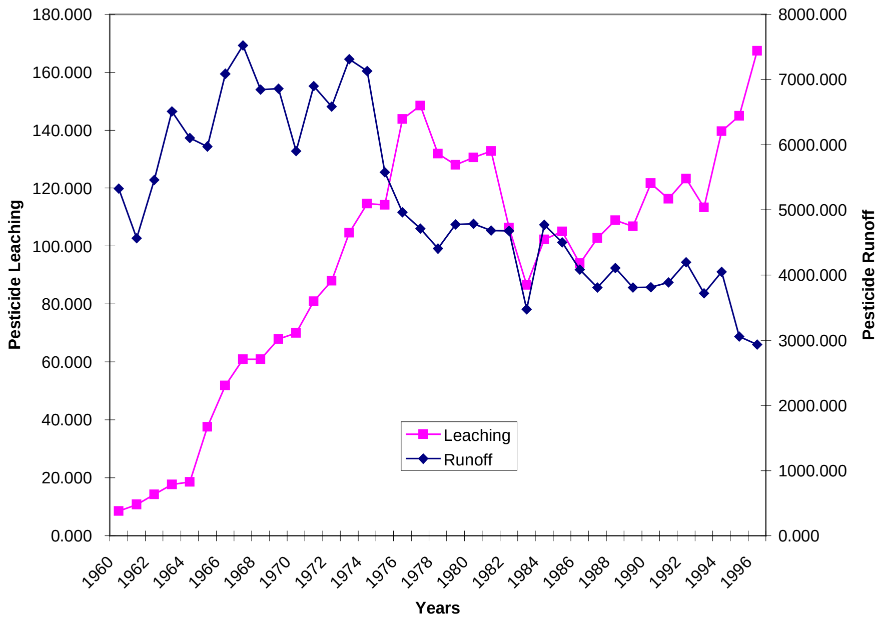

Figure 2. Pesticide Leaching and Runoff, U.S Agriculture (million Threshold Exceedence Units)

