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Effective Costs and Chemical Use in US Agricultural Production: Benefits and Costs of Using the Environment as a "Free" Input

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Benefits and Costs of Using the Environment as a "Free" Input

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Abstract

This study uses a cost-function-based model of production processes in the U.S. agricultural sector to represent producers' input and output decisions, and the implied costs of reductions in risk associated with leaching and runoff from agricultural chemical use. The model facilitates evaluation of the statistical significance of measured shadow values of "bad" outputs and their input- and output-specific components. Of special interest are the impacts on pesticide demand and its quality and quantity aspects. The shadow values of risk reduction are statistically significant, and imply increased demand for "effective" pesticides that come mainly from embodied technology leading to improvements in quality.

Introduction

The benefits and costs of chemical[1] use in U.S. agriculture, in terms of the augmentation of effective production and the increased risk from toxicity, have long been debated. Clearly, such chemicals have both private and social value, in that they allow farmers (producers) to expand output (and revenue) which, in turn, ensures a greater supply of agricultural products for both U.S. consumers and export. But there are also private and social costs – from the private (purchase) costs incurred by producers to risks associated with leaching and runoff.

While the private cost of applied chemicals obviously includes their per unit price, the true economic cost for pesticides is represented by the per unit price of pesticide *abatement*. This abatement cost includes research developments embodied in the pesticide input (through its chemical composition), that both augment its effective impact and reduce risk. The associated research costs are primarily reflected in the purchase price (and thus borne by the user), but are also partially paid for by taxpayers through general R&D expenditures. Social costs accrue from the use of the environment as a "free" input, as producers dispose of excess pesticides, potentially imposing risk and damage to both human health and the broader ecological environment.

The benefits to producers of using the environment as a free input take the form of higher output, or lower input costs for a given amount of production, than if producers were required to reduce the "bad" outputs associated with production. That is, lowering risk implies either decreasing marketed outputs (since "bad" outputs are joint with "good" outputs) or increasing inputs (by substitution for the chemical input or alternative waste disposal). Thus, policy legislation requiring reduction of risks will impose private costs on the agricultural community.

In this study we explore these relationships using a detailed cost-function-based model of the production structure of U.S. agriculture. The analysis is performed using a rich state-level (48 states for 1960-96) panel data set from the USDA/ERS with a multi

[1] When referring to agricultural "chemicals" from this point forward we are referring to fertilizers and pesticides, though much of the analysis focuses on the effects of pesticide use.

-output and -input base, and including measures of pesticide use and human and fish risk associated with leaching and runoff.

The costs of risk reduction may be represented by shadow values for the bad outputs. These shadow values are characterized as the foregone marginal benefits of being able to use the environment freely, or, conversely, the amount farmers would be willing, on the margin, to pay for the ability to use the environment. The magnitude of these economic benefits can therefore be examined by estimating the costs that would be incurred in lowering risk for a given level of output. This, in turn, involves substitution among outputs and inputs. Thus, shadow values depend on both the technological substitution possibilities and the input demand and output supply behavior underlying agricultural production processes.

Measuring the shadow values of risk from agricultural chemical use and their link to the demand for pesticides and other components of the production structure requires a detailed estimable model of agricultural production. Such a model permits a detailed analysis of output and input supply, demand, and composition changes associated with substitution among netputs in agricultural processes – all of which aid in assessing costs and benefits of chemical use. Econometric implementation of the model allows statistical inference about the determinants of costs associated with reductions in bad outputs (risk) and effective production of good (marketed) outputs.

We find shadow values of risk factors to be significant, larger for leaching than for runoff, and increasing in magnitude over time. This implies that substantive (and increasing) costs would be imposed on the agricultural sector by legislation requiring reductions in human-toxic risk from leaching and runoff. The results also indicate that these potential costs to farmers are associated with increases in *effective* pesticide use – as well as higher levels of most other inputs except land – for a given level of agricultural output. The implied costs of augmented pesticide use stem from chemical composition changes undertaken to improve the abatement power of pesticides and to diminish risk. This embodied innovation represents increased, but costly, pesticide quality.

The Methodology: model and measures

Measuring the costs and benefits of agricultural chemical use and associated environmental damage involves explicitly modeling the production structure, recognizing the wide variety of output (revenue) and input (cost) patterns exhibited in the data. Our state-level data set includes information on the production of two "good" outputs (crops and animals) and four associated "bad" outputs (human and fish risk from leaching and runoff), and the use of six inputs (including pesticides and fertilizer). The data thus facilitate the representation of a wide range of output and input substitution and composition relationships.

We base our analysis on a cost-function characterization of input demand in U.S. agricultural production that not only encompasses our broad array of inputs, but also incorporates the deviations between pounds of pesticides used and quality-adjusted "effective" pesticide use. For empirical implementation, this cost function is augmented by price determination equations[2] to represent profit maximization over "good" outputs, and by spatial and temporal fixed effects to accommodate differences across states and time periods. This detailed modeling framework allows us to explore a rich set of interactions among chemical application, environmental damage (risk), output production, and input demand.

More specifically, our cost function takes the general form TC = TC(**Y**,**B**,**w**,**D**,t) where **Y** is a vector of outputs (crops, Y_C, and animal products, Y_A); **B** is a vector of "bad" outputs or proxies for risk factors from human-toxic leaching and runoff (B_{HL}, B_{HR});[3] **w** is a vector of input prices (land, LD; labor, L; capital, K; pesticides, P; fertilizers, F; and other materials, M); **D** is a vector of dummy variables corresponding to fixed effects for each state, specific time periods, the corn states as a group, the cotton states; and t is a time trend.

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[2] Preliminary investigation using a profit function framework resulted in slopes of the materials demand equation and crop and animal output supply equations that violated standard regularity conditions. This could be due to presence of negative profits implied in the U.S. agricultural sector when adjustments to land, capital and other inputs are made to recognize their effective values. The alternative $p_m = MC_m$ equations (where MC is the marginal cost and p_m the market price of output Y_m) take the form of pricing rather than output choice equations. This may seem more valid in an imperfectly competitive market framework where the price is set where marginal revenue is equal to marginal cost. But when such a model was estimated, the gap between marginal revenue and output price was insignificantly different from zero, suggesting that the data represent true economic prices facing agricultural producers. We retained these equations for estimation because omitting them reduced the robustness of the marginal cost estimates.

[3] The data construction procedures for these indexes are summarized in Kellogg *et al*. In preliminary estimation fish stock risk from leaching and runoff were also included as bad outputs, but when both types of leaching and runoff were included the shadow values for fish risk were invariably insignificant (and sometimes not the expected sign), so they were dropped.

B is included in the cost function on the realization that bad outputs are produced jointly with **Y**, or, conversely, that the environment is used as an unpaid input by producers disposing effluent.[4] Production of bads allows more effective marketed or good outputs **Y** to be produced for a given level of inputs, or, alternatively, less input costs for a given amount of **Y**. Thus, requirements to reduce risk are costly to producers in terms of net output – output per unit of input or cost – reductions. That is, for any level of output they lead to increased input costs due to substitution toward non-chemical inputs, or toward less risky, but more costly substitute chemicals.

The associated shadow values (SV) of the bad outputs, or the (input) cost benefit from allowing risk, may be measured as the vector of cost effects $\nabla_{\mathbf{B}}TC = \mathbf{SV_B}$. For example, the marginal benefit to the firm of permitting leaching that may cause risk to human health (B_{HL}) is $SV_{BHL} = \partial TC/\partial B_{HL} < 0$. Analogously, for any B_k component, this becomes $SV_{Bk} = \partial TC/\partial B_k$. These shadow values reflect the marginal amount the producer would be willing to pay for the right to increase B_{Hk}. From the reverse perspective, SV_{Bk} represents the input costs that would be incurred on the margin if a decrease in B_{Hk} were legislated.

In our framework, these shadow values incorporate the behavioral motivations underlying cost-efficient production choices, as well as technological substitution possibilities. SV_{Bk} should thus be interpreted in the context of a *private* value to producers, since it represents the amount that expenditure on other inputs would have to increase (at a given output level) if the environment couuld not be freely used.[5] In terms of *social* costs, therefore, SV_{Bk} indicates the amount a marginal reduction in risk must be thought to benefit society overall to justify legislation requiring B_{Hk} reductions.

The first-order cost relationships determining the shadow values, $\partial TC/\partial B_k=SV_{Bk}$, may be decomposed into their input-specific effects, or the individual impacts of B_k "production" on the demand for the various inputs. In particular, the linkage between bad output production and chemical use may be explored in terms of the impact of risk reduction on pesticide and fertilizer demand decisions.

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[4] This is similar to the development of the notion that reduction of bad outputs is costly in the context of a technological representation in Ball *et al*.

