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Abstract

This study uses a cost-function-based model of production processes in U.S. agriculture 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 for "bad" outputs, and their input- and output-specific components, with a focus on the impacts on pesticide demand and its quality and quantity aspects. We find that the magnitudes of the shadow values vary substantively by region, are statistically significant, and imply increased demand for effective pesticides over time, stemming largely from improvements in quality due to embodied technology.

Introduction

The benefits and costs of chemical[1] use in U.S. agriculture, in terms of the augmentation of both effective production and environmental degradation, 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 of chemical use – in particular the private (purchase) costs incurred by producers, and the resulting environmental risks.

While the private cost of pesticide abatement obviously includes the per unit price of the chemical inputs, the true economic cost of pesticides also reflects the research developments embodied in the pesticide input (through its chemical composition), that both augment its effective impact and reduce risk. These associated research costs may be primarily reflected in the purchase price (and thus borne by the user), but are also supported through public R&D expenditures. Social costs also accrue from the use of the environment as a "free" input, as producers' use of pesticides potentially imposes risks to both human health and the broader ecological environment.

The benefit to producers of using the environment as a free input takes the form of increased output for a given level of inputs (or lower input costs for a given production level), than would be possible if producers were required to reduce environmental risk. That is, lowering risk implies either decreased output (since production of desirable and undesirable outputs is joint), or increased input use (by substitution for the chemical inputs or by employing alternative waste disposal practices). Thus, policy legislation

[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.

requiring reduction of risks associated with pesticide use will impose costs on the agricultural community, which in turn has implications for agricultural commodity prices.

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 state-by-year panel data (48 states for the period 1960-96) for multiple outputs as well as inputs, and including measures of pesticide use and undesirable or "bad" outputs (human risk associated with leaching and runoff). The pesticide data are constructed by calculating hedonic measures of effective (quality-constant) prices, based on application rate, human risk scores, and half-life characteristics across a broad range of pesticide types. The bad output data represent the extent to which the concentration of a specific pesticide exceeds a water quality threshold. These data incorporate both direct information on human risk according to LD50 measures, and data on climate, types of soils, and application rates and timing. Our data set thus allows a more detailed evaluation of production patterns, and their link with pesticide use and environmental damage, than has been possible in previous studies.

The costs associated with reducing risk are represented by shadow values for the bad outputs, which embody underlying technological changes and their effects on output and input composition. These shadow values may be interpreted as the foregone marginal benefits of being able to use the environment freely, or, conversely, as the amount farmers would be willing to pay (on the margin) for the use of the environment.

The shadow values of bad outputs, or risk from agricultural chemical use and resulting leaching and runoff, thus depend on both the technological substitution possibilities, and the input demand and output supply behavior, underlying agricultural production processes. Measuring these values, and determining their link to the demand for pesticides and other components of the production structure, requires a detailed estimable production model. Such a model permits a comprehensive analysis of output and input supply, demand, and composition changes associated with substitution among netputs in agricultural production, all of which aid in assessing the costs and benefits of chemical use. Econometric implementation of the model allows statistical inference about the costs, and their determinants, of reductions in bad outputs (risk), and effective demand for inputs (including pesticides), associated with good output production.

The results generated by this comprehensive model and dataset indicate that the shadow values of risk factors are statistically significant, and larger and increasing over time for pesticide leaching as compared to runoff. This implies that substantive (and rising) costs would be imposed on the agricultural sector by requirements to reduce environmental risk deriving from pesticides. These costs are associated with increases in "effective" pesticide use, for a given level of agricultural output, that stem primarily from innovation-induced chemical composition changes that improve abatement power while diminishing risk. This embodied innovation represents increasing, but costly, pesticide quality. Changes in overall netput composition associated with decreases in risk, including higher levels of other inputs (except land), and a potential shift toward animal as compared to crop output, are also implied by the measures. And the costs of risk reduction are clearly differentiated both temporally and spatially.

