ACCOUNTING FOR BADS IN THE MEASUREMENT OF PRODUCTIVITY GROWTH: The Malmquist Cost Productivity Measure and its Application to U.S Agriculture

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1. Introduction

Concerns about environmental degradation have prompted the adoption of 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 (or bad) outputs could be freely disposed. This has required that models of production be extended to accommodate joint production of “goods” and “bads”. Early contributors included 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 (see, for example, Färe *et al*., 1989; Färe, Grosskopf, and Pasurka, 1986 and 1989; Färe, Grosskopf, and Tyteca, 1996; Tyteca, 1996 and 1997; Zaim and Taskin, 2000; Ball *et al.*, 2002). As Ball *et al*. (2002) point out, 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 *et al*., 2001; Hailu and Veeman, 2001).

The objective of the present study is to derive an alternative measure of productivity growth within a “cost” framework, which we term the Malmquist Cost Productivity (MCP) index. We believe that the MCP measure represents an attractive alternative to the Malmquist-Luenberger index of productivity, since it uses price information as well as information on quantities of inputs and outputs.

In constructing our MCP 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 good and bad outputs. Second, our representation of technology reflects restrictions on the disposability of bad outputs. 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.[1] Finally, we assume that bad outputs 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 introduces the MCP index and its decomposition into efficiency change and technical change components. 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 introduce the cost-based Malmquist productivity index. The cost functions on which our index is based are computed using an "environmental" activity analysis model. By "environmental" we mean that the model incorporates both good and bad outputs and that these outputs are weakly disposable and null-joint. A mathematical representation is provided below. In words, weak disposability implies that feasible outputs (good or bad) can be proportionally reduced. Null-jointness implies that to produce good outputs, some bad outputs must also be produced. There cannot be fire without smoke.

We begin with some notation. Let us denote desirable (or good) outputs by $y = (y_1,..., y_M) \in R_+^M$ and undesirable (or bad) outputs by $b = (b_1,..., b_I) \in R_+^I$. The vector of outputs $(y,b) = (y_1,..., y_M, b_1,..., b_I)$ is produced from inputs $x = (x_1,..., x_N) \in R_+^N$ using technology

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

Next we formulate the technology as an activity analysis model. We assume that there are *K* observations on inputs and outputs, where *k* indexes firms (or states):

$$\{(x^k, y^k, b^k) : \ k = 1,..., K\}. \tag{2}$$

Following Shephard (1970, p. 283) we assume that

$$
\begin{aligned}
&\text{(i)} \ \sum_{k=1}^{K} x_{kn} > 0, \ n = 1,\ldots,N. \\
&\text{(ii)} \ \sum_{n=1}^{N} x_{kn} > 0, k = 1,\ldots,K. \\
&\text{(iii)} \sum_{k=1}^{K} y_{km} + \sum_{k=1}^{K} b_{ki} > 0, \ m = 1,\ldots,M, \ i = 1,\ldots,I. \\
&\text{(iv)} \sum_{m=1}^{M} y_{km} + \sum_{i=1}^{I} b_{ki} > 0, \ k = 1,\ldots,K.
\end{aligned} \tag{3}
$$

Condition (i) says that each input must be used in at least one activity and (ii) says that each activity must use at least one input. Conditions (iii) and (iv) for outputs mimic conditions (i) and (ii) for inputs.

In addition to conditions (i)-(iv) we assume that outputs (good or bad) are weakly dsposable. In terms of T this means that

$$(x, y, b) \in T \text{ and } 0 \le \theta \le 1 \text{ imply } (x, \theta y, \theta b) \in T. \tag{4}$$

In words, a proportional contraction of feasible outputs is feasible. This models the idea that it is costly in terms of good outputs to decrease production of bads. We will model this by use of equalities in our activity analysis setting.

The bad outputs are assumed to be byproducts of production of good outputs which is modelled by null-jointness. Formally,

$$(x, y, b) \in T \text{ and } b = 0 \text{ imply } y = 0. \tag{5}$$

In words, if no bads are produced then it is not feasible to produce good outputs. This condition is imposed by assuming that

(v) $\sum_{k=1}^{K} b_{ki} > 0,\ i = 1,...,I.$

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

The first set of inequalities says that each bad output is produced by at least one activity, and (vi) tell us that each activity produces at least one bad output.

If, in addition, we assume that good outputs are freely disposable as represented by expression (7) below

$$(x, y, b) \in T \text{ and } y' \leq y \text{ imply } (x, y', b) \in T, \tag{7}$$

then our activity analysis model of technology is

$$\begin{aligned} T = \{(x, y, b):\ & \sum_{k=1}^{K} z_k x_{kn} \leq x_n, \quad n = 1,...,N, \\ & \sum_{k=1}^{K} z_k y_{km} \geq y_m, \quad m = 1,...,M, \\ & \sum_{k=1}^{K} z_k b_{ki} = b_i, \qquad i = 1,...,I, \\ & z_k \geq 0, \qquad\qquad k = 1,...,K\}, \end{aligned} \tag{8}$$

where $z_k, k = 1,...,K$, are intensity variables.

Given input prices $w = (w_1,...,w_N) \in R_+^N$, then following Shephard (1970, p. 287), we may compute minimum cost by solving the linear programming problem

$$C(y, b, w) = \min\{wx : (x, y, b) \in T\}. \tag{9}$$

Now suppose that for each observation *k*, we have observations for each time period $t, t = 1,...,T$. Then we can compute the cost functions that make up our Malquist productivity index. Suppressing the subscript *k*, these cost functions are

$$\begin{aligned} &c^t(y^{t+1}, b^{t+1}, w^{t+1}) \\ &c^t(y^t, b^t, w^t) \\ &c^{t+1}(y^{t+1}, b^{t+1}, w^{t+1}) \\ &c^{t+1}(y^t, b^t, w^t). \end{aligned} \tag{10}$$

If we denote the observed cost by

$$c^t = \sum_{n=1}^{N} w_n^t x_n^t \text{ and } c^{t+1} = \sum_{n=1}^{N} w_n^{t+1} x_n^{t+1}, \tag{11}$$

the Malmquist Cost Productivity (MCP) index is given by

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

(12)

This index may be derived either from the usual Malmquist (input-based) productivity index assuming allocative efficiency or from the cost-indirect index by assuming constant returns to scale (see Fare, Grosskopf and Lovell, 1994).