Because bad outputs (risk factors) are apparently directly related to the use of chemical inputs, it would seem that decreases in P and F would be associated with declines in B_k (while increases in most other inputs may be required to reduce risk). It turns out, however, that improvements in the quality of the chemical inputs that lead to *increased* use of effective (quality-adjusted) P are associated with decreases in B_k.

The link between pesticide use and risk factors is represented by using the 1st order Shephard's lemma result that pesticide input demand may be captured by $P = \partial TC/\partial w_P$ (where w_P is the market price of P). Then the elasticity of this demand relationship with respect to a change in B_k (a 2nd order cost effect) is constructed to reflect the dependence of effective pesticide use on the ability to dispose of waste in the form of leaching or runoff.

The use of Shephard's lemma implies that the price and quantity of P have been measured in effective units, so that the cost derivative reflects the true economic quantity of pesticide abatement. If w_P (or P) are not measured appropriately, the application of Shephard's lemma could be invalid.

In this case we could write the cost derivative as $SQ_P = \partial TC/\partial w_P$, where SQ denotes the "shadow quantity" or true economic/effective quantity of P, that may or may not be well represented by its measured level. Or, if the quantity instead of price of P were included as an argument in $TC(\cdot)$ (as are the B_k factors), the shadow would be $SV_P = \partial TC/\partial P$. In equilibrium with correctly measured quantities and prices, SQ_P=P and SV_P=w_P, but with mis-measurement deviations would instead be evident between the shadow and measured quantities or prices.[6]

Since an important issue in the literature on pesticide use and productivity is the appropriate measurement of pesticide *abatement* price and quantity, this distinction between true and measured price or quantity provides the basis for adapting the measured pesticide data to accommodate quality changes.

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[5] Note that since the producer does not have to pay directly for use of the environment the shadow value represents a clear net benefit for him/her as long as $SV_{Bk}<0$ (risk increases are cost diminishing). But this also implies there will be a tendency to overuse the environment due to the perspective that it's a "free input."

[6] Such a deviation would imply that the optimization equation for P should not be used for estimation purposes. Although in our model the P optimization equation seems valid for estimation purposes, this development provides the basis for identifying separate quantity and quality components of the effective pesticide quantity and price (based on the hedonic analysis by Nehring and Grube underlying the pesticide data used for this study).

However, in our study, preliminary empirical investigation indicated that the pesticide data justifiably represent the true price and quantity of pesticide abatement.[7]

Relying on Shephard's lemma, therefore, we can construct an elasticity to represent the pesticide demand response to requirements for risk reduction as $\varepsilon_{P,Bk} = \partial \ln P/\partial \ln B_k$. Although the overall cost elasticity $\varepsilon_{TC,Bk} = \partial \ln TC/\partial \ln B_k = SV_{Bk} \cdot B_k/TC$ should be negative, since $SV_{Bk}<0$ if risk reduction is costly, if P and B_k are in some sense joint or complementary $\varepsilon_{P,Bk}$ would instead be positive. If so, an input bias in absolute terms is implied; if overall input costs increase to reduce risk factors, but P declines, other inputs must increase even more than would be implied by the total cost elasticity. Even if the $\varepsilon_{P,Bk} = \partial \ln P/\partial \ln B_k$ measure is negative but smaller (in absolute value) than the cost elasticity, reductions in risk are biased since the responses of different inputs to B_k changes differ.

More generally, such elasticity measures can be constructed for any input to capture the input-specific impacts of risk reduction. Changes in input demand and thus composition depend on evaluation and comparison of $\varepsilon_{xj,Bk} = \partial \ln x_j /\partial \ln B_k$ elasticities, where $x_j = \partial TC(\cdot)/\partial w_j$ for j=F,LD,L,K,M,P. And if the substitution patterns underlying the overall shadow value SV_{Bk} are biased, each $\varepsilon_{xj,Bk}$ measure may well differ from each other substantially – even possibly varying in sign.

The impacts on the marginal costs of the good outputs from restricting bad outputs may be measured similarly. The shadow value (true economic value or contribution to production) of an output Y_m is represented by its marginal cost: $SV_{Ym} = MC_m = \partial TC/\partial Y_m$. The elasticities $\varepsilon_{MCm,Bk} = \partial \ln MC_m/\partial \ln B_k$ indicate the impacts of risk-reduction on the marginal costs of the outputs, providing some indication of producers' motivations to adapt output levels and composition by equating output price and marginal cost to maximize profits. That is, an increase in MC_m resulting from risk-reduction requirements would suggest reduced production of Y_m.

These marginal cost elasticities also provide insights about cost (scale and scope) economy changes resulting from limitations on risk. Because the shadow value measure SV_{Bk} indicates the total *and* the average

[7] In particular, although studies such as Lichtenberg and Zilberman, Chambers and Lichtenberg have often found that P equations have the wrong slope or even sign, in our analysis this was not the case. Using Shephard's lemma seemed justifiable both because regularity conditions on the demand equations were satisfied, and because estimation without Shephard's lemma imposed generated substantively equivalent results.

cost impact of a change in B_k, and economies of scale are based on the ratio of marginal to average costs, the relative impacts of B_k on the marginal- to- average-cost ratio also influence scale economies.

In addition, scope economies, based on jointness among outputs, can be examined through 2nd order cost effects. Scope economies (SC) are typically measured from a cost function model as $SC=([\Sigma_m TC(Y_m) - TC(\mathbf{Y})]/TC(\mathbf{Y}))$, where $TC(Y_m)$ is the minimum cost of producing Y_m. Thus, SC depends on the cost-interaction terms for the outputs, or the second derivatives $\partial^2 TC/\partial Y_m \partial Y_n$ or $\partial MC_m/\partial Y_n$.[8] If the bad outputs are handled like the good outputs, the scope economy impacts of B_k changes are captured by the $\varepsilon_{MCm,Bk}$ elasticities. These will be negative if increases in the bad outputs reduce the marginal costs of the good outputs, as would be suggested by jointness.

From another perspective, the relationships between input (pesticide) demand, “good outputs,” and bad outputs, represented above through the $\varepsilon_{xj,Bk}$ and $\varepsilon_{MCm,Bk}$ elasticity measures, can alternatively be characterized directly on the shadow values of the bad outputs. The shadow value measures $SV_{Bk} = \partial TC/\partial B_k$ will be a function of all arguments of the $TC(\cdot)$ function if the underlying cost relationship is approximated by form flexible enough to construct the corresponding elasticities from 2nd order terms. So, from Young’s theorem, the impact of a change in, say, w_j, on SV_{Bk} is symmetric to the effect of a change in B_k on the demand for x_j; $\partial SV_{Bk}/\partial w_j = \partial^2 TC/\partial B_k \partial w_j = \partial^2 TC/\partial w_j \partial B_k = \partial x_j/\partial B_k$. The elasticity representing this effect is thus $\varepsilon_{SVk,j} = \partial \ln SV_{Bk}/\partial \ln w_j$. Although the resulting indicators are not as conceptually appealing as the $\varepsilon_{xj,Bk} = \partial \ln x_j/\partial \ln B_k$ elasticities, analogous and more interpretable relationships will hold for the variables that are not optimized over in the cost function framework – the components of the **Y** and **D** vectors and the time trend, t.

For example, elasticities with respect to output levels, $\varepsilon_{SVk,Ym} = \partial \ln SV_{Bk}/\partial \ln Y_m$, indicate how the value of allowing risk – or unrestricted use of the environment for leaching and runoff – adapts in response to changes in (the exogenous) demand for a particular commodity. This intuitively appealing elasticity is analytically symmetric to the effect on MC_m of a change in risk. $\varepsilon_{SVk,Ym}>0$ suggests that at higher Y_m levels the cost of

[8] See Paul for more elaboration of these types of measures.

restricting risk to farmers in terms of input costs is heightened, or, in reverse, that output increases further enhance the value of using the environment.

Similarly, the impacts of variations in the shift factor t and fixed effects **D** (representing geographic location, specific output intensities, and structural changes in P and F) indicate time- and space-dependent differences in the cost to producers of risk reduction. These effects can be represented as elasticities of the SV_{Bk} measures with respect to each of these variables: $\varepsilon_{SVk,t} = \partial \ln SV_{Bk}/\partial t$, and $\varepsilon_{SVk,Ds} = \partial \ln SV_{Bk}/\partial D_s$.

The various cost and demand relationships developed above are characterized through 1st and 2nd order derivatives or elasticities of the cost function with respect to the arguments of $TC(\cdot)$. However, divergence in input demand patterns from those appropriately represented by Shephard's lemma would complicate or preclude the estimation and interpretation of these elasticities. Even though in our data set such deviations from standard assumptions of basic microeconomic theory did not emerge in the end, the knowledge that they might stimulated preliminary empirical investigation of alternative models that recognize these potential difficulties.