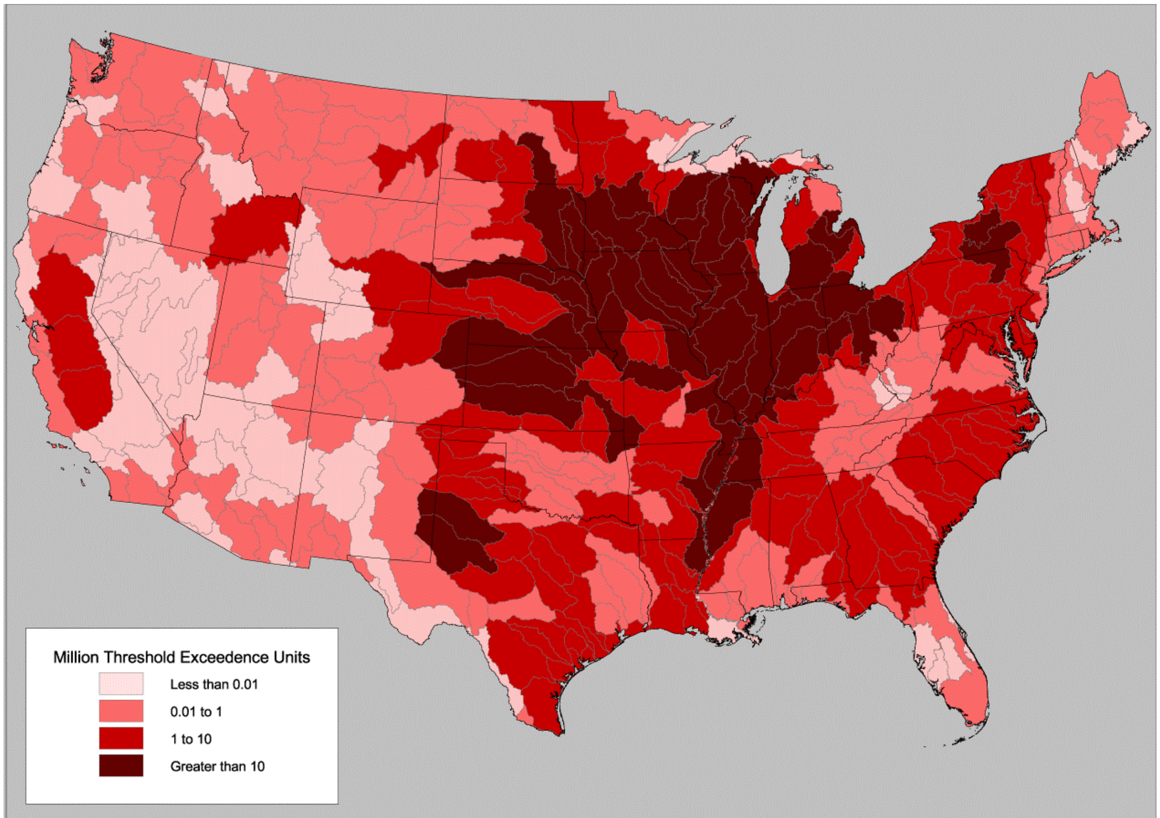

Figure 3. Regional Distribution of Pesticide Runoff, 1996

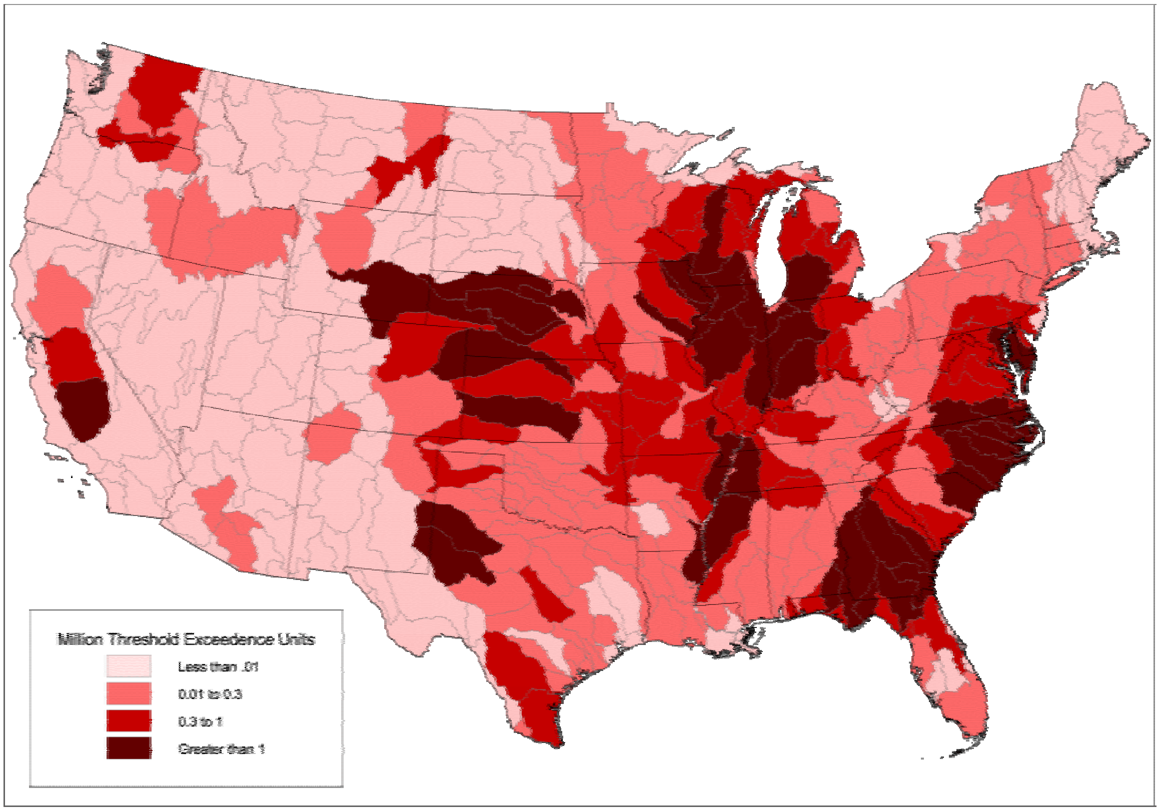