The Methodology

The Estimating Model

Measuring the costs and benefits of agricultural chemical use, and their link to environmental damage, involves explicitly modeling the production structure and 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 and two associated "bad" outputs (human risk from leaching and runoff), and the use of six inputs (including pesticides and fertilizer). The output and input data are based on carefully constructed multilateral price and implicit quantity indexes, using detailed state-specific data and taking into account quality changes, as documented in Ball et al. [1999]. The bad output and pesticide data are constructed via comprehensive hedonic representations, as elaborated in Kellogg et al., and Nehing and Grube, respectively.

Our analysis is founded on a cost-function characterization of U.S. agricultural production processes, which represents a broad array of interactions among the underlying inputs and outputs, including chemical application and environmental damage. For empirical implementation, this cost function is augmented by price determination equations to represent profit maximization over good outputs, and by spatial and temporal fixed effects to accommodate differences across states and time periods.[2] The form of the pesticide data allows us to incorporate and analyze the

[2] Preliminary investigation instead using a profit function framework resulted in materials demand 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 used here (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 according to marginal revenue, but empirical results indicated that the p_m data correctly represent marginal

deviation between pounds of pesticides and the quality-adjusted “effective” pesticides used in production. And recognizing the presence of bad outputs in the production structure permits evaluation not only of shadow values for risk factors, but also of their linkages with inputs and outputs – in particular, pesticide quantity and quality.

More specifically, our cost function takes the general form TC = TC(**Y**,**B**,**w**,**D**,t) where **Y** is a vector of good outputs (crops, Y_C, and livestock or animal products, Y_A); **B** is a vector of bad outputs (proxies for environmental risk from pesticide leaching and runoff, B_{HL} and 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, and the cotton states; and t is a time trend.

Perhaps the most difficult “netputs” to measure in this model are the risk factors or bad outputs, **B**, which are fundamentally connected with pesticide use. Concerns about pesticide residues found in ground and surface water have stimulated pesticide regulatory changes, and, in turn, the development of chemicals that are less harmful to humans and the environment, or less likely to migrate and thus contaminate water supplies. Kellogg et al. have developed indicators to measure the existence, and temporal and spatial patterns, of the potential risk to health and the environment due to pesticide loss from farm fields. These indicators are estimates of relative risk, reflecting pesticide concentrations from leaching and runoff that exceed “safe” thresholds for chronic exposure. The estimates are based on pesticide application rates, and determinants of

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revenues for agricultural producers. And omitting these equations reduced the robustness of the marginal cost estimates. Thus they were retained for the final empirical specification.

pesticide loss such as the leaching/runoff potential of soils, chemical properties of the pesticides, annual rainfall, and changes in cropping patterns.

More specifically, Kellogg et al. use data on physical properties of pesticides such as soil sorption propensity, vapor pressure and solubility, and the persistence of the pesticide in the environment, which affect the tendency of chemicals to leach or runoff. Pesticide loss from fields is then estimated using a process model (GLEAMS), which incorporates the complex interactions among these soil and pesticide characteristics, and the contribution of weather factors, into risk indicators that represent changes over time (year) and space (state) in the potential for agricultural contamination of water resources.[4] We use these proxies for contamination as our risk or bad output variables, B_k.

Bad Output Implications: Shadow Values and Input/Output Composition Effects

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.[5] Production of bads allows more effective good – or marketed – outputs to be produced for a given input level, or, conversely, lower input costs for a given amount of **Y**. Thus, reducing risk is costly to producers in terms of net output – output per unit of input – because it requires substitution toward non-chemical inputs, or less risky, but more costly, alternative chemicals.

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[3] 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.
[4] Further details about this estimation process is available in Kellogg et. al. Documentation is also available at the website www.nhq.nrcs.usda.gov/land/index/publication.html.
[5] The notion that a reduction of a bad output is similar to an increase in a good output, in the sense of defining the technological frontier, also provides the basis for the distance function specification of undesirable output impacts in Ball *et al.* [2000].