Like other Malmquist productivity indexes, this index can be decomposed into an efficiency change and a technical change component (see Färe *et al.*, 1992). The efficiency change component is

$$EFFCH_t^{t+1} = \frac{C^{t+1}(y^{t+1}, b^{t+1}, w^{t+1}) / c^{t+1}}{C^t(y^t, b^t, w^t) / c^t}, \tag{13}$$

and the technical change component is

$$TECH_t^{t+1} = \left[\frac{C^t(y^{t+1}, b^{t+1}, w^{t+1})}{C^{t+1}(y^{t+1}, b^{t+1}, w^{t+1})} \frac{C^t(y^t, b^t, w^t)}{C^{t+1}(y^t, b^t, w^t)} \right]^{1/2}. \tag{14}$$

The product of the two component measures equals the productivity index

$$MCP_t^{t+1} = EFFCH_t^{t+1} \cdot TECH_t^{t+1}. \tag{15}$$

Note that the efficiency change component is the ratio of two Farrell measures of cost efficiency. The Malmquist index (15) 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 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".

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

The index number procedure derived in the previous section is used to measure productivity growth in the U.S. farm sector. Before turning to the empirical results, however, we provide a discussion of our data.

3.1 The Data

The data used to construct our productivity indexes based on desirable (or good) outputs alone are described in Ball *et al*. (1999). We identify two output, crops and livestock. The inputs include services of capital, land, labor, and intermediate inputs. The data are available for the forty-eight contiguous states for the period 1960 to 1996 and are used to construct a state-by-year panel.

As a first step, we construct longitudinal indexes of real output across states at one point in time. An index of relative real output between two states is obtained by dividing the nominal output value ratio for the two states by the corresponding output price index. We construct relative output price indexes using a method proposed independently by Eltetö (1964) and Köves and Szulc (1964). The "EKS" index is based on the idea that the most appropriate index to use when comparing two states is the binary Fisher index. However, when the number K of states exceeds two, the application of the Fisher index number procedure to the $K(K-1)/2$ possible pairs of states gives results that may not satisfy Fisher's circularity test. The problem, therefore, is to obtain results that satisfy transitivity and that deviate the least from the binary Fisher indexes.

Let P_F^{jk} denote the bilateral Fisher index for state *j* relative to state *k*. If P_{EKS}^{jk} denotes the multilateral index, then the EKS method suggests that P_{EKS}^{jk} should deviate the least from the bilateral index P_F^{jk}. Thus P_{EKS}^{jk} should minimize the follow distance criteria:

$$\sum_{j=1}^{K}\sum_{k=1}^{K}(\ln P_{EKS}^{jk} - \ln P_F^{jk})^2. \tag{16}$$

Using first-order conditions for a minimum, it can be shown that the multilateral index with the minimum distance is given by:

$$P_{EKS}^{jk} = \left(\prod_{i=1}^{K} P_F^{ji} \cdot P_F^{ik}\right)^{1/K}, \; j,k = 1,\ldots,K. \tag{17}$$

The EKS index may, therefore, be expressed as the geometric mean of the K indirect comparisons of states *j* and *k* through other states.

Using (17), we construct indexes of relative output prices in a single base year. The corresponding quantity indexes are formed implicitly. The indexes in the base year are then extrapolated to earlier and later years in the sample by the ratio of the intertemporal

indexes for the comparison and numeraire states. In this approach, we adjust the levels of the price and quantity series in relation to the numeraire state while preserving the original time paths of prices and quantities in each state.

Measures of relative inputs across states require data on relative input prices. Relative prices of capital inputs are obtained based on relative investment goods prices, taking into account the flow of capital services per unit of capital stock in each state.

Differences in the relative efficiency of land prevent the direct comparison of observed prices. Our estimates of the relative price of land in each state are based on hedonic regressions. For our cross section of states, we estimate the following equation by least squares:

$$\ln(w_k^j) = \sum_{k=1}^{K} \delta_k D_k + \sum_{c=1}^{C} \beta_c x_{kc}^j + \varepsilon_{kj}, \tag{18}$$

where w_k^j is the price of land in region j in state k, x_k^j is a vector of land characteristics, D_k is a dummy variable equal to unity for the corresponding state and zero otherwise, and ε_{kj} is a stochastic error term. When the log of prices is related to linear state dummy variables, a hedonic price index can be calculated from the antilogs of the δ_k coefficients.

In constructing indexes of relative labor input, we assume that the relative efficiency of an hour worked is the same for a given type of labor in all forty-eight states. Hours worked and average hourly compensation are cross classified by sex, age, education, and employment class (employee versus self-employed and unpaid family workers). Since average compensation data are not available for self-employed and unpaid family workers, each self-employed worker is imputed the mean wage of hired workers with the same demographic characteristics.

Agricultural pesticides are an important intermediate input. We construct relative prices of pesticides from hedonic regression results. Price differences among pesticides at a point in time are assumed due to differences in physical characteristics such as toxicity, persistence in the environment, and leaching potential. The corresponding quantity indexes are formed implicitly.

A unique feature of our data series is that it also contains a number of undesirable or bad outputs, which is crucial for our analysis of productivity growth. A detailed discussion of the construction these series is provided in Kellogg *et al*. (2002). Here we provide a brief overview. The bad outputs are indicators of risk to human health from exposure to agricultural pesticides in drinking water. We construct indicators of risk from exposure to pesticide runoff into surface water and pesticide leaching into groundwater.

Our assessment of risk is based on the extent to which the concentration of a specific pesticide exceeds a water quality threshold. For each of some 200 pesticides applied to twelve crops, we estimate the annual concentration at the bottom of the root zone and the edge of the field for 4,700 representative soils. These concentrations are compared to water quality thresholds that represent safe levels for chronic exposure. When the concentration of a specific pesticide exceeds the threshold, an indicator of risk is constructed using the concentration-threshold ratio. More specifically, we estimate the number of "threshold exceedence units" for each pesticide and then sum across all pesticides used.

Finally, 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.

3.2. The Empirical Results

We begin by computing the MCP index including only good outputs. This provides a benchmark which can be used to assess the bias associated with ignoring bad outputs. We report the average annual rates of change in the MCP 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.

Before reporting productivity growth rates that account for the detrimental effects on water quality, we examine the trends in production of the bad outputs. Figure 1 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 trended downward between 1976 and 1984. After 1984, pesticide leaching resumed its upward trend, while pesticide runoff continued to decline.[2]

Average annual rates of change in pesticide leaching and runoff for each of the forty-six states are reported in Table 2 for the complete 1960-96 period and for two sub-periods--1960-74 and 1974-96. Our choice of sub-periods delineates the era of increased regulatory scrutiny of pesticides.[3] During the 1960-74 period, all forty-six states in our sample 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 reversed 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.