Figure 4. Regional Distribution of Pesticide Leaching, 1996

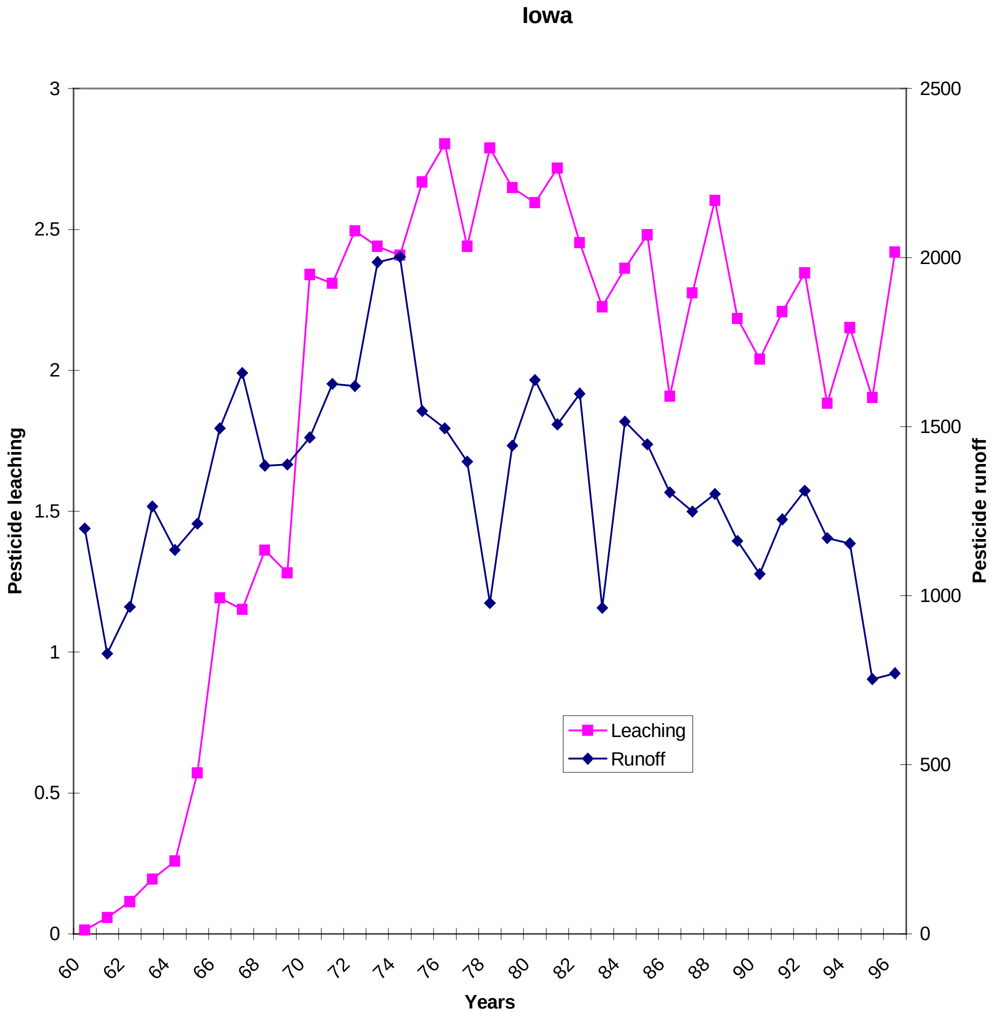

Figure 5. Pesticide Leaching and Runoff, Iowa (million Threshold Exceedence Units)