The shadow values (SV) of the bad outputs, or the (input) cost benefits from generating risk, may thus be measured as the vector of cost effects $\nabla_{\mathbf{B}}TC = \mathbf{SV_B}$. For example, the marginal benefit of permitting leaching that may cause risk to human health (B_{HL}) is $SV_{HL} = \partial TC/\partial B_{HL} < 0$, or more generally, $SV_{Bk} = \partial TC/\partial B_k$. From the reverse perspective, SV_{Bk} represents the input costs that would be incurred on the margin if a decrease in B_k were legislated. So these shadow values reflect the marginal amount the producer would be willing to pay for the right to increase B_k. The sign and significance of such measures is thus a primary issue to explore in our analysis of pesticide and resulting bad output impacts on U.S. agricultural production. [6]

Indicators of the temporal and structural patterns of the shadow values may also be constructed by computing elasticities of the SV_{Bk} measures with respect to the time-shift factor, t, and the components of the **D** vectors (representing structural changes in P and F, and geographic location): $\varepsilon_{SVk,t} = \partial \ln SV_{Bk}/\partial t$, and $\varepsilon_{SVk,Ds} = \partial \ln SV_{Bk}/\partial D_s$. Constructing such measures allows us to evaluate time- and space-dependent differences in the costs of risk reduction for agricultural producers.

In addition, the SV_{Bk} measures – unlike technological measures of marginal products or primal-side shadow values of pesticides or bad outputs such as those in Headley, or Ball et al. [2000][7] – incorporate the behavioral motivations underlying cost-

[6] SV_{Bk} should be interpreted in the context of a *private* value to producers, since it represents the amount that their expenditure on other inputs would have to increase (for a given output level) if the environment could not be freely used. In terms of *social* costs, SV_{Bk} therefore indicates the amount a marginal risk reduction must be thought to benefit society overall to justify legislation requiring such reductions.

[7] The measurement of marginal products to represent the productivity of agricultural chemicals, and thus the costs of reducing their use, has been the focus of a large literature, beginning with studies such as Headley, and Campbell. The more comprehensive dataset and model used in this study allows, however, a much more detailed specification of the impacts of pesticides and associated negative outputs than has previously been possible.

efficient production choices as well as technical substitution possibilities. Thus, the overall cost-effects represented by the SV_{Bk} measures may be decomposed into their input-specific demand effects. In particular, the linkage between bad outputs and chemical use may be explored in terms of the impact of risk reduction on pesticide and fertilizer demand; this is another primary issue we wish to empirically explore.

That is, based on Shephard's lemma, pesticide input demand is represented by $P = \partial TC/\partial w_P$ (where w_P is the market price of P). Elasticities of this demand relationship with respect to changes in in the risk factors B_k, $\varepsilon_{P,Bk} = \partial \ln P/\partial \ln B_k$, thus reflect the dependence of pesticide use on the ability to dispose of waste in the form of leaching or runoff. Such elasticity measures can similarly be constructed for any input to represent the input-specific impacts of risk reduction. That is, assessing changes in input demand and thus composition depend on the 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.

Although the overall cost elasticity with respect to B_k, $\varepsilon_{TC,Bk} = \partial \ln TC/\partial \ln B_k = SV_{Bk} \cdot B_k/TC$, is negative if risk reduction is costly, if P and B_k are joint or complementary (as one might expect due to the direct relationship between P use and risk), $\varepsilon_{P,Bk}$ would instead be positive. In this case, an input bias in absolute terms is implied; if overall input costs increase to reduce B_k, but P declines, other inputs must increase even more than would be implied by the total cost elasticity. It may be, however, that improvements in the quality of the chemical inputs cause increased use of *effective* (quality-adjusted) P to be associated with decreases in B_k, in which case the associated $\varepsilon_{P,Bk}$ would be negative. If it is smaller (in absolute value) than the cost elasticity, however, reductions in risk remain biased, but in relative terms. Evaluation of these demand relationships and associated biases thus can provide important insights for assessing B_k effects.