The most common problem of this sort is the quasi-fixity of factors such as capital, land, and labor. If full adjustment to equilibrium input levels does not take place within the time frame of the data, Shephard's lemma will not appropriately represent input demand behavior. This rigidity problem is often dealt with by incorporating levels instead of prices in the $TC(\cdot)$ function for inputs with binding fixity constraints, with the implied divergence from equilibrium demand (or, equivalently, variations from full utilization) represented by the deviations between a factor's shadow value ($SV_{xj} = \partial TC/\partial x_j$) and its market price ($w_j$).

Alternatively, the true/effective quantity demand of an input may be represented by directly adapting the *data* to embody the discrepancy. In particular, if the true (or shadow or virtual) price of the factor w_j^* is used as an argument of $TC(\cdot)$ rather than an unadjusted market price, the validity of Shephard's lemma is maintained.[9]

Although the data for this study were carefully constructed to reflect the input flow values, sensitivity checks were carried out to determine the validity of the assumption of variable inputs. These checks supported our final empirical specification; the assumption seemed justified by the appropriate levels and shapes of the

[9] See Fulginiti and Perrin for a detailed discussion of the conceptual basis and use of the virtual price framework.

resulting demand equations. In fact, when K, LD and/or L were not characterized as choice variables, so the additional structure of the input demand equations was not incorporated, the results were not as justifiable as when Shephard's lemma was implemented.[10]

More to the point for this project, as alluded to above, previous studies of pesticides demand have typically identified violations of standard regularity conditions in marginal product or input demand functions. Such violations have been attributed to mis-measurement of the true pesticide input as a physical quantity (say, pounds) rather than in terms of pest abatement services, rather than to constraints on behavior, or rigidities. If the actual input demanded by the farmer is true abatement (or increases in effective output from pest reduction, that depends on the chemical composition of the pesticides), the input should be specified accordingly.[11]

In the data used for this study, however, careful adaptations were made to identify the impacts of pesticide characteristics on their true or effective price, and thus their implicit quantity. More specifically, hedonic analysis was used by Nehring and Grube to accommodate pesticide application rates, toxicity (chemical composition) and persistence in their measure of the true economic price of the quality-adjusted pesticides input. This adjusted pesticide price measure or virtual price, w_P*, was used to deflate the pesticide expenditure data to reflect real effective pesticide quantities, P*.[12]

Our empirical findings based on these data suggest that this adjustment was carried out in a manner consistent with economic theory. The use of Shephard's lemma seems justified by both the correct (in terms of required regularity conditions) and intuitively plausible estimates of demand behavior. And when optimization equations were not imposed for the P input, so its true shadow value (or quantity) could be indirectly imputed, the resulting production structure pattern estimates remained substantively unchanged.

In addition, the distinction between w_P and w_P* (and thus P and P*) provides us a useful basis from which to separately identify changes in the demand for physical pesticide quantity as compared to that for its

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[10] This is similar conceptually to the finding in Ball *et al* that "inefficiency" in their framework seemed virtually nonexistent. In addition, the cross-section dimension of the panel data, and the detailed input and output decomposition, may better represent true utilization and equilibrium or long run substitution patterns that with more limited time series data sets.
[11] See, for example, Lichtenberg and Zilberman, and Chambers and Lichtenberg.
[12] See Nehring and Grube [1997] for more details about these computations.

quality or effectiveness. Such an exercise can generate useful insights about the quantity/quality tradeoff itself and the costs of increasing pesticide quality versus quantity associated with the reduction of risk factors. This distinction is particularly relevant since adaptations in the characteristics of the pesticide input captured in the hedonic analysis incorporate (or embody) both general technical change, and requirements or desires to respond to environmental concerns (induced innovation).

The virtual pesticide price can be written as $w_P^* = ADJ_P \cdot w_P$, where the AJP_P quality index adapts the price of P in terms of pounds (w_P) to one embodying characteristics, quality, or effective pesticide application according to the underlying hedonic representation.[13] It follows that w_P^* can justifiably be used as a basis for Shephard's lemma; $P^* = \partial TC/\partial w_P^*$, where P* is effective pesticide demand. But with the explicit $w_P^* = ADJ_P \cdot w_P$ specification, variations in the effective pesticide price can be divided into a combination of deviations in the "quantity-price" versus the "quality-price." These relationships are also imbedded in the identify $w_P P = w_{P*} P^* = VAL_P$, so $w_P^*/w_P = P/P^*$, where VAL_P is the dollar expenditure on pesticides, which can be used to motivate and interpret these measures.

The multiplicative (or log-linear, as is typical for a hedonic equation) specification of w_P^* implies that the contribution of a percentage increase in pesticide use (or price) is the same whether it stems from quality (ADJ_P) or quantity (w_P) changes. At any point in time, given $TC(w_P^*,\ldots)=TC(ADJ_P \cdot w_P,\ldots)$, the marginal cost of changing the pesticide price (either the measured or quality-adjusted price) is reflected by differing (shadow) quantities of the pesticide input.

So when focusing on the quality adjusted price, $\partial TC/\partial w_P^* = SQ_{P*}$ yields the shadow quantity of the true effective pesticide input, which will equal P* if Shephard's lemma holds. If instead we take the derivative with respect to the unadjusted pesticide price, using the equality $w_P P = w_{P*} P^*$, we obtain $\partial TC/\partial w_P = ADJ_P \cdot \partial TC/\partial w_P^* = (w_P^*/w_P) \cdot P^* = (P/P^*) \cdot P^* = P = SQ_P$. Thus the shadow quantities of the true effective – as compared to measured – pesticide quantity differ only by the adjustment factor $ADJ_P = w_P^*/w_P = P/P^*$.[14] In turn, the impact

[13] This is similar conceptually to the adaptation to capital to accommodate utilization as $K^*=uK$ or $w^*_K=w_K/u$, along the lines of Jorgenson and Griliches.

[14] This also stems from the fact that the "shares" $\partial \ln TC/\partial \ln w_P = P \cdot w_P/TC$ and $\partial \ln TC/\partial \ln w_P^* = P^* \cdot w_P^*/TC$ are identical by definition.

on costs of a change in only the quality component becomes $\partial TC/\partial ADJ_P = w_P \cdot \partial TC/\partial w_P^*$, which can be rewritten as VAL_P/ADJ_P – the quality-adjusted pesticide value.[15]

Even though the differences in these shadow quantities depend only on the adjustment factor, they will vary over time and across regions. In fact, the pure quantity and quality-adapted measures could move in opposite directions if the adjustment factor differs sufficiently. For example, over time, if the adjustment factor is growing rapidly enough, P (SQ_P) could drop even as P* (SQ_{P*}) rises.

This brings us back to the relationship between P and B_k posited above. The supposition that declines in risk require pesticide use to fall focuses on the P level, not the P* factor (that incorporates quality characteristics). In fact, decreases in risk could well be associated with increases in effective pesticide use, due to the induced changes in quality, that incur their own cost on the producer.

That is, producers pay for quality that derives from technical change – perhaps derived from R&D expenditures – embodied in P*, as well as other changes in composition explicitly related to risk potential. These adaptations should be recognized as part of the cost of reducing risk. A change in P* includes adaptations in both quantity and quality, with separately identifiable cost implications, which can be disentangled through their implied share in P*, as represented by ADJ_P.

The Results: econometric implementation and estimates

The cost function implied from the model overviewed in the previous section takes the general form TC = $TC(Y_A,Y_C,B_{HL},B_{HR},w_P^*,w_K,w_L,w_{LD},w_M,w_F,t,D_P,D_F,D_{CT}, D_{CN},\mathbf{D_s})$, where the general vector representation has been expanded to make the individual arguments of the function explicit.[16] The vector of fixed effects includes two dummy variables for structural shifts in pesticides and fertilizer use (D_P, D_F)[17] and two for the cotton and

[15] Note that ADJ_P<1 since the quality contribution to the measured pesticide price is removed, VAL/ADJ_P will exceed the measured value of the pesticide input.

[16] The prices of the inputs other than P may also be thought of as effective or virtual prices, accommodating in the data the stock/flow effects of fixities (for, say, K, LD), or other "quality" characteristics (such as education for labor), although we will not make this explicit using *s since this is not the focus of the current analysis..

[17] The D_P dummy variable (with interaction terms for all w_P* cross-effects) represents a 1984 break in the pesticide data found with the hedonic research to indicate roughly the year in which most cropping sectors switched from or reduced use of many of the old line chemicals to the new. The D_F dummy variable (with interaction terms for all w_F cross-effects) for the post-1979 time period represents results from chow tests that indicate this an important point of structural change in

corn states as groups (D_{CT}, D_{CN}).[18] To have state-specific intercepts in each estimating equation, 48 state-level dummies ($\mathbf{D}_s$) were used, with cross effects for each input price and output quantity.