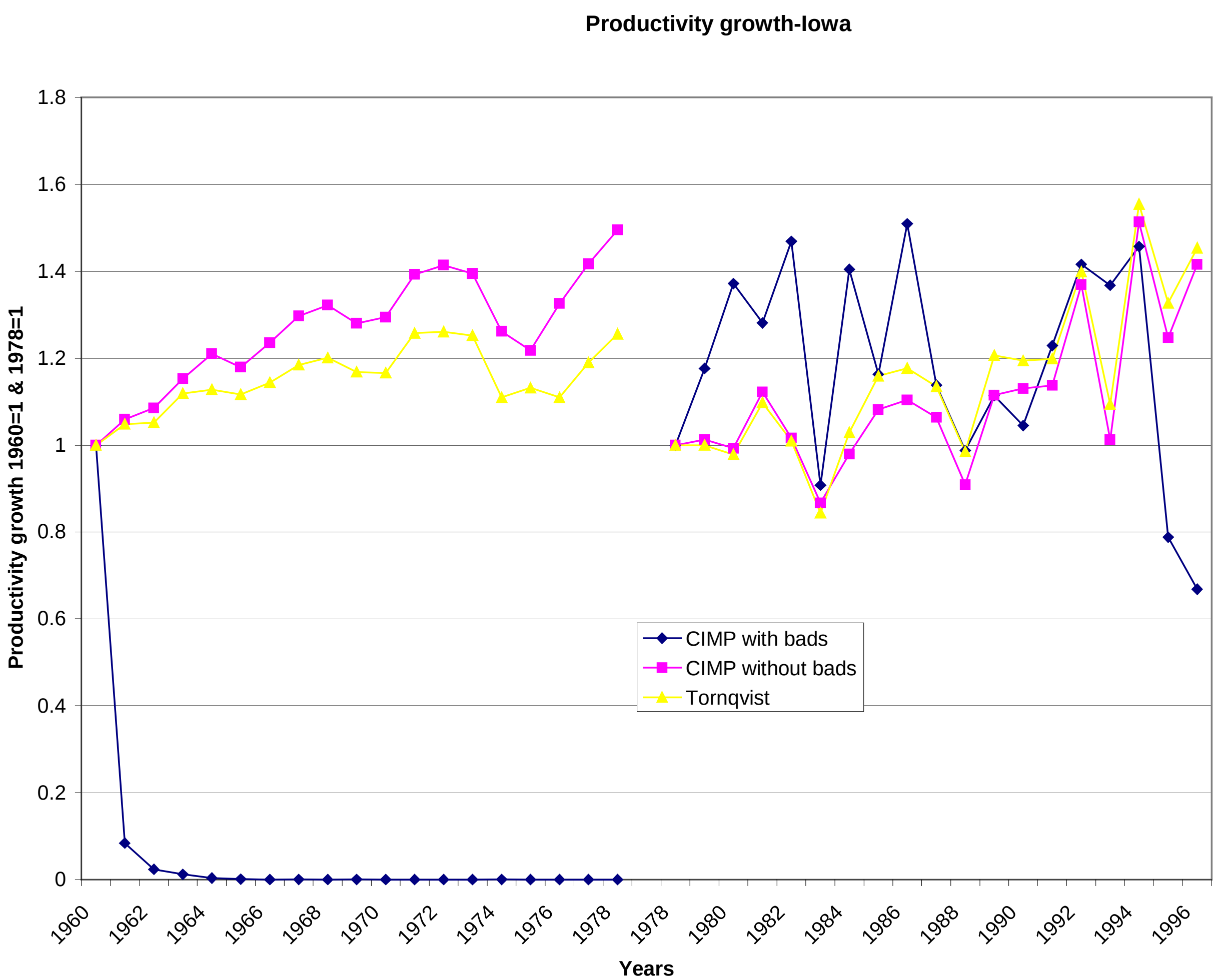

Figure 6. Alternative Productivity Growth Rates for Iowa 1960-1996

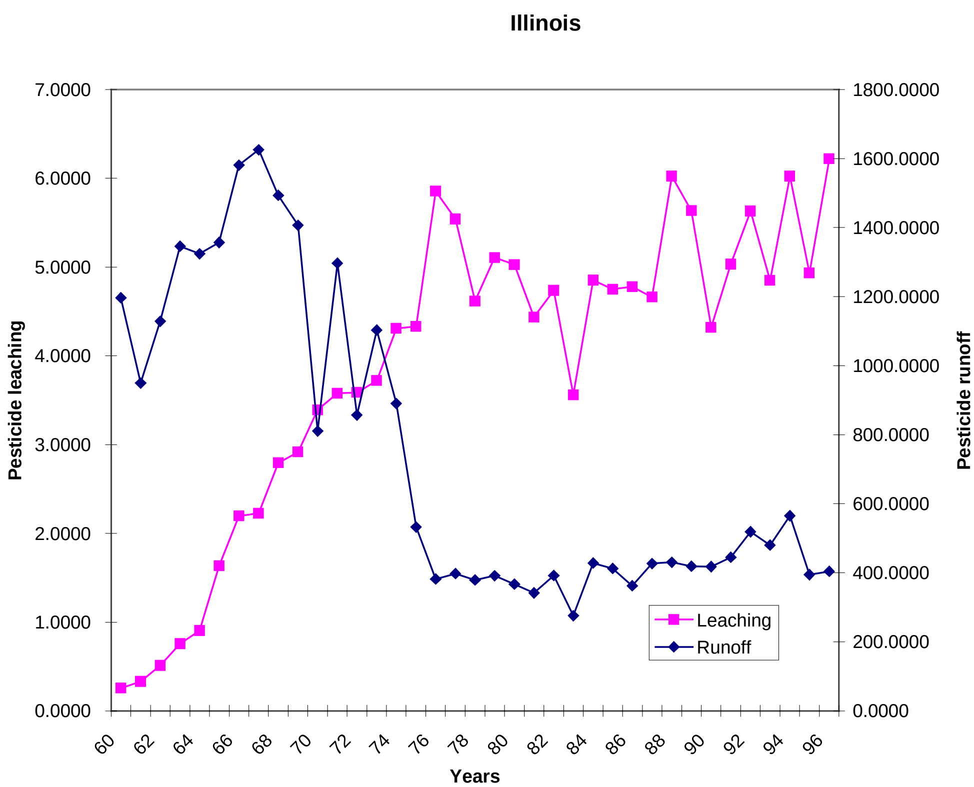

Figure 7. Pesticide Leaching and Runoff, Illinois (million Threshold Exceedence Units)