The impacts on marginal costs of the good outputs from restrictions on bad output production may also be measured to facilitate a full analysis of the input- and output-specific costs of risk reduction. That is, the shadow or true economic value of an output, Y_m, is represented by its marginal cost: $SV_{Ym} = MC_m = \partial TC/\partial Y_m$. The elasticities $\varepsilon_{MCm,Bk} = \partial \ln MC_m/\partial \ln B_k$ thus provide indicators of producers' motivations to adapt output levels and composition in order to reduce risk.

Pesticide Demand: The Quantity and Quality of Pesticide Inputs

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 of input demand patterns from those appropriately represented by Shephard's lemma often complicates or precludes the estimation and interpretation of such measures. For example, fixities, market power, or changes in quality/composition, may cause the true economic value or quantity of an input to deviate from its market value. One way to deal with such a problem is to directly adapt the price and quantity data to embody the discrepancy, by computing true effective (or shadow or virtual) prices to be used as arguments of the cost function.[8]

Such an issue prevails in our current application[9], as violations of standard regularity conditions, and thus problems with estimated marginal product or input

[8] See Fulginiti and Perrin for a detailed discussion of the conceptual basis and use of the virtual price framework.
[9] Although not the focus here, sensitivity checks were also performed for the potential deviation of measured and shadow values for the K, L and LD variables, which could rise due to quasi-fixity. Our assumption that the careful measurement of these variables maintained their consistency with Shephard's lemma was empirically supported.

demand functions, have often been found for pesticides.[10] These 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. Whereas measurement of abatement power – increases in effective output from pest reduction, that depends on the chemical composition of the pesticides – should be the goal if this is actually the "input" that is being demanded.

Thus, in the pesticide data used for this study (developed by Nehring and Grube), careful data adaptations were made through hedonic analysis to identify the impacts of pesticide characteristics on their true or effective price, and thus their implicit quantity, as motivated by Fernandex-Cornejo and Jans, and Beach and Carlson. In particular, Beach and Carlson show that productive characteristics tend to be positively associated with pesticide price (application rates are inversely related to potency), while hazardous characteristics are negatively related to pesticide price. Accordingly, Nehring and Grube accommodate pesticide application rates, toxicity (chemical composition), and environmental variables reflecting persistence, mobility, and water quality levels in their measures of the true economic or effective prices of the quality-adjusted pesticides inputs, as elaborated in the Appendix. The resulting adjusted shadow or virtual pesticide prices of constant-quality chemicals, w_P*, were then used to deflate the pesticide expenditure data to reflect real effective pesticide quantities, P*.[11]

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[10]See, for example, Lichtenberg and Zilberman, and Chambers and Lichtenberg.

[11] See Nehring and Grube for more details about these computations, and further discussion of the patterns of the adjusted as compared to unadjusted data.

These quality-adjusted or "effective" pesticide price and quantity measures thus accommodate changing pesticide composition.[12] Such changes are reflected in "higher quality" pesticides over time; w_P* (P*) grows at a slower (faster) rate than w_P (P), which can be interpreted as a shift to relatively efficacious, less toxic, chemicals, through both general technical change and responses to environmental concerns (induced innovation). The magnitude of, and time- and space- variations in, the gap between w_P* and w_P (P* and P) can thus be interpreted as the impacts of new technologies embodied in the pesticide input. And explicit recognition of this quality-gap allows us to distinguish changes in the demand for physical pesticide quantities from those related to its quality or effectiveness.

More formally, we can write the virtual pesticide price as $w_P^* = ADJ_P \cdot w_P$, where the AJP_P quality index adapts the price of P in terms of pounds to one embodying quality characteristics according to the underlying hedonic model.[13] And since by definition $w_P P = w_{P^*} P^* = VAL_P$ (where VAL_P is the dollar expenditure on pesticides, and P* is computed as VAL_P/w_{P^*}), $w_P^*/w_P = P/P^*$, or P*=P/ADJ. The multiplicative[14] specification of w_P* (and thus P*) implies that the contribution of a percentage increase in pesticide price (use) is the same whether it stems from quality (ADJ_P) or quantity (w_P, P) changes, but that we can distinguish these two components.