The risk from pesticide leaching and runoff varied markedly over space as well as over time. The spatial distributions for the two indicators are displayed in Figures 2 and 3.[4] We see that the risk from pesticide runoff is greatest in the Upper Mississippi, Ohio, and Great Lakes Water Resource Regions. The risk from pesticide leaching is high in some of these same areas, but is also a concern in the South Atlantic and Gulf regions.

This brings us to the main theme of this paper, the measurement of productivity when there are externalities in production. Table 3 provides estimates of productivity growth for each state that account for joint production of good and bad outputs. 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 Spearman rank correlation coefficient between the two models is 0.32.

Consider the sub-period 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 measures that ignore bad outputs. 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 MCP index including bad outputs increases more slowly than does the MCP index excluding bads. In eight states (AL, DE, FL, GA, MD, OR, VA, and WV) where the MCP index including bad outputs 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 MCP 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 MCP 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 MCP index including bad outputs grew more rapidly than the alternative measure 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 period of years rather than on actual year-to-year changes in the series.

To investigate, we examine the time paths of production of the bad outputs and the alternative measures of productivity for selected states. Figure 4 plot the indexes of pesticide leaching and runoff for Iowa for the period 1960 to 1996. Observe that pesticide leaching increased sharply from 1960 to 1978, and declined thereafter. The increase in pesticide runoff over this period was less pronounced. If our concern is the measurement of productivity growth over the 1960-78 period, we would expect the MCP index including bads to increase relatively slowly. Conversely, if our focus is the 1978-96 period when the production of bads was declining, we would expect this measure to exhibit more rapid productivity growth.

Indeed, Figure 5 shows a dramatic slowdown in productivity growth between 1960 and 1978 based on the more inclusive measure. The MCP index excluding bads suggests strong productivity growth over this period. The MCP index including bads increased more rapidly over the 1978-96 period, reflecting the decline in both pesticide leaching and runoff.

In Figure 6, we present the indicators of environmental risk for Illinois. 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 7 that our MCP index including bads increases more slowly than does the alternative. However, when the level of risk is constant (as is the case for the period 1980 to 1996), the two measures of productivity growth are quite similar.

Our last state is Nebraska. Figure 8 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 sub-period from 1968 to 1978 when the risk from pesticide leaching is increasing most rapidly. We see from Figure 9 that our MCP index including bads increases more slowly. Also note that during the period 1978 to 1986 when both leaching and runoff trended downward, our MCP index including bads points to more rapid productivity growth. Finally, during the sub-period 1988 to 1996 when production of both bads are increasing, our MCP 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.[5] Referring to Figure 1, we see that both pesticide leaching and runoff increased from 1960

to 1972. Both series trend downward from 1972 to 1984. After 1984, the two series diverge. We plot indexes of productivity growth over these three sub-periods in Figure 10. And again we see that ignoring bads when their production is increasing results in an overstatement of productivity growth. In fact, our MCP index including bads shows negative productivity growth over the 1960-72 period, while its counterpart points to gains in productivity. Ignoring reductions in bads results in an understatement of productivity growth over the period 192 to 1984. Finally, when the two series move in opposite directions, as in the 1984-96 period, our MCP index including bads points to stronger growth in productivity than does the alternative.

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 measures of productivity growth that ignore bad outputs are biased upward when the production of bads is increasing. Conversely, when the environmental risks associated with production are decreasing, this same measure understates the social benefits of production and, hence, productivity growth.

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Tables

Table 1. Productivity Growth in U.S. Agriculture, 1960-96

STATE	MCP	EFFCH	TECH
AL	1.0267	1.0034	1.0232
AR	1.0360	1.0096	1.0262
AZ	1.0071	0.9813	1.0263
CA	1.0241	0.9980	1.0262
CO	1.0219	0.9951	1.0269
CT	1.0346	1.0102	1.0241
DE	1.0336	1.0078	1.0256
FL	1.0287	1.0000	1.0287
GA	1.0382	1.0113	1.0266
IA	1.0210	0.9964	1.0247
ID	1.0321	1.0026	1.0294
IL	1.0247	0.9952	1.0297
IN	1.0265	0.9974	1.0292
KS	1.0213	0.9945	1.0269
KY	1.0269	0.9991	1.0278
LA	1.0368	1.0084	1.0282
MA	1.0291	1.0048	1.0242
MD	1.0258	1.0025	1.0233
ME	1.0240	0.9997	1.0242
MI	1.0312	1.0037	1.0274
MN	1.0192	0.9952	1.0241
MO	1.0184	0.9944	1.0242
MS	1.0375	1.0081	1.0291
MT	1.0150	0.9866	1.0289
NC	1.0393	1.0108	1.0282
ND	1.0295	1.0007	1.0288
NE	1.0265	0.9983	1.0282
NH	1.0261	1.0004	1.0257
NJ	1.0260	1.0000	1.0260
NM	1.0257	0.9998	1.0258
NY	1.0171	0.9932	1.0241
OH	1.0233	0.9946	1.0288
OK	1.0155	0.9896	1.0261
OR	1.0243	0.9961	1.0283
PA	1.0263	1.0010	1.0253
SC	1.0374	1.0082	1.0289
SD	1.0209	0.9980	1.0230
TN	1.0199	0.9956	1.0244
TX	1.0175	0.9930	1.0246
UT	1.0151	0.9896	1.0258
VA	1.0255	1.0005	1.0249
VT	1.0282	1.0030	1.0251
WA	1.0334	1.0017	1.0316
WI	1.0109	0.9892	1.0219
WV	1.0151	0.9919	1.0234
WY	1.0103	0.9828	1.0280

Table 2. Growth Rates of Undesirable Outputs, 1960-96

	Average annual growth rates Leaching			Average annual growth rates Runoff		
State	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. Productivity Growth Including and Excluding Bads