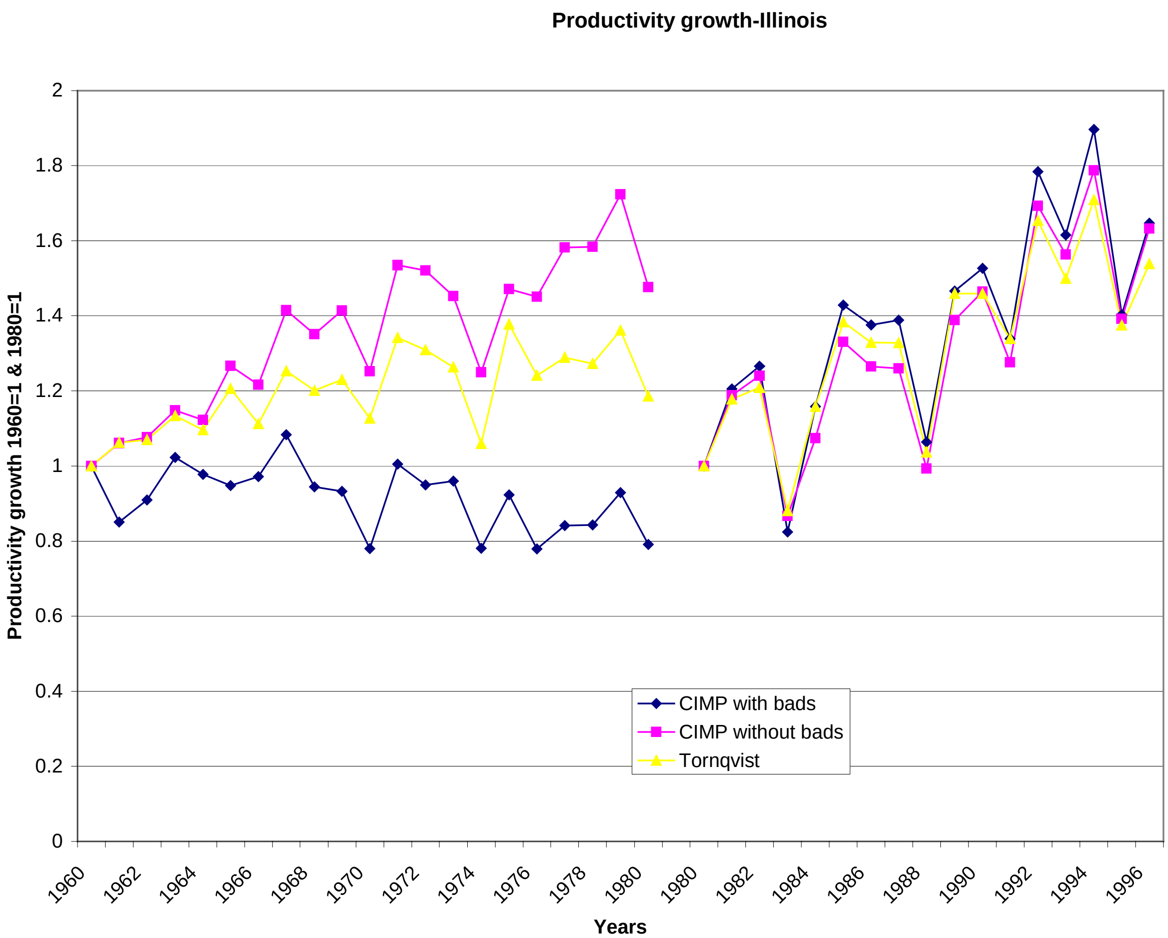

Figure 8. Alternative Productivity Growth Rates for Illinois 1960-1996