That is, the derivative $\partial TC/\partial w_P^* = SQ_{P^*}$ yields the shadow quantity of the effective pesticide input, which will equal P* (the P* demand function) if Shephard's lemma holds. If instead we take the derivative with respect to the unadjusted price, using

[12] Note that pesticide "effectiveness" is here defined according to hedonic analysis in terms of a quality-constant price and implicit quality-adjusted quantity, rather than its effective application.

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

the equality $w_P P = w_{P*}P^*$, we obtain $\partial TC/\partial w_P = ADJ_P \cdot \partial TC/\partial w_P^* = (w_P^*/w_P) \cdot P^* = (P/P^*) \cdot P^* = P = SQ_P$. The difference between these values is obviously directly dependent on the ADJ_P measure, but this quality gap between P* and P will differ spatially and temporally, as well as potentially according to output composition patterns.

It is thus useful for understanding pesticide quantity and quality demand variations to compare these measures by time period and regional breakdown. Patterns may also be distinguished by considering effective and physical pesticide demand elasticities, such as $\varepsilon_{P*,t} = \partial \ln P^*/\partial t = \partial \ln SQ_{P*}/\partial t$, representing time patterns of P* use, as compared to $\varepsilon_{P,t} = \partial \ln P/\partial t = \partial \ln SQ_P/\partial t$ for P. Such elasticities may also be computed for other arguments of the TC and thus SQ_{P*}, function; e.g., the deviation between $\varepsilon_{P*,C} = \partial \ln P^*/\partial \ln Y_C$ and $\varepsilon_{P,C} = \partial \ln P/\partial \ln Y_C$ indicates the effect of Y_C demand changes on P* versus P. However, since the difference between P* and P is simply multiplicative, one would not expect substantive differences in the 2nd order relationships, except in terms of trend patterns.

The Results

Econometric Implementation

The cost function 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 vector representation has been expanded to make explicit the individual arguments of the function.[15] The vector of fixed effects includes two dummy variables

[14] Or log-linear, as is typical for a hedonic equation: $\ln w_P^* = \ln ADJ_P + \ln w_P$.
[15] 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..

for structural shifts in pesticides and fertilizer use (D_P, D_F)[16] and two for the cotton and corn states as groups (D_{CT}, D_{CN}).[17] To incorporate state-specific intercepts in each estimating equation, 48 state-level dummies ($\mathbf{D_s}$) were used, with cross effects included for each input price and output quantity.

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

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

[16] 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 show this is an important point of structural change in 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 insignificance in preliminary empirical investigation.

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

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. [18] The system of estimating equations derived from this function comprises six factor demand equations, two output pricing equations, and the cost function itself. The factor demand estimating equations are defined via Shephard's lemma; $P^*=\partial TC/\partial w_P^*$, $F=\partial TC/\partial w_F$, $K=\partial TC/w_K$, $L=\partial TC/\partial w_L$, $LD=\partial TC/\partial w_{LD}$, and $M=\partial TC/\partial w_M$. The output pricing equations are defined according to $p_m=MC_m$ equalities representing optimization over outputs (where p_m is the market price of Y_m); $p_A = \partial TC/\partial Y_A$, and $p_C = \partial TC/\partial Y_C$).[19]

The resulting equation system was estimated using seemingly unrelated (SUR) econometric procedures. Instrumental variable (IV) techniques are instead often used in the production literature when it is believed that potential errors in variables may be present (for example, if quality-unadjusted pesticide data were used as a proxy for the abatement input). Use of the IV approach, however, may introduce further problems if one does not specify the instruments appropriately (or if relevant instruments do not exist), and is often not robust to alternative specifications. IV can also cause problems when used in conjunction with panel data, or in models in which an autoregressive structure is explicitly incorporated, especially if the values of the lagged exogenous variables are used as instruments (as is often done). Due to these problems, and the care

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[18] The $j\neq M$ and $i\neq j$ requirements for the cross w_j-Y_m and cross-input-price terms is due to the otherwise linear dependency from the w_j summation before the fixed effects.