	MCP Including Bads			Infeasible	MCP Excluding Bads		
	1960-1974	1974-1996	1960-1996	solutions	1960-1974	1974-1996	1960-1996
AL	1.2108	1.0220	1.0968		1.0336	1.0219	1.0267
AR	1.0419	1.0301	1.0350	24	1.0460	1.0289	1.0360
AZ	0.9916	1.0728	1.0247		1.0120	1.0036	1.0071
CA	1.0171	1.0217	1.0212	18	1.0282	1.0212	1.0241
CO	1.0110	1.0320	1.0232		1.0229	1.0212	1.0219
CT	1.0191	1.0526	1.0385		1.0222	1.0435	1.0346
DE	1.2514	1.0078	1.1324	10	1.0384	1.0301	1.0336
FL	1.0460	1.0261	1.0390	16	1.0430	1.0186	1.0287
GA	1.3166	1.0204	1.1493	6	1.0516	1.0287	1.0382
IA	0.5595	0.9706	0.7716		1.0132	1.0267	1.0210
ID	1.0123	1.0358	1.0254	11	1.0330	1.0314	1.0321
IL	0.9947	1.0166	1.0074		1.0261	1.0238	1.0247
IN	1.0277	1.0190	1.0226		1.0244	1.0280	1.0265
KS	1.0250	1.0242	1.0245		1.0207	1.0218	1.0213
KY	1.0193	1.0293	1.0252		1.0226	1.0299	1.0269
LA	1.0375	1.0279	1.0319		1.0430	1.0324	1.0368
MA	0.9982	1.0285	1.0168	2	1.0308	1.0278	1.0291
MD	1.0901	1.0308	1.0551		1.0304	1.0226	1.0258
ME	0.9906	1.0128	1.0013	7	1.0302	1.0195	1.0240
MI	1.0686	1.0156	1.0374		1.0407	1.0245	1.0312
MN	0.9941	1.0456	1.0238		1.0110	1.0250	1.0192
MO	0.9646	1.0163	0.9944		1.0131	1.0222	1.0184
MS	1.0624	1.0172	1.0358		1.0545	1.0255	1.0375
MT	1.0178	1.0088	1.0125		1.0244	1.0084	1.0150
NC	1.0183	1.0315	1.0260		1.0469	1.0340	1.0393
ND	0.8019	0.6046	0.7444	17	1.0373	1.0240	1.0295
NE	1.0326	1.0293	1.0307		1.0217	1.0299	1.0265
NH	1.0194	1.0147	1.0163	7	1.0444	1.0132	1.0261
NJ		1.0344	1.0344	15	1.0156	1.0335	1.0260
NM	1.0291	1.0477	1.0394	2	1.0344	1.0195	1.0257
NY	0.9955	1.0269	1.0154	3	1.0160	1.0179	1.0171
OH	0.8738	1.0112	0.9515		1.0367	1.0138	1.0233
OK	1.0286	1.0021	1.0131		1.0285	1.0063	1.0155
OR	1.2636	1.0361	1.1070	30	1.0421	1.0117	1.0243
PA	1.0128	1.0316	1.0237		1.0214	1.0298	1.0263
SC	1.0267	1.0263	1.0265		1.0489	1.0292	1.0374
SD	1.0119	1.1622	1.0933	2	1.0076	1.0306	1.0209
TN	1.0487	1.0129	1.0277		1.0301	1.0127	1.0199
TX	1.0368	1.0133	1.0230		1.0302	1.0085	1.0175
UT		1.1738	1.1738	35	1.0111	1.0179	1.0151
VA	1.0401	1.0320	1.0353	1	1.0295	1.0226	1.0255
VT	0.9709	1.0229	1.0037	3	1.0465	1.0153	1.0282
WA	1.0426	1.0398	1.0410	9	1.0437	1.0261	1.0334
WI	1.0288	1.0106	1.0181		1.0071	1.0136	1.0109
WV	1.0355	1.0293	1.0319		1.0218	1.0104	1.0151
WY	0.9981	1.0668	1.0330	5	1.0147	1.0071	1.0103

Figures

Figure 1. Environmental Indicators for U.S. Agriculture, 1960-96 (in million TEUs)

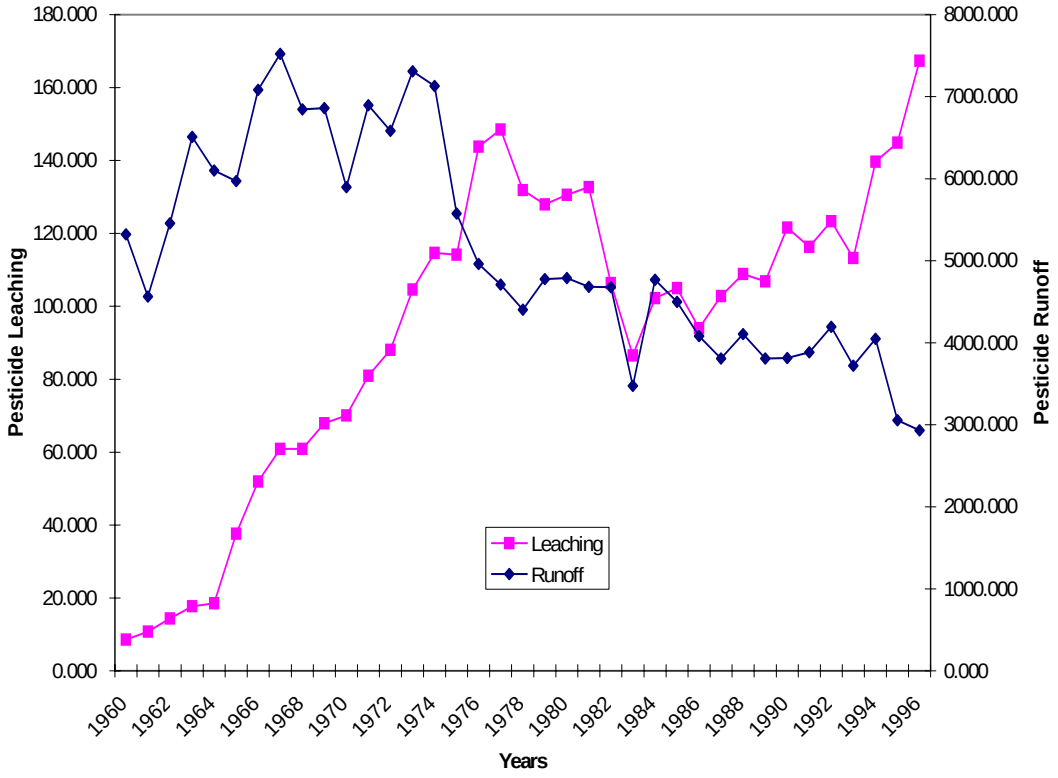


Figure 2. Regional Distribution of Pesticide Leaching, 1996 (in million TEUs)