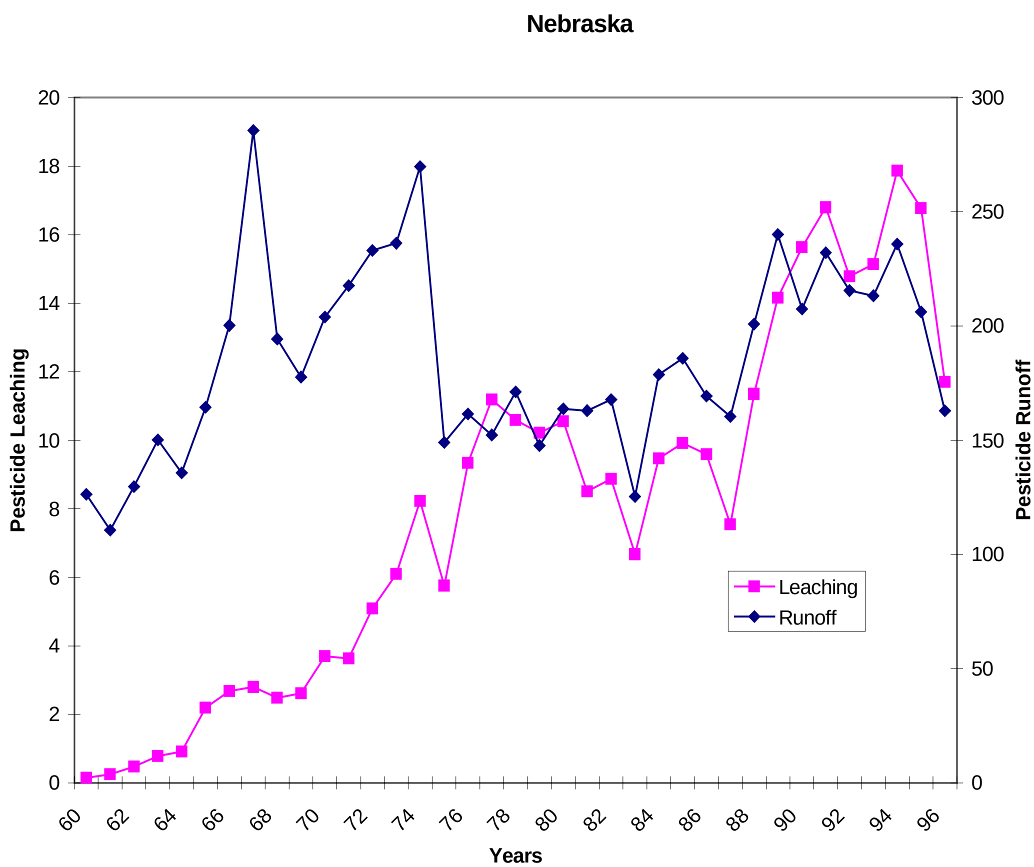

Figure 9. Pesticide Leaching and Runoff, Nebraska (million Threshold Exceedence Units)