Econometric implementation of the model and construction of parametric derivative and elasticity measures first requires specifying a functional form for TC(·). We choose to approximate the underlying cost relationship with a generalized Leontief form, where the output levels and shift factors are included in quadratic rather than square root form, as in Paul:

$$
\begin{aligned}
(1)\quad TC(\mathbf{Y},\mathbf{B},\mathbf{p},\mathbf{D},t) \;=\; & \delta_{P1}\, p_P{*}D_P + \delta_{F1}\, p_F\, D_F + \Sigma_s\Sigma_i\, \delta_{sj}\, p_j\, D_s + \Sigma_j p_j \cdot (\Sigma_s\Sigma_m\, \delta_{sm}\, Y_m\, D_s) \\
& + \Sigma_j\Sigma_{i\ (i\neq j)}\, \alpha_{ji}\, p_j^{.5}\, p_i^{.5} + \Sigma_j\, \alpha_{jDP}\, p_j^{.5}\, p_P{*}^{.5}\, D_P + \Sigma_j\, \alpha_{jDF}\, p_j^{.5}\, p_F^{.5}\, D_F \\
& + \Sigma_j\Sigma_{m\ (j\neq M)}\, \delta_{jm}\, p_j\, Y_m + \Sigma_m\Sigma_r\, \delta_{mPDr}\, Y_m\, p_p{*}\, D_r + \Sigma_m\Sigma_r\, \delta_{mFDr}\, Y_m\, p_F\, D_r \\
& + \Sigma_j\Sigma_k\, \delta_{jk}\, p_j\, B_k + \Sigma_k\, \delta_{kDP}\, B_k\, p_p{*}\, D_P + \Sigma_k\, \delta_{kDF}\, B_k\, p_F\, D_F \\
& + \Sigma_j\, \delta_{jt}\, p_j\, t + \Sigma_r\, \delta_{tPDr}\, t\, p_p{*}\, D_r + \Sigma_r\, \delta_{tFDr}\, t\, p_F\, D_r \\
& + \Sigma_j p_j\, (\Sigma_m\Sigma_n\, \gamma_{mn}\, Y_m\, Y_n + \Sigma_m\Sigma_k\, \gamma_{mk}\, Y_m\, B_k + \Sigma_k\Sigma_l\, \gamma_{lk}\, B_k\, B_l \\
& + \gamma_{tt}\, t^2 + \Sigma_m\, \gamma_{mt}\, Y_m\, t + \Sigma_k\, \gamma_{kt}\, B_k\, t)\ ,
\end{aligned}
$$
[19]

where (i,j) denote the input market or virtual prices of the inputs, (m,n) the good outputs, (k,l) the bad outputs, and r the D_P, D_F, D_{CT} and D_{CN} fixed effects. The estimating model derived from this function is based on a system of six factor demand equations, two output pricing equations, and the function (1) itself. In particular, the factor demand estimating equations are defined via Shephard's lemma; $P^*=\partial TC/\partial p_P^*$, $F=\partial TC/\partial p_F$, $K=\partial TC/p_K$, $L=\partial TC/\partial p_L$, $LD=\partial TC/\partial p_{LD}$, and $M=\partial TC/\partial p_M$. The output pricing equations are defined according to standard $p_m=MC_m$ equalities representing optimization over outputs (where p_m is the market price of Y_m); $p_A = \partial TC/\partial Y_A$, $p_C = \partial TC/\partial Y_C$.

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the fertilizer input, reflecting the energy crisis. Note also that the corn and cotton dummy interaction terms were not included for the bad outputs (B_k) due to their continued insignificance in preliminary empirical investigation.

[18] These fixed effects are intended to reflect important differences in production structure with respect to chemicals use in these areas, since the corn areas tend to continue to use more old line chemicals with water quality but not toxicity issues, and have lower pesticide prices, than do the cotton states.

[19] Note that the j≠M requirement for the cross w_j-Y_m terms was due to the otherwise linear dependency from the w_j summation before the fixed effects for the Y_m (the δ_{sm} parameters), and similarly for the i≠j for the input price cross-terms.

Because with competitive markets producers would be expected to choose output levels given observed output prices, the behavioral implications of the output pricing specification initially seem questionable. However, scale economy measures derived from a model estimated with no structure incorporated for output choice were implausible. And output supply equations from a profit function framework tended to have perverse estimated curvature. In addition, when the pricing equations from the cost function framework were transformed into $MR_m=MC_m$ expressions (where marginal revenue, MR_m, is defined as $p_m+\partial p_m/\partial Y_m \cdot Y_m$), to allow for markup behavior, the estimated $\partial p_m/\partial Y_m$ "wedge" between p_m and MR_m was invariably insignificant. An *ex-post* pricing mechanism clearly tends to dominate. A possible reason is that prices in agricultural markets are determined by the amount of output available *after* the growing period (for either a crop or animal product).

This equation system was estimated by non-linear seemingly unrelated (SUR) systems procedures instead of instrumental variables (IV), which is often used to take into account potential output endogeneity or errors in variables. We opted not to use IV because of the care taken in data development, such that both the input demand and output pricing equations appear well characterized. The use of panel data and our specification to correct for first-order autoregressive disturbances also could cause problems if lagged values of exogenous variables are used as instruments, as is typically done. Thus, SUR was retained for the final estimation.

Adaptations were made to accommodate potential unknown sources of heteroskedasticity. One such "fix" – changing the input demand equations to input/output measures to reduce variations in scale across states and time – did not affect the estimates substantively. Instead we used the procedure in TSP that computes White's heteroskedastic-consistent covariance matrix to generate appropriate standard errors.

Durbin-Watson tests indicated that autocorrelated errors were present in the cost and input demand equations. Therefore, an AR(1) term was directly incorporated into the cost equation, and $TC = TC(\cdot) + \rho_{TC} \varepsilon_{t-1} + \varepsilon_t$ was estimated (where ρ_{TC} is the cost function-specific AR(1) parameter, and ε_t is the period t estimation error for $TC(\cdot)$). Analogous adaptations were made to the input demand equations based in the general form **Y**

$= \beta\mathbf{X} + \rho_Y \varepsilon_{t-1} + \varepsilon_t$.[20] While the inclusion of the AR(1) structure led to a non-linear system (increasing estimation time substantially), the resulting estimates of the ρ's were very significant, and standard statistical tests indicated that the adjustment adapted for autocorrelation in the estimates.

The parameter estimates for this model are presented in the Appendix (with the coefficients on the state dummies omitted to keep the table manageable). Although in a model this complex, the individual parameter estimates have limited interpretation, the overall statistical significance of the parameters is notable; even most of the states dummies were significant. Also, the R^2s indicate excellent "fits" for the estimated equations – all reaching at least 0.92.

The primary bad output and pesticide cost and benefit indicators computed from the estimated parameters for the full data sample are presented in Table 1. The reported estimates are (non-weighted) averages across all states and time periods for each measure. The t-statistics are based on computation of the measures evaluated at the average (mean) values of the data.[21] The measures were constructed for these data using the delta method (essentially a generalized Wald test) by the ANALYZ command in TSP. This procedure computes the constraints underlying the hypothesis that the measure is equal to zero, as well as the associated covariance matrix, evaluated at the estimated parameter vector for a given data point.

The primary measures for evaluating the marginal benefits of using the environment for disposal of leaching and runoff are the shadow values SV_{Bk} for B_{HL} and B_{HR}. These measures are both negative (indicating that allowing higher risk factors is cost-saving for the producer) and statistically significant at approximately the 5% level on average for the whole sample (the SV_{HR} and SV_{HL} p-values are 0.051 and 0.034).[22]

Risk reduction is clearly pesticide-using in the sense that lowering risk requires more *effective* pesticide use; $\varepsilon_{P*,HL} < 0$ and $\varepsilon_{P*,HR} < 0$, and are significant both statistically and in terms of magnitude (especially for

[20] Because of this specification, the first observation for each state was dropped for estimation.
[21] Reporting estimates of the elasticities based on the mean values of the data seemed less justifiable conceptually than estimating them for each data point. However, for this data sample the implications from either procedure were very equivalent in their substantive implications.
[22] When additional leaching and runoff risk factors for fish stocks were also included, their shadow values were almost invariably statistically insignificant, although when they were incorporated without the associated human risk factors their estimates were similar to those for the HL and HR measures, suggesting that their costs are not separately identifiable for these data.

runoff). This implies that the technology or innovations embodied in P* must increase substantively to reduce risk. That is, although P* may rise through either quantity or quality increases, this relationship clearly indicates the dominance of the latter. By contrast, the only input insignificantly related to both risk factors is fertilizer.

The negative $\varepsilon_{K,HL}$ and $\varepsilon_{K,HR}$ measures also suggest that capital has a tendency to “substitute” for the environment, in the sense that additional capital is required to reduce human risk factors, although $\varepsilon_{K,HL}$ is insignficant. The M elasticities with respect to B_{HL} and B_{HR} are also negative and both relatively large and significant. In contrast, land seems, in a sense, “complementary” with risk; risk reduction implies lower land use. The indications for labor are mixed.