[19] The behavioral implications of the output pricing specification might initially seem questionable, since producers would be expected to output levels given observed output prices in the presence of competitive markets. However, as alluded to above, in preliminary investigation other specifications based on just a cost model, a profit function, and an imperfectly competitive market specification, generated implausible estimates. An *ex-post* pricing mechanism clearly dominates, possibly because prices in agricultural markets are determined by the amount of output available *after* the growing period (for either a crop or animal product).

taken in our data development, such that both the input demand and output pricing equations appear empirically well characterized, SUR is preferable for this application.

Adaptations were made to the estimating model to accommodate potential heteroskedasticity. A standard way to accomplish this is to transform the input demand equations into input/output measures, which reduces variations in scale across states and time periods, but this did not affect the estimates substantively. We thus, however, simply used a procedure in PC-TSP that computes White's heteroskedastic-consistent covariance matrix, to generate appropriate standard errors.

Also, Durbin-Watson tests indicated that first-order 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 on the general form $\mathbf{Y} = \beta\mathbf{X} + \rho_Y\,\varepsilon_{t-1} + \varepsilon_t$.[20] This approach led to a complex non-linear estimating system, but the resulting estimates of the ρ's were very significant, and standard statistical tests indicated that the adjustment accounted for autocorrelation.

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 multifaceted 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, with all of them reaching at least 0.92.

[20] Because of this specification, the first observation for each state was dropped for estimation.

The Overall Estimates: Risk Shadow Values, Pesticide Demand, and Netput Interactions

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. The t-statistics are based on evaluation of the measures at the mean values of the data, using the ANALYZ command in PC-TSP to implement a generalized Wald test.[21]

The primary measures indicating the marginal benefits of using the environment for leaching and runoff are the shadow values $SV_{Bk}=\partial TC/\partial B_k$ 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]

Overall patterns in bad output shadow values associated with time and structural trends may also be assessed from the estimates in Table 1. The positive $\varepsilon_{SVHL,t} = \partial \ln SV_{HL}/\partial t$ elasticity, for example, shows 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}.[23] In the post-1979 and post-1984 periods (represented by D_F and D_P), SV_{HL} seems to have risen slightly and then fallen from trend (in absolute value), although SV_{HR} seems to have been consistently ratcheting upward. None of these relationships are, however, statistically significant.

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[21] The procedure computes the constraints for the hypothesis that the measure equals zero, and the associated covariance matrix, evaluated at the estimated parameter vector for a given data point.

[22] When 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 B_{HL} and B_{HR} measures. This suggests that their costs are not separately identifiable for these data.

[23] 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.

In terms of input-specific patterns, risk reduction is clearly pesticide-using in the absolute sense that lowering risk requires increasing effective pesticide use; $\varepsilon_{P^*,HL} = \partial \ln P^*/\partial \ln B_{HL}$ and $\varepsilon_{P^*,HR} = \partial \ln P^*/\partial \ln B_{HR}$ are negative and significant, both statistically and in terms of magnitude (especially for runoff). This implies that technology or innovations embodied in P* increase substantively to attenuate risk. By contrast, the only input insignificantly related to both risk factors is the other chemical input, fertilizer.

The analogous negative $\varepsilon_{K,HL}$ and $\varepsilon_{K,HR}$ measures 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 insignificant. The M elasticities with respect to B_{HL} and B_{HR} are also negative and both relatively large and significant. Land instead seems in some sense “complementary” with risk; risk reduction implies lower land use. The indications for labor are mixed, although generally toward substitutability, as for capital.

The input composition effects associated with marginal changes in risk are clearly biased, as indicated by comparison of these input/risk elasticities to each other and to the overall cost elasticities $\varepsilon_{TC,HL} = -0.009$ and $\varepsilon_{TC,HR} = -0.008$ (where $\varepsilon_{TC,Bk} = \partial \ln TC/\partial \ln B_k = SV_{Bk} \cdot B_k/TC$). For a B_{HL} decrease, for example, P* is affected the most (reducing human risk 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). So input composition adapts substantially to accommodate risk reduction.