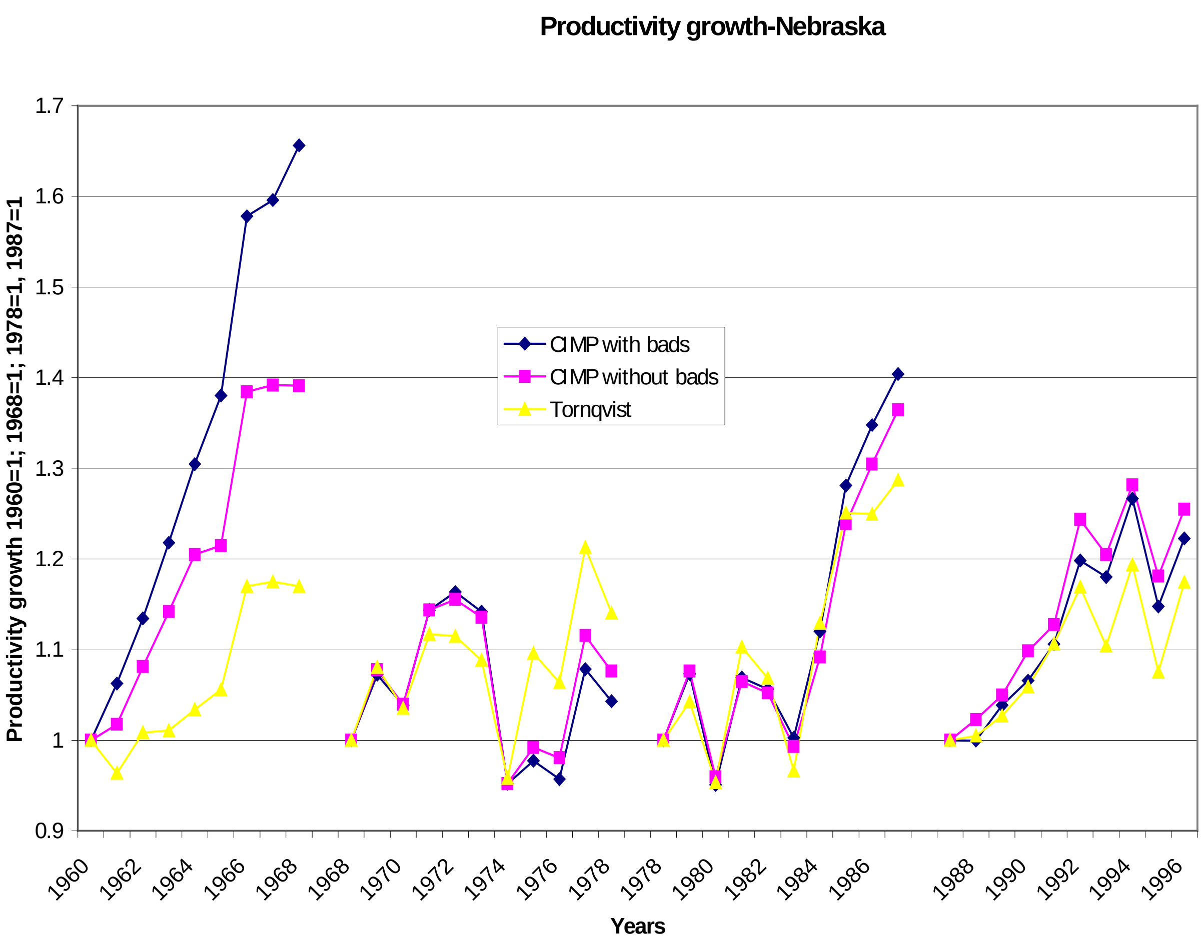

Figure 10. Alternative Productivity Growth Rates for Nebraska, 1960-1996