The input composition implications underlying these benefits of allowing risk, or marginal costs of reducing risk to the producer, are quite biased. The implied biases are indicated by comparing the size of these elasticities to each other and to the overall or “average” cost elasticities $\varepsilon_{TC,HL}$=0.009 and and $\varepsilon_{TC,HR}$=0.008. For a B_{HL} decrease, for example, P* is affected the most (human risk reduction from leaching is greatly P*-using), L and M demands rise relative to other inputs, capital changes less than overall input use (a relative capital-saving bias) and land use decreases (an absolute land-saving bias). Thus, input composition adapts substantially to accommodate risk reduction.

For the outputs, the elasticities $\varepsilon_{MCm,Bk}$ are small, and most are positive, implying that scope economies or jointness between the risk factors and outputs are limited. At least for the animal inputs this makes intuitive sense, in that they would have little linkage with leaching and runoff from chemical use.[23] In particular, the positive (but small and not quite significant at the 5% level with p levels of 0.083 and 0.06) $\varepsilon_{MCA,HL}$ and $\varepsilon_{MCA,HR}$ elasticities indicate that reductions in human risk are consistent with somewhat lower marginal costs of animal production, in turn implying some motivation toward producing A rather than C outputs. In contrast, the negative and significant $\varepsilon_{MCC,HR}$ estimate indicates jointness between crop production and risk from runoff.

[23] Of course risk from animal waste is also a major issue, at least in some states. Although we do not currently have measures of such factors, work is proceeding to generate such measures that will be used in later research to establish these relationships.

Next, implications about the level of P* demand versus P – i.e., quality versus quantity – are evident from the SQ_{P*}, SQ_P, and SQ_{ADJP} estimates in Table 1. The fitted shadow value of P* is on average about twice as large as the unadjusted P level[24], implying an average measured quality adaptation factor of approximately 0.5.[25] These relationships indicate that most of the measured variation in P* involves quality rather than quantity, supporting the result that decreases in risk require increases in P* through quality changes. In fact, in terms of the value measures SQ_{ADJP} and VAL the quality-based measure exceeds the one without the adjustment by a factor of more than 2.5.

Some interesting implications may be derived from the bad output shadow value elasticities in Table 1. The positive $\varepsilon_{SVHL,t}$ elasticity suggests that SV_{HL} is increasing (in absolute value, so the costs of reducing B_{HL} are greater) over time, whereas the reverse seems true for SV_{HR}.[26] Changes in the structure of the fertilizer input (D_F, post-1979) caused SV_{HL} to increase even more, although in the post-1984 period (D_P, that coincides with changes in the form of pesticides) the cost of reducing B_{HL} drops slightly. By contrast, in both the post-1979 and post-1984 periods, SV_{HR} seems somewhat higher in absolute value. None of these relationships are, however, statistically significant.

Consider also the impacts of shift factors, and output levels and composition, on the demand for the effective pesticide input. Note that all measured elasticities of P* demand are statistically significant and positive except that for the fertilizer structural change (D_F), which would not be expected to have a significant effect on P*. In particular, effective pesticide use seems to have increased significantly over time ($\varepsilon_{P*,t}$>0), and especially after 1984 ($\varepsilon_{P*,DP}$>0). P* demand is also more extensive in both the corn and cotton states relative to others ($\varepsilon_{P*,DCN}$ and $\varepsilon_{P*,DCT}$ are positive). And, the impacts of increases in crop production are quite dramatic – a 1 percent augmentation of crop output implies a 1.5 percent rise in P* ($\varepsilon_{P*,C}\approx 1.5$), so scale increases with respect to the crop output are biased toward pesticide use. In contrast, higher levels of animal outputs generate a much

[24] In reverse, the SQ_{ADJP} measure is nearly twice the SQ_{P*} value.
[25] Note, however, that the (unweighted) average ADJ_P in the data is around 0.9. Although the differences in these measures depend entirely on ADJ_P, the actual deviation in the presented measures is based on an average of the shadow values or quantities, which implicitly weights the ADJP numbers according to the shadow quantity itself.
[26] Note that a negative value for the $\varepsilon_{SV,r}$ elasticity implies a positive measure of $\partial SV_{BK}/\partial r$, since the derivative is multiplied by the (negative) SV_{BK} value to construct the elasticity.

smaller (less than 50%) proportional change in pesticide inputs, possibly associated with greater crop production for animal feed.

Certain insights may be gained from alternative specifications estimated in preliminary investigation of the data. For example, a comparison specification using a pesticide demand equation (erroneously) defined in terms of pounds of pesticide use and an unadjusted pesticide price (w_P) was estimated. The results (not tabled here) indicated that SV_{HR} is essentially zero (and insignificant), whereas SV_{HL} is slightly larger (in absolute value) than in the P* specification. But SQ_P and SQ_{P*} are virtually the same (SQ_{ADJP} is very low). The discrepancies for the P*-B_k relationships are more pronounced; B_{HL} and B_{HR} are positively rather than negatively related to P demand, suggesting their jointness. But this supports our finding that although effective P* use increases for risk reduction, the pure quantity measure, P, decreases. The impact of D_P on P is smaller than for P*; structural adaptations in the pesticide input (embodied innovations) increased the quality rather than quantity component of P*. P is also considerably smaller in the corn and cotton states than P*.

In another alternative specification, to gauge the relevance of the optimality assumption, the pesticide demand equation was omitted (both for the base specification and for one in which P* instead of w_P* was used as an argument of TC(·)). The resulting shadow measures (SQ_{P*} and SV_{P*}, respectively) are very similar with or without estimating the P* optimization equation, supporting the notion that Shephard's lemma is valid for these data. The main differences across these specifications appeared in the implied P* demand elasticities, which are magnified when the P* equation is not estimated (likely due to the small share of P* in costs).

For specifications in which P* instead of w_{P*} was included as an argument of TC(·), SV_{P*} is similar in both cases, but SV_P is approximately 0.4 (compared to 0.6 for SV_{P*}) with the optimization equation, and negative without it. Also, $\varepsilon_{SVP,HL}$ and $\varepsilon_{SVP,HR}$ are both negative, in contrast to $\varepsilon_{SVP*,HL}$ and $\varepsilon_{SVP*,HR}$ suggesting that decreasing risk is associated with increases in the imputed effective price – or shadow value – of pesticides. Similarly to the results for the base model, these elasticities are much smaller when an optimization equation for w_P* is included than when it is not.

It is also informative to compare some of the primary elasticity estimates across time periods and regions. For the time dimension, we report measures separated into pre- and post-1984, to represent the structural break in pesticide composition, and the four decades covered in the data for the analysis – 1960s, 1970s, 1980s, and 1990s. In addition to the corn- and cotton-state distinction, we define 10 regions (for the 48 contiguous states), according to the breakdown used by the USDA to report regional productivity data:

CN	*Corn States*	IL, IN, IA, MI, MN, MO, NB, OH, WI, SD
CT	*Cotton States*	AL, AZ, AR, CA, GA, LA, MS, NC, TN, TX
Region 1	*Northeast*	CT, ME, MA, NH, RI, VT, DE, MD, NJ, NY, PA
Region 2	*Corn Belt*	IL, IN, IA, MO, OH
Region 3	*Lake States*	MI, MN, WI
Region 4	*Northern Plains*	KS, NE, ND, SD
Region 5	*Appalachian*	KY, NC, TN, VA, WV
Region 6	*Southeast*	AL, Fl, GA, SC
Region 7	*Delta*	AR, LA, MS
Region 8	*Southern Plains*	OK, TX
Region 9	*Mountain*	AZ, CO, ID, MT, NV, NM, VT, WY
Region 10	*Pacific*	CA, OR, WA

The pre- and post-1984 $\varepsilon_{TC,HL}$ and $\varepsilon_{TC,HR}$ values in Table 2 indicate an upward trend in the *proportional* agricultural sector marginal-cost-benefits of B_{HL} disposal, but the reverse occurs for B_{HR}.[27] This is consistent with the implications for the associated pesticide costs; pesticide-quality-enhancing costs of reducing B_{HL}

[27] It is important to present these in proportional (real) terms to see these trends, since the nominal trends reflected in the SV_{Bk} values are somewhat misleading, The tendency for the B_{HL} value to increase is exacerbated if one looks instead at

(represented by $\varepsilon_{P*,HL}$) are increasing over time, and of B_{HR} (from $\varepsilon_{P*,HR}$) are declining. These trends are also evident in the values presented by decades

For the corn and cotton state division in Table 2 the cotton states have a far greater marginal cost of risk reduction, at least for leaching, than do the corn states. Leaching-risk reductions in the corn states seem associated with *lower* effective pesticide use (which may stem from either quantity or quality differences, whereas in the cotton states it is significantly *higher*. By contrast, the costs of reducing runoff are significantly larger in the corn states, with reductions in runoff related quite dramatically to increased effective pesticide applications.[28]

Limiting the corn states to the corn belt in the more specific regional breakdown highlights a different trend. Leaching and effective pesticide use clearly "move together" in this area; $\varepsilon_{P*,HL}>0$. This is also true for the northern plains and Pacific states. But $\varepsilon_{P*,HL}$ is larger, and the associated (proportional) marginal cost of reducing B_{HL} is lower.