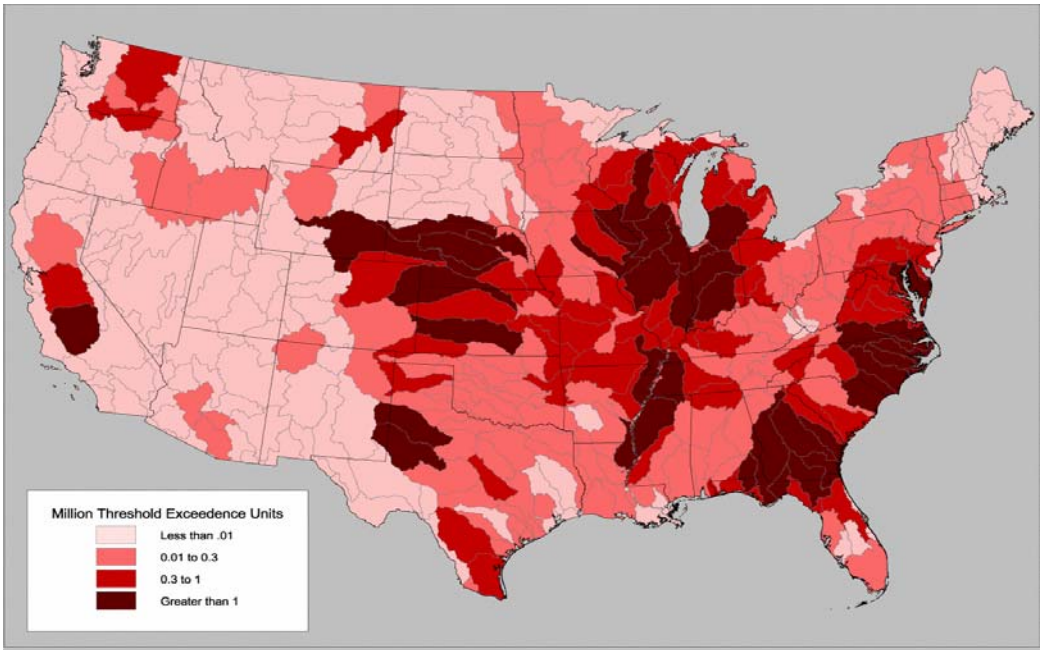


Figure 3. Regional Distribution of Pesticide Runoff, 1996 (in million TEUs)

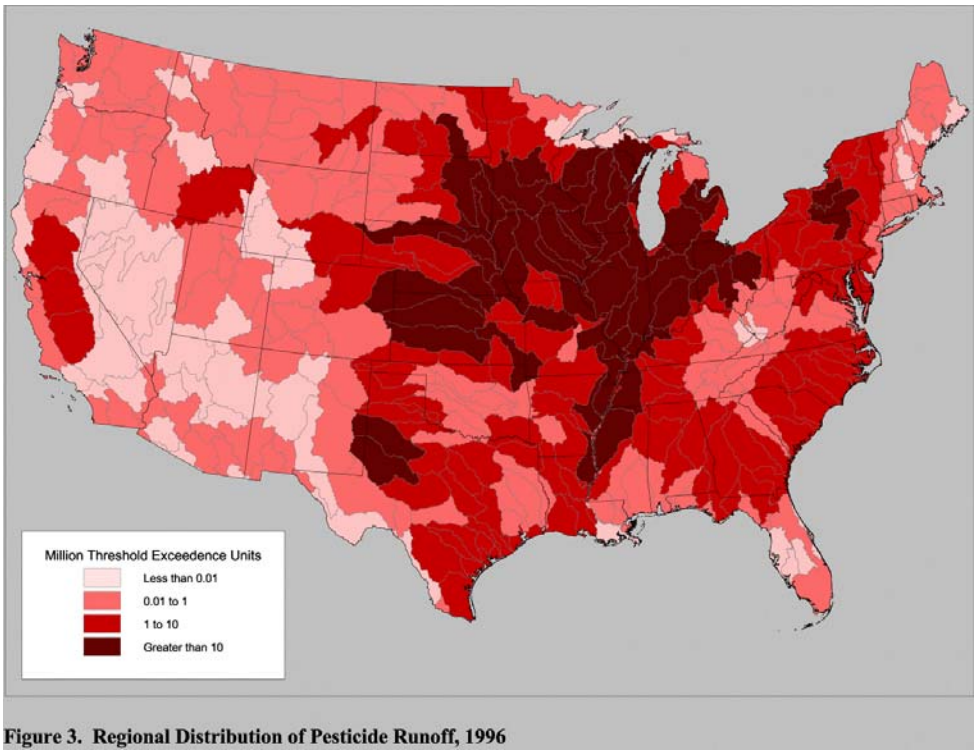


Figure 4. Environmental Indicators for Iowa, 1960-96 (in million TEUs)