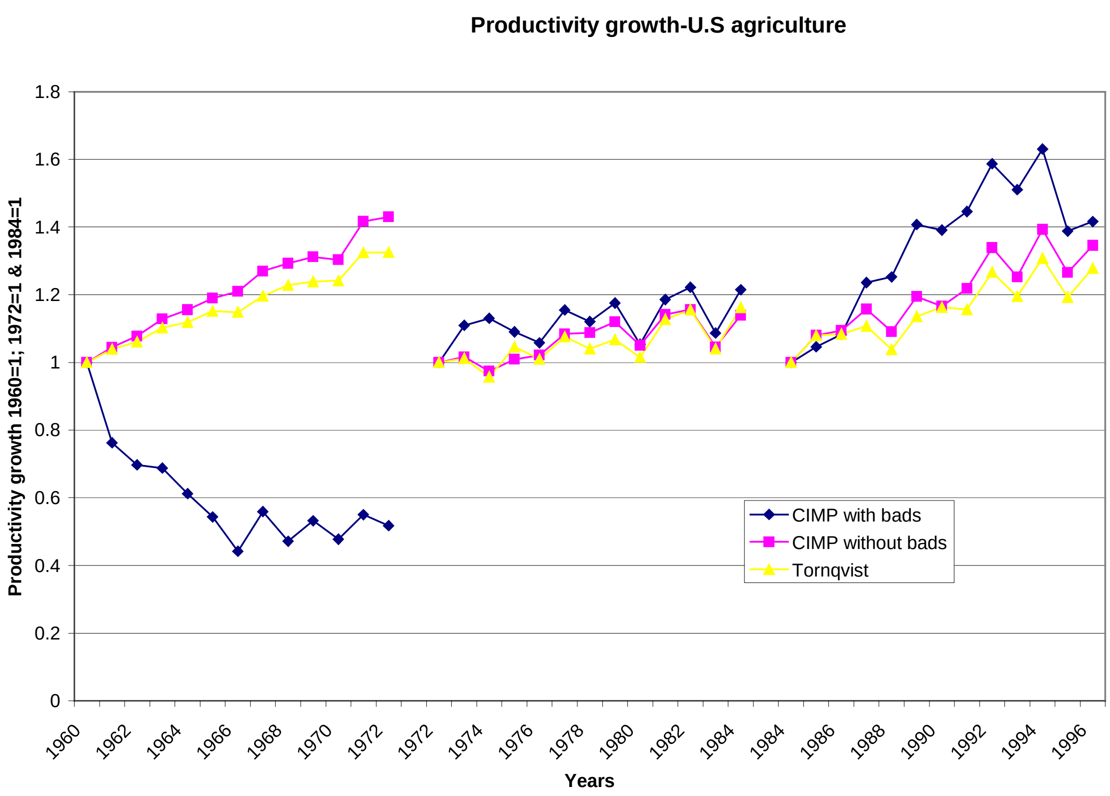

Figure 11. Alternative Productivity Growth Rates for U.S Agriculture, 1960-1996