The *proportional* cost of reducing B_{HL} is highest in the southeast and the Appalachian regions, while the (absolute) nominal values are higher in the northeast and mountain area. The implied proportional change in pesticide use follows closely, with the Appalachian and southeast states requiring more augmentation of P* than the northeast to reduce leaching risk, and the mountain states significantly less. By contrast, the cost of reducing risk from runoff, both overall and for pesticides, is by far the greatest in the corn belt. The states with the next highest costs of reducing runoff are in the southeast, lake, and delta areas. The northern plains require less than one-third the pesticide adjustment of the corn belt states, and in the Pacific region almost no change in effective pesticide use seems necessary.

The shadow quantity-quality tradeoffs in pesticides across time and region are evident from the measures in Table 3. Although the shadow quantity of P* is increasing over time, the difference between the quantity- and quality- measures is lower before than after 1984. From the decade breakdowns this reduction

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the SV_{Bk} values, and that for B_{HR} appears slightly upward rather than downward as it is when looking at percentage changes.

[28] Note that in nominal terms (using the SV_{Bk} measures) the costs of runoff seem slightly higher in the cotton than in the corn states.

seem particularly noticeable in the 1980s. The wrong signs on the fitted values for the quantity-based measures in the early years of the sample (as well as for some regions) emphasize the importance of focusing on the quality-adjusted or effective use of pesticide as an abatement factor, rather than the pure quantity measure.

In Table 4, effective pesticide demand elasticities are presented. The $\varepsilon_{P*,t}$ measures indicate that P* is on an upward trend, given other production structure characteristics, at least since the 1970s, and more dramatically so in the 1990s. This increase is particularly marked in the northeast, whereas the southern plains and Pacific states have experienced a decline in effective pesticide use over time (holding all other production characteristics constant). The impact of the changing structure of pesticides in the mid-1980s also seems to be the most substantive in the northeast states.

The elasticities with respect to the outputs suggest that effective pesticide use increased at more than double the rate of crop production in the pre-1984 period ($\varepsilon_{P*,C}\approx 2.08$), although less than proportionately afterward ($\varepsilon_{P*,C}\approx 0.60$). The linkage of pesticide use with animal production also changes over time; although $\varepsilon_{P*,A}<1.0$ in the earlier period, $\varepsilon_{P*,A}<0$ in the later period. For regions, less variation is evident, but the exacerbating effect of production scale changes on effective pesticide demand is particularly striking in the corn states.

Concluding Remarks

This study uses a detailed model of the production structure in U.S. agriculture to measure the potential costs to agricultural producers of legislation pertaining to pesticide use and resulting human risk. When production plans are adjusted to reduce such risk, we find that the associated interactions among netputs involve changes in output and input composition, and induced innovation to augment the pesticide quality.

Reducing human risk from leaching and runoff seems significantly to affect producers' costs . But a primary determinant (and cost) of risk reduction stems from increases in effective pesticide quantities –

pesticides that are both more effective against pests and more environmentally benign. This effectiveness is embodied in the pesticides themselves through R&D and associated technological change.[29]

These patterns may indicate that changes in human risk levels stemming from agricultural production are not only related to the quality of pesticides used, but also are linked to adaptations in the composition of the materials input (including primarily feed, seed and livestock), and labor (perhaps according to educational attainment). This suggests important further issues to pursue in subsequent research on the production structure of the U.S. agricultural sector.

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[29] Results also suggest that lowering risk from chemical use seems to require more materials and less land use and, possibly, a slight movement toward animal rather than crop production. While lowering risk through effective pesticide use often entails more labor (e.g., monitoring, more careful application).

Table 1: Shadow Value and Elasticity Measures, overall averages

measure	*estimate*	*t-statistic*			
SV_{HL}	**-0.0164**	*-2.118*	SQ_{P*}	**0.0884**	*1.955*
SV_{HR}	**-0.0004**	*-1.951*	SQ_{P}	**0.0440**	*3.816*
$\varepsilon_{TC,HL}$	**-0.0090**	*-2.118*	SQ_{ADJP}	**0.1682**	*3.816*
$\varepsilon_{TC,HR}$	**-0.0077**	*-1.951*	VAL	**0.0660**	
$\varepsilon_{P*,HL}$	**-0.0243**	*-1.887*	$\varepsilon_{SVHL,t}$	**0.0175**	*1.058*
$\varepsilon_{P*,HR}$	**-0.0644**	*-2.472*	$\varepsilon_{SVHR,t}$	**-0.0104**	*-0.556*
			$\varepsilon_{SVHL,DF}$	**0.0155**	*0.926*
$\varepsilon_{F,HL}$	**0.0035**	*0.175*	$\varepsilon_{SVHR,DP}$	**-0.0030**	*-0.640*
$\varepsilon_{F,HR}$	**-0.0151**	*-1.273*	$\varepsilon_{SVHR,DF}$	**0.0132**	*0.406*
$\varepsilon_{LD,HL}$	**0.0086**	*2.157*	$\varepsilon_{SVHR,DP}$	**0.0145**	*1.196*
$\varepsilon_{LD,HR}$	**0.0107**	*2.348*			
$\varepsilon_{L,HL}$	**-0.0205**	*-1.867*	$\varepsilon_{P*,t}$	**0.3750**	*5.162*
$\varepsilon_{L,HR}$	**0.0144**	*1.961*	$\varepsilon_{P*,DF}$	**-0.0650**	*-0.981*
$\varepsilon_{K,HL}$	**-0.0017**	*-1.063*	$\varepsilon_{P*,DP}$	**0.6482**	*-3.881*
$\varepsilon_{K,HR}$	**-0.0074**	*-2.563*	$\varepsilon_{P*,DCT}$	**1.0128**	*7.724*
$\varepsilon_{M,HL}$	**-0.0141**	*-1.850*	$\varepsilon_{P*,DCN}$	**0.9902**	*8.269*
$\varepsilon_{M,HR}$	**-0.0255**	*-2.875*	$\varepsilon_{P*,A}$	**0.4591**	*2.441*
			$\varepsilon_{P*,C}$	**1.5444**	*23.472*
$\varepsilon_{MCA,HL}$	**0.0039**	*1.731*			
$\varepsilon_{MCA,HR}$	**0.0053**	*1.884*			
$\varepsilon_{MCC,HL}$	**0.0055**	*1.295*			
$\varepsilon_{MCC,HR}$	**-0.0001**	*-1.943*			

Table 2: Bad Output Measures, temporal and spatial

overall average		***pre-1984***		***post-1984***		***corn states***		***cotton states***	
$\varepsilon_{TC,HL}$	**-0.0090**	$\varepsilon_{TC,HL}$	**-0.0070**	$\varepsilon_{TC,HL}$	**-0.0130**	$\varepsilon_{TC,HL}$	**-0.0033**	$\varepsilon_{TC,HL}$	**-0.0184**
$\varepsilon_{TC,HR}$	**-0.0077**	$\varepsilon_{TC,HR}$	**-0.0095**	$\varepsilon_{TC,HR}$	**-0.0044**	$\varepsilon_{TC,HR}$	**-0.0192**	$\varepsilon_{TC,HR}$	**-0.0086**
$\varepsilon_{P^*,HL}$	**-0.0243**	$\varepsilon_{P^*,HL}$	**-0.0210**	$\varepsilon_{P^*,HL}$	**-0.0302**	$\varepsilon_{P^*,HL}$	**0.0252**	$\varepsilon_{P^*,HL}$	**-0.0333**
$\varepsilon_{P^*,HR}$	**-0.0644**	$\varepsilon_{P^*,HR}$	**-0.0888**	$\varepsilon_{P^*,HR}$	**-0.0218**	$\varepsilon_{P^*,HR}$	**-0.2079**	$\varepsilon_{P^*,HR}$	**-0.0387**