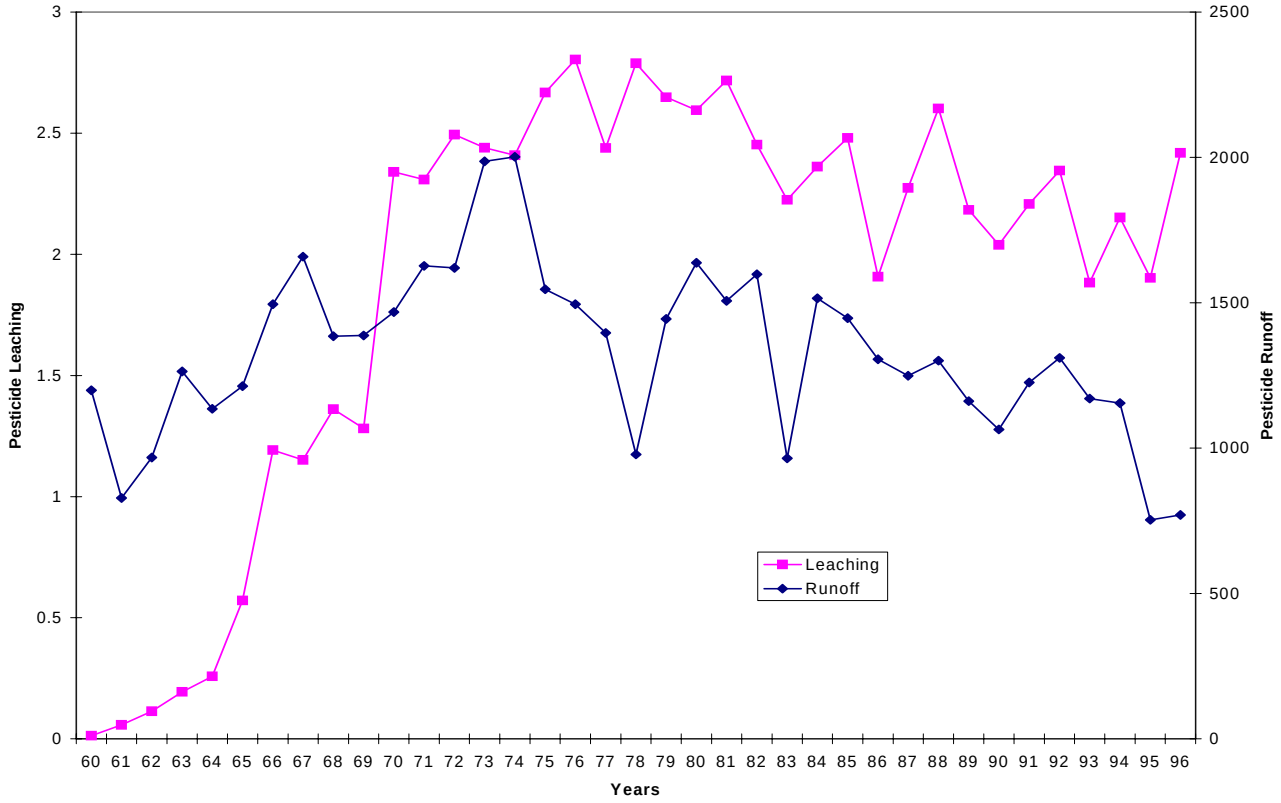


Figure 5. Alternative Productivity Growth Rates for Iowa, 1960-96

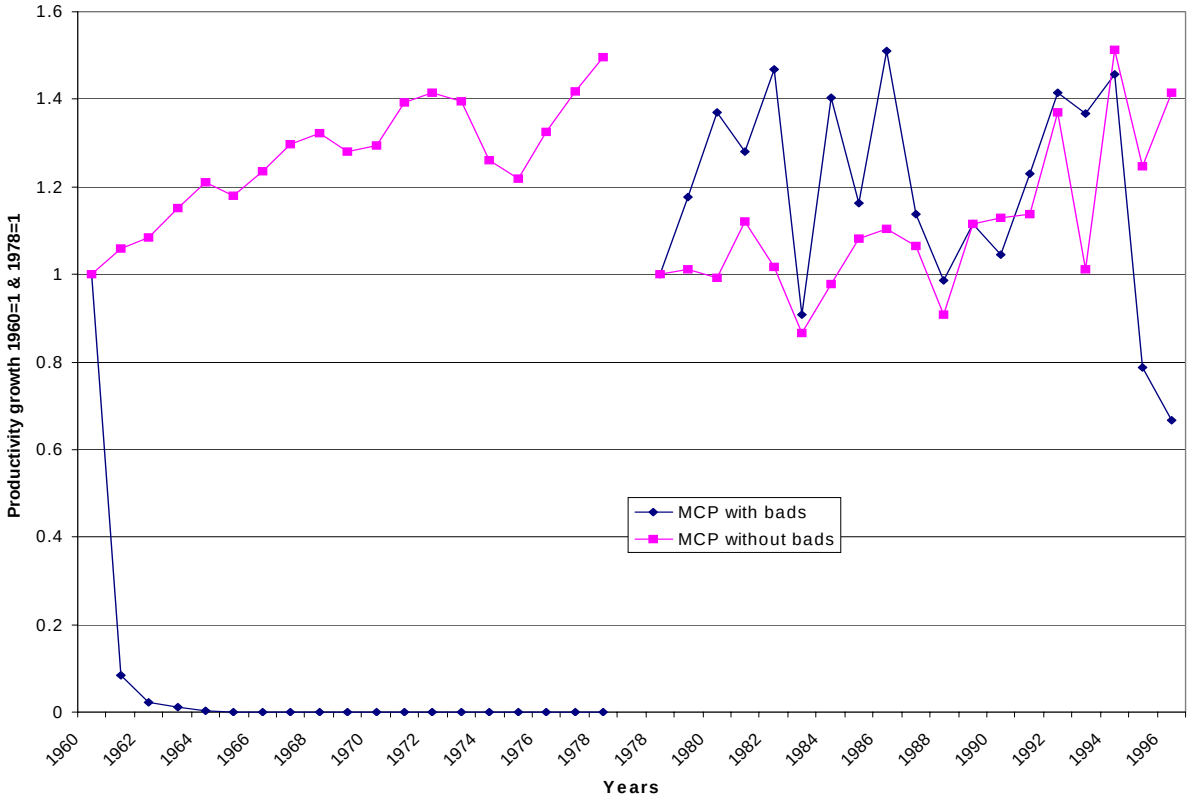


Figure 6. Environmental Indicators for Illinois, 1960-96 (in million TEUs)