1960s		***1970s***		***1980s***		***1990s***	
$\varepsilon_{TC,HL}$	**-0.0033**	$\varepsilon_{TC,HL}$	**-0.0099**	$\varepsilon_{TC,HL}$	**-0.0092**	$\varepsilon_{TC,HL}$	**-0.0148**
$\varepsilon_{TC,HR}$	**-0.0131**	$\varepsilon_{TC,HR}$	**-0.0084**	$\varepsilon_{TC,HR}$	**-0.0047**	$\varepsilon_{TC,HR}$	**-0.0039**
$\varepsilon_{P^*,HL}$	**-0.0073**	$\varepsilon_{P^*,HL}$	**-0.0294**	$\varepsilon_{P^*,HL}$	**-0.0299**	$\varepsilon_{P^*,HL}$	**-0.0312**
$\varepsilon_{P^*,HR}$	**-0.1708**	$\varepsilon_{P^*,HR}$	**-0.0434**	$\varepsilon_{P^*,HR}$	**-0.0222**	$\varepsilon_{P^*,HR}$	**-0.0180**

northeast		***corn belt***		***lake states***		***northern plains***		***appalachian***	
$\varepsilon_{TC,HL}$	**-0.0088**	$\varepsilon_{TC,HL}$	**-0.0007**	$\varepsilon_{TC,HL}$	**-0.0077**	$\varepsilon_{TC,HL}$	**-0.0031**	$\varepsilon_{TC,HL}$	**-0.0177**
$\varepsilon_{TC,HR}$	**-0.0031**	$\varepsilon_{TC,HR}$	**-0.0264**	$\varepsilon_{TC,HR}$	**-0.0134**	$\varepsilon_{TC,HR}$	**-0.0068**	$\varepsilon_{TC,HR}$	**-0.0080**
$\varepsilon_{P^*,HL}$	**-0.0534**	$\varepsilon_{P^*,HL}$	**0.0406**	$\varepsilon_{P^*,HL}$	**-0.0035**	$\varepsilon_{P^*,HL}$	**0.0130**	$\varepsilon_{P^*,HL}$	**-0.0691**
$\varepsilon_{P^*,HR}$	**-0.0200**	$\varepsilon_{P^*,HR}$	**-0.3059**	$\varepsilon_{P^*,HR}$	**-0.0817**	$\varepsilon_{P^*,HR}$	**-0.1004**	$\varepsilon_{P^*,HR}$	**-0.0595**

southeast		***delta***		***southern plains***		***mountain***		***pacific***	
$\varepsilon_{TC,HL}$	**-0.0399**	$\varepsilon_{TC,HL}$	**-0.0079**	$\varepsilon_{TC,HL}$	**-0.0020**	$\varepsilon_{TC,HL}$	**-0.0022**	$\varepsilon_{TC,HL}$	**-0.0015**
$\varepsilon_{TC,HR}$	**-0.0116**	$\varepsilon_{TC,HR}$	**-0.0111**	$\varepsilon_{TC,HR}$	**-0.0031**	$\varepsilon_{TC,HR}$	**-0.0009**	$\varepsilon_{TC,HR}$	**-0.0004**
$\varepsilon_{P^*,HL}$	**-0.0827**	$\varepsilon_{P^*,HL}$	**-0.0153**	$\varepsilon_{P^*,HL}$	**-0.0001**	$\varepsilon_{P^*,HL}$	**-0.0173**	$\varepsilon_{P^*,HL}$	**0.0119**
$\varepsilon_{P^*,HR}$	**-0.0461**	$\varepsilon_{P^*,HR}$	**-0.0334**	$\varepsilon_{P^*,HR}$	**-0.0204**	$\varepsilon_{P^*,HR}$	**-0.0085**	$\varepsilon_{P^*,HR}$	**-0.0020**

Table 3: P, P* and ADJP measures, temporal and spatial

overall average		***pre-1984***		***post-1984***		***corn states***		***cotton states***	
SQ_{P*}	**0.0884**	SQ_{P*}	**0.0654**	SQ_{P*}	**0.1297**	SQ_{P*}	**0.1631**	SQ_{P*}	**0.1385**
SQ_{P}	**0.0440**	SQ_{P}	**0.0170**	SQ_{P}	**0.0903**	SQ_{P}	**0.0233**	SQ_{P}	**0.0906**
SQ_{ADJP}	**0.1682**	SQ_{ADJP}	**-0.0238**	SQ_{ADJP}	**0.5423**	SQ_{ADJP}	**0.1975**	SQ_{ADJP}	**0.2410**
VAL	**0.0660**	VAL	**0.0353**	VAL	**0.1223**	VAL	**0.1258**	VAL	**0.1084**

1960s		***1970s***		***1980s***		***1990s***	
SQ_{P*}	**0.0333**	SQ_{P*}	**0.0737**	SQ_{P*}	**0.1162**	SQ_{P*}	**0.1407**
SQ_{P}	**-0.0540**	SQ_{P}	**0.0439**	SQ_{P}	**0.1056**	SQ_{P}	**0.0822**
SQ_{ADJP}	**-0.0491**	SQ_{ADJP}	**-0.0231**	SQ_{ADJP}	**0.0797**	SQ_{ADJP}	**0.8470**
VAL	**0.0115**	VAL	**0.0379**	VAL	**0.0890**	VAL	**0.1434**

northeast		***corn belt***		***lake states***		***northern plains***		***appalachian***	
SQ_{P*}	**0.0227**	SQ_{P*}	**0.2042**	SQ_{P*}	**0.1361**	SQ_{P*}	**0.1088**	SQ_{P*}	**0.0490**
SQ_{P}	**0.0169**	SQ_{P}	**0.0903**	SQ_{P}	**-0.0178**	SQ_{P}	**-0.0021**	SQ_{P}	**0.0449**
SQ_{ADJP}	**-0.0211**	SQ_{ADJP}	**0.4373**	SQ_{ADJP}	**-0.0398**	SQ_{ADJP}	**0.3696**	SQ_{ADJP}	**-0.0528**
VAL	**0.0124**	VAL	**0.1590**	VAL	**0.1040**	VAL	**0.0778**	VAL	**0.0388**

southeast		***delta***		***southern plains***		***mountain***		***pacific***	
SQ_{P*}	**0.0923**	SQ_{P*}	**0.1356**	SQ_{P*}	**0.1641**	SQ_{P*}	**0.0334**	SQ_{P*}	**0.1717**
SQ_{P}	**0.0326**	SQ_{P}	**0.1097**	SQ_{P}	**0.0731**	SQ_{P}	**0.0448**	SQ_{P}	**0.1156**
SQ_{ADJP}	**0.0168**	SQ_{ADJP}	**-0.0065**	SQ_{ADJP}	**0.8150**	SQ_{ADJP}	**-0.0157**	SQ_{ADJP}	**1.1566**
VAL	**0.0761**	VAL	**0.0948**	VAL	**0.0994**	VAL	**0.0192**	VAL	**0.1602**

Table 4: Pesticide Demand Elasticities, temporal and spatial

	overall average		***pre-1984***		***post-1984***		***corn states***		***cotton states***
$\varepsilon_{P*,t}$	**0.3750**	$\varepsilon_{P*,t}$	**0.2894**	$\varepsilon_{P*,t}$	**0.5535**	$\varepsilon_{P*,t}$	**0.2733**	$\varepsilon_{P*,t}$	**0.1378**
$\varepsilon_{P*,DP}$	**0.6482**	$\varepsilon_{P*,DP}$	**0.0000**	$\varepsilon_{P*,DP}$	**1.9446**	$\varepsilon_{P*,DP}$	**0.0233**	$\varepsilon_{P*,DP}$	**0.0509**
$\varepsilon_{P*,A}$	**0.4591**	$\varepsilon_{P*,A}$	**0.9228**	$\varepsilon_{P*,A}$	**-0.3845**	$\varepsilon_{P*,A}$	**0.9127**	$\varepsilon_{P*,A}$	**0.8292**
$\varepsilon_{P*,C}$	**1.5444**	$\varepsilon_{P*,C}$	**2.0756**	$\varepsilon_{P*,C}$	**0.5918**	$\varepsilon_{P*,C}$	**2.2566**	$\varepsilon_{P*,C}$	**1.6210**