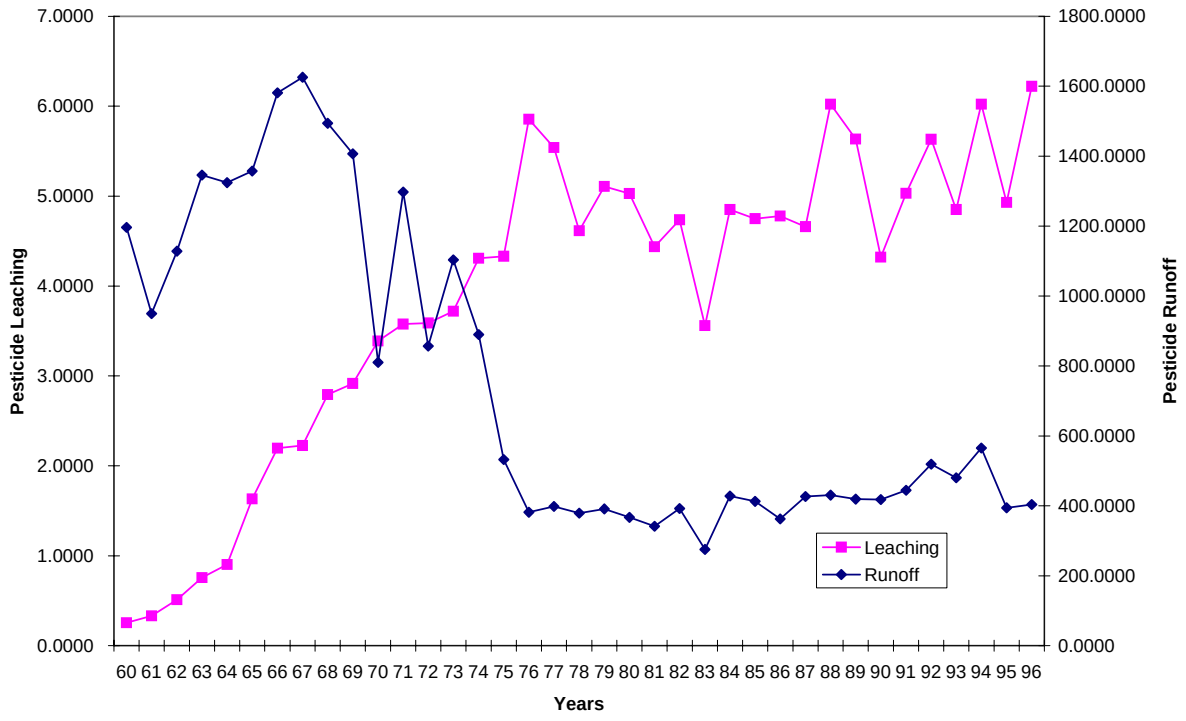


Figure 7. Alternative Productivity Growth Rates for Illinois, 1960-96

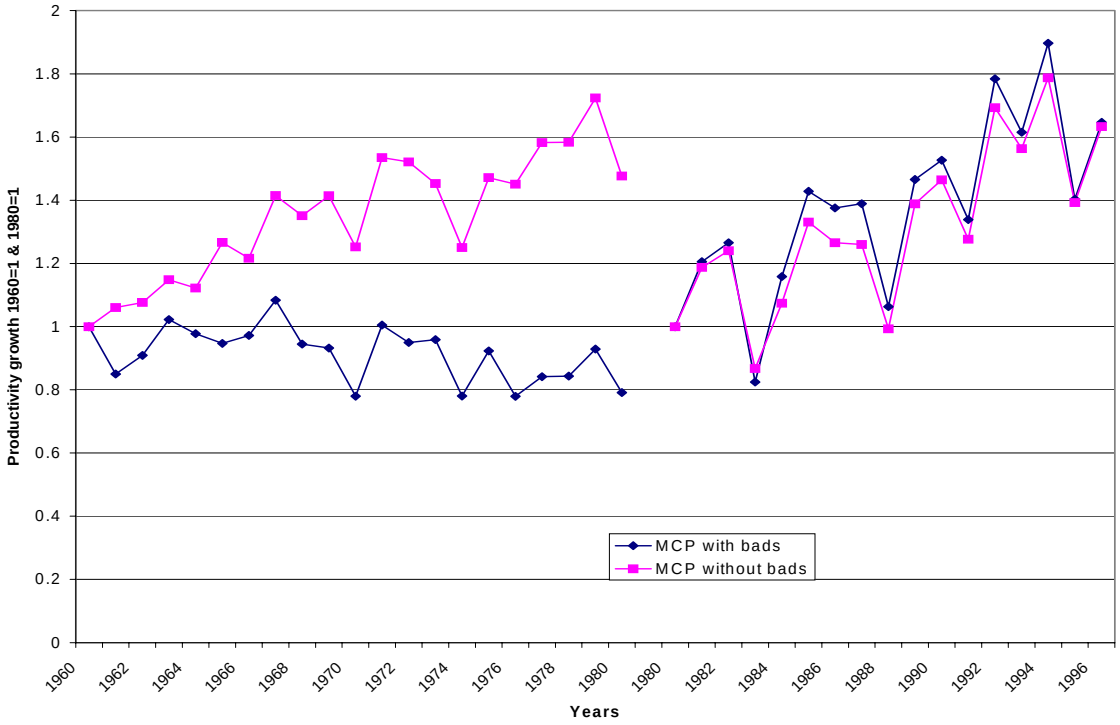


Figure 8. Environmental Indicators for Nebraska, 1960-96 (in million TEUs)