	1960s		***1970s***		***1980s***		***1990s***
$\varepsilon_{P*,t}$	**0.3797**	$\varepsilon_{P*,t}$	**0.2365**	$\varepsilon_{P*,t}$	**0.3865**	$\varepsilon_{P*,t}$	**0.5505**
$\varepsilon_{P*,DP}$	**0.0000**	$\varepsilon_{P*,DP}$	**0.0000**	$\varepsilon_{P*,DP}$	**0.4412**	$\varepsilon_{P*,DP}$	**2.7034**
$\varepsilon_{P*,A}$	**1.8036**	$\varepsilon_{P*,A}$	**0.4967**	$\varepsilon_{P*,A}$	**-0.1167**	$\varepsilon_{P*,A}$	**-0.5010**
$\varepsilon_{P*,C}$	**3.3367**	$\varepsilon_{P*,C}$	**1.4237**	$\varepsilon_{P*,C}$	**0.7855**	$\varepsilon_{P*,C}$	**0.4967**

	northeast		***corn belt***		***lake states***		***northern plains***		***appalachian***
$\varepsilon_{P*,t}$	**1.0342**	$\varepsilon_{P*,t}$	**0.2211**	$\varepsilon_{P*,t}$	**0.2558**	$\varepsilon_{P*,t}$	**0.1889**	$\varepsilon_{P*,t}$	**0.1495**
$\varepsilon_{P*,DP}$	**2.0302**	$\varepsilon_{P*,DP}$	**0.0130**	$\varepsilon_{P*,DP}$	**0.0261**	$\varepsilon_{P*,DP}$	**0.0314**	$\varepsilon_{P*,DP}$	**0.3765**
$\varepsilon_{P*,A}$	**-0.2273**	$\varepsilon_{P*,A}$	**0.6795**	$\varepsilon_{P*,A}$	**0.4577**	$\varepsilon_{P*,A}$	**1.7253**	$\varepsilon_{P*,A}$	**0.3135**
$\varepsilon_{P*,C}$	**0.8552**	$\varepsilon_{P*,C}$	**2.2025**	$\varepsilon_{P*,C}$	**1.9123**	$\varepsilon_{P*,C}$	**2.8125**	$\varepsilon_{P*,C}$	**1.5313**

	southeast		***delta***		***southern plains***		***mountain***		***pacific***
$\varepsilon_{P*,t}$	**0.0921**	$\varepsilon_{P*,t}$	**0.1046**	$\varepsilon_{P*,t}$	**-0.0183**	$\varepsilon_{P*,t}$	**0.3272**	$\varepsilon_{P*,t}$	**-0.0044**
$\varepsilon_{P*,DP}$	**0.0821**	$\varepsilon_{P*,DP}$	**0.0250**	$\varepsilon_{P*,DP}$	**0.0696**	$\varepsilon_{P*,DP}$	**0.7494**	$\varepsilon_{P*,DP}$	**0.0309**
$\varepsilon_{P*,A}$	**0.6362**	$\varepsilon_{P*,A}$	**0.7404**	$\varepsilon_{P*,A}$	**1.1438**	$\varepsilon_{P*,A}$	**0.4592**	$\varepsilon_{P*,A}$	**0.1894**
$\varepsilon_{P*,C}$	**1.0910**	$\varepsilon_{P*,C}$	**1.2780**	$\varepsilon_{P*,C}$	**1.5082**	$\varepsilon_{P*,C}$	**1.7100**	$\varepsilon_{P*,C}$	**1.3918**

Appendix Table A1: Coefficient Estimates

	Estimate	*t-statistic*		*Estimate*	*t-statistic*		*Estimate*	*t-statistic*
δ_{F1}	**-0.139**	*-5.74*	α_{PFCN}	**0.036**	*3.55*	δ_{HLDP}	**0.0005**	*0.77*
δ_{P1}	**-0.190**	*-6.32*	α_{FDP}	**-0.002**	*-0.83*	δ_{LDHR}	**0.00004**	*1.68*
α_{LDL}	**-0.013**	*-2.09*	δ_{LDA}	**-0.971**	*-76.43*	δ_{LHR}	**0.0001**	*3.08*
α_{LDK}	**0.082**	*8.12*	δ_{LA}	**-0.921**	*-54.45*	δ_{KHR}	**-0.0001**	*-5.42*
α_{LDF}	**-0.004**	*-0.91*	δ_{KA}	**-0.900**	*-66.55*	δ_{FHR}	**-0.0001**	*-2.88*
α_{LDDF}	**0.012**	*3.61*	δ_{FA}	**-0.905**	*-58.76*	δ_{HRDF}	**-0.00001**	*-0.89*
α_{LDFCT}	**-0.025**	*-3.48*	δ_{ADF}	**0.015**	*4.90*	δ_{MHR}	**-0.0006**	*-8.24*
α_{LDFCN}	**-0.007**	*-0.97*	δ_{PA}	**-0.931**	*-65.03*	δ_{PHR}	**-0.0001**	*-3.61*
α_{LDM}	**-0.034**	*-3.74*	δ_{ADP}	**-0.001**	*-0.56*	δ_{HLDP}	**-0.00003**	*-2.18*
α_{LDP}	**0.006**	*1.19*	δ_{APCT}	**0.026**	*2.43*	γ_{AA}	**-0.0003**	*-0.43*
α_{LDDP}	**-0.012**	*-3.21*	δ_{APCN}	**-0.014**	*-1.29*	γ_{CC}	**-0.0011**	*-3.13*
α_{LDPCT}	**0.001**	*0.09*	δ_{AFCT}	**-0.013**	*-1.07*	γ_{HLHL}	**0.00003**	*1.86*
α_{LDPCN}	**0.013**	*1.50*	δ_{AFCN}	**-0.029**	*-2.44*	γ_{HRHR}	**0.00000001**	*1.41*
α_{LK}	**0.012**	*1.65*	δ_{LDC}	**-0.623**	*-87.22*	γ_{At}	**-0.0018**	*-26.53*
α_{LF}	**-0.022**	*-1.93*	δ_{LC}	**-0.584**	*-55.48*	γ_{Ct}	**-0.0018**	*-28.78*
α_{LDF}	**0.013**	*1.30*	δ_{KC}	**-0.576**	*-88.39*	γ_{HLt}	**-0.0001**	*-1.54*
α_{LFCT}	**0.026**	*1.47*	δ_{FC}	**-0.571**	*-69.82*	γ_{HRt}	**0.000001**	*1.27*
α_{LFCN}	**0.075**	*4.46*	δ_{CDF}	**0.004**	*2.00*	γ_{AHL}	**0.0003**	*2.20*
α_{LM}	**0.234**	*8.70*	δ_{PC}	**-0.613**	*-84.63*	γ_{CHL}	**0.0005**	*3.62*
α_{LP}	**0.016**	*2.30*	δ_{CDP}	**-0.001**	*-0.49*	γ_{HLHR}	**0.000005**	*2.20*
α_{LDP}	**-0.001**	*-0.15*	δ_{CPCT}	**0.021**	*4.48*	γ_{AHR}	**0.00001**	*2.43*
α_{LPCT}	**0.014**	*1.21*	δ_{CPCN}	**0.009**	*2.43*	γ_{CHR}	**-0.00001**	*-2.85*
α_{LPCN}	**-0.0004**	*-0.04*	δ_{CFCT}	**-0.011**	*-1.81*	γ_{AC}	**-0.0016**	*-2.60*
α_{KF}	**0.019**	*3.40*	δ_{CFCN}	**-0.006**	*-1.23*	ρ	**0.835**	*85.77*
α_{KDF}	**0.034**	*10.25*	δ_{LDt}	**0.004**	*5.67*	ρ_{L}	**0.607**	*54.85*
α_{KFCT}	**0.024**	*2.08*	δ_{Lt}	**-0.009**	*-10.71*	ρ_{F}	**0.786**	*59.89*
α_{KFCN}	**0.016**	*1.30*	δ_{Kt}	**-0.013**	*-9.63*	ρ_{M}	**0.883**	*114.40*
α_{KM}	**-0.066**	*-5.01*	δ_{Ft}	**-0.003**	*-4.17*	ρ_{P}	**0.967**	*294.84*
α_{KP}	**0.031**	*3.90*	δ_{tDF}	**0.005**	*4.62*	ρ_{LD}	**0.896**	*108.39*
α_{KDP}	**0.018**	*4.09*	δ_{Mt}	**-0.023**	*-8.54*	ρ_{K}	**0.954**	*284.05*
α_{KPCT}	**0.028**	*1.68*	δ_{Pt}	**0.003**	*2.29*			
α_{KPCN}	**-0.004**	*-0.20*	δ_{tDP}	**0.005**	*4.22*	Equation: R-squared		
α_{FM}	**0.047**	*4.07*	δ_{tPCT}	**0.010**	*4.84*			
α_{MDF}	**0.0004**	*0.03*	δ_{tPCN}	**0.022**	*10.52*	TC	**0.989**	
α_{MFCT}	**0.161**	*6.27*	δ_{tFCT}	**0.004**	*4.75*	L	**0.974**	
α_{MFCN}	**0.169**	*6.16*	δ_{tFCN}	**0.007**	*8.89*	F	**0.932**	
α_{MP}	**-0.019**	*-2.16*	δ_{LDHL}	**0.002**	*1.18*	M	**0.970**	
α_{MDP}	**0.043**	*4.15*	δ_{LHL}	**-0.009**	*-3.52*	P*	**0.966**	
α_{MPCT}	**0.088**	*4.46*	δ_{KHL}	**-0.002**	*-1.14*	LD	**0.999**	
α_{MPCN}	**0.042**	*1.87*	δ_{FHL}	**0.0001**	*0.06*	K*	**0.996**	
α_{FP}	**0.008**	*2.25*	δ_{HLDF}	**-0.001**	*-1.60*	MC_{A}	**0.942**	
α_{PDF}	**0.013**	*3.38*	δ_{MHL}	**-0.012**	*-2.56*	MC_{C}	**0.920**	
α_{PFCT}	**0.007**	*0.79*	δ_{PHL}	**-0.002**	*-1.85*			