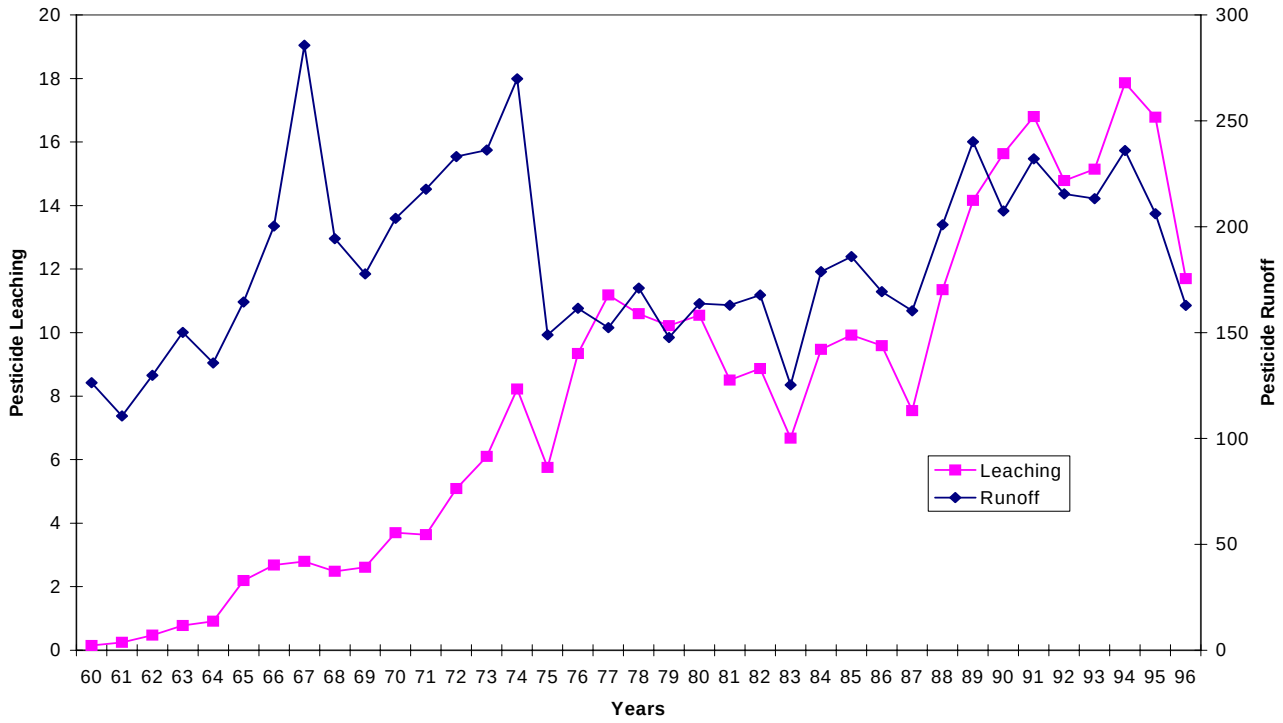


Figure 9. Alternative Productivity Growth Rates for Nebraska, 1960-96

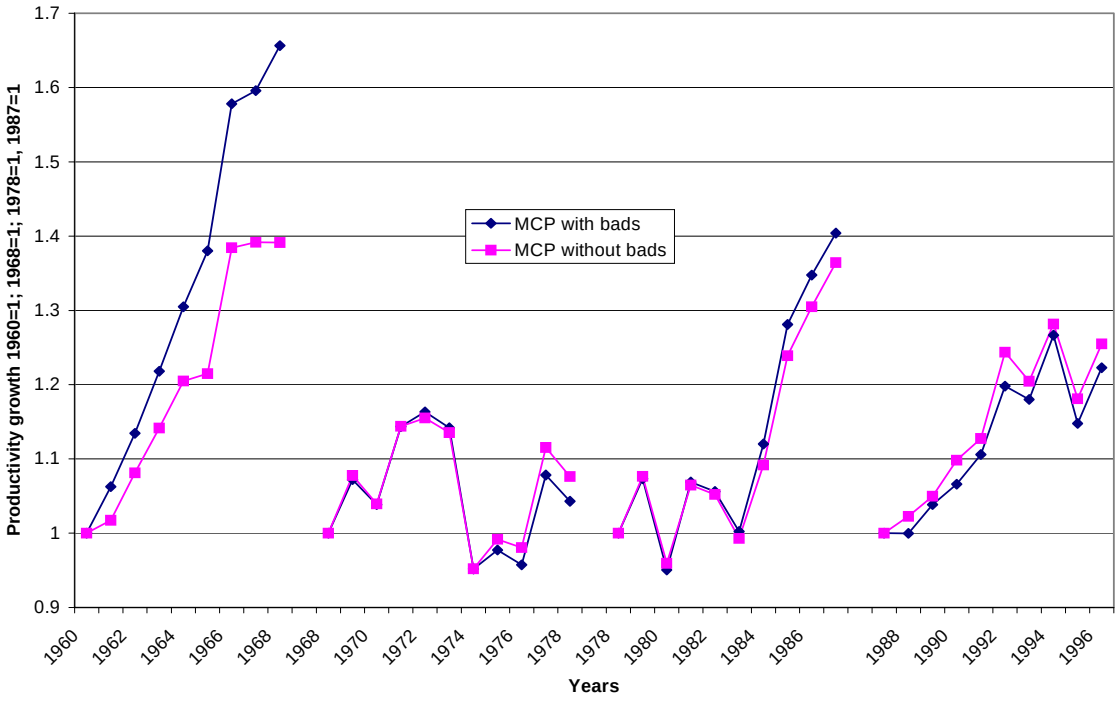
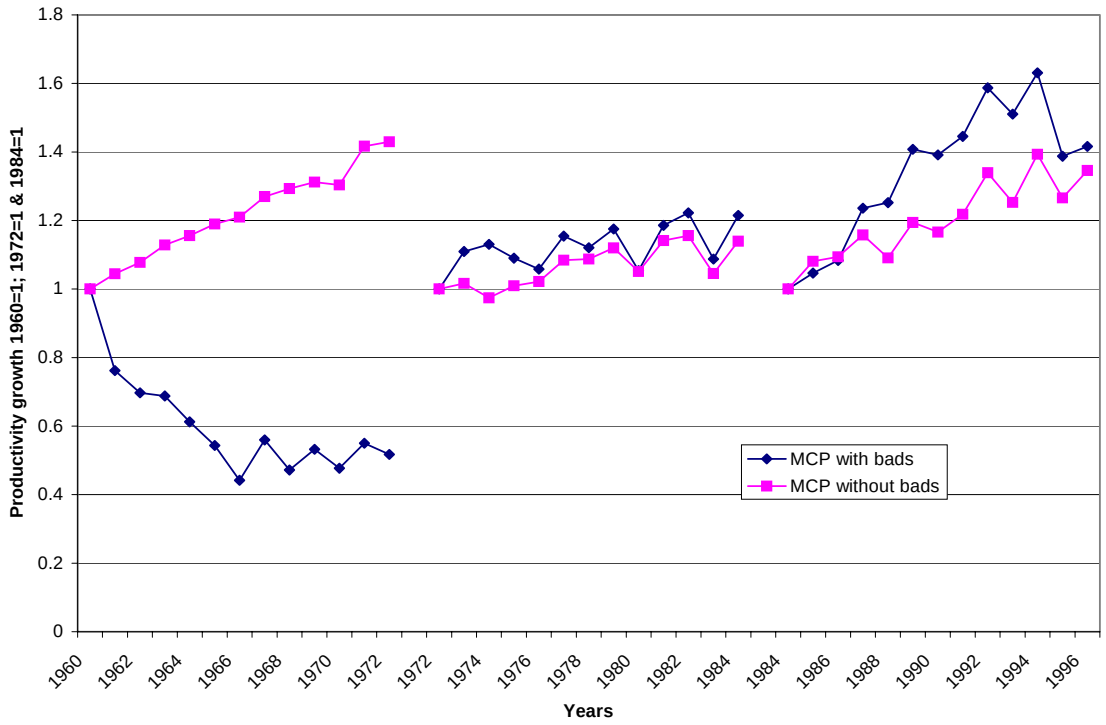


Figure 10. Alternative Productivity Growth Rates for U.S Agriculture, 1960-96



[1] This property, which is referred to as weak disposability in the non-parametric 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 cost with respect to a bad output is negative (see Ball *et al.*, 2002).

[2] We attribute the observed reduction in risk from exposure to pesticides to 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 di dnot cause unreasonable adverse effects to human health or the environment. It also reguired an examination of the safety of all previously registered pesticides using new health and environmental criteria. Pesticides with risks that exceeded those criteria were subject to cancellation.

[3] See Note 2 above.

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

[5] Productivity growth for the aggregate farm sector is computed as the weighted geometric mean of productivity growth rates across individual states, where the weights are the optimal cost shares for each state. These optimal cost shares are computed from the solution of our linear programming problems.