For the outputs, the $\varepsilon_{MCm,Bk} = \partial \ln MC_m/\partial \ln B_k$ elasticities are small and generally positive. In particular, the positive (but small and not quite significant at the 5% level)

$\varepsilon_{MCA,HL}$ and $\varepsilon_{MCA,HR}$ elasticities suggests that human risk reduction is consistent with lower marginal costs of animal production, thus implying some motivation toward producing Y_A rather than Y_C. This is intuitively plausible, since one might expect Y_A to have little connection to leaching and runoff from chemical use.[24] By contrast, the negative and significant $\varepsilon_{MCC,HR}$ estimate indicates jointness between crop production and risk from runoff, or higher marginal costs of crops associated with lower risk levels.

In turn, implications about pesticide demand, and its quality as compared to quantity components (P* versus P) are evident from the overall SQ_{P^*}, SQ_P, and ADJ_P measures in Table 1. The fitted shadow value of P* is on average nearly 1.5 times as large as the unadjusted P level, implying an average measured quality adaptation factor of approximately 0.70. The average ADJ_P is instead approximately 0.88. So quality-adjusted pesticide use P* exceeds P by more than the average adjustment factor.[25] This suggests that a large portion of the measured variation in P* involves quality rather than quantity differentials, in turn supporting the notion that the increases in P* required to decrease risk are driven primarily by quality change, or embodied innovation.

The impacts of (temporal and spatial) shift factors and output composition on P* as compared to P demand can also be evaluated using the indicators presented in Table 1. Note that all measured elasticities of P* demand with respect to these factors are statistically significant and positive, except that relating to fertilizer structural change, ($\varepsilon_{P^*,DF} = \partial \ln P^*/\partial D_F$), which might be expected. In particular, measured effective

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[24] Of course risk from animal waste is also a major issue, particularly 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.

[25] The difference between P* and P implicitly weights the ADJ_P measures, since we are computing the average of the multiplicative relationship $SQ_P{}^*$ = fitted P*= fitted P/ADJ_P = SQ_P, rather than averaging P*, P and ADJ_P separately and then multiplying them.

pesticide use increased significantly over time ($\varepsilon_{P^*,t} = \partial \ln P^*/\partial t > 0$), and especially after 1984 ($\varepsilon_{P^*,DP} = \partial \ln P^*/\partial D_P > 0$). However, these positive relationship are much smaller in magnitude for P than for P*,[26] again suggesting that structural adaptations in the pesticide input have primarily worked to increase the quality component of P*.

P* demand is also strong, in terms of levels, in both the corn and cotton states relative to others ($\varepsilon_{P^*,DCN}$ and $\varepsilon_{P^*,DCT}$ are positive), although in this case this differential is even more marked for P then P* ($\varepsilon_{P^*,DCN}$ and $\varepsilon_{P^*,DCT}$ fall short of $\varepsilon_{P,DCN}$ and $\varepsilon_{P,DCT}$) And the impacts of greater crop products in the output mix are quite dramatic – a 1 percent augmentation of crop output implies a dramatic 2.7 percent rise in P* ($\varepsilon_{P^*,C} = \partial \ln P^*/\partial \ln Y_C \approx 2.7$, with $\varepsilon_{P,C} \approx 1.5$), so scale increases with respect to the crop output are biased toward pesticide use. By contrast, higher levels of animal outputs generate a much smaller (less than 0.3 percent) but still positive proportional change in quality-adjusted pesticide inputs (although a more than 0.45 percent change in P), possibly associated with greater crop production for animal feed.

Temporal and Spatial Patterns

It is also informative to explore more explicitly the temporal and spatial patterns of the shadow value and pesticide use/quality measures by comparing some primary elasticity estimates across time periods and regions. For the temporal dimension, we separate the measures by the decades covered in the data – the 1960s, 1970s, 1980s, and 1990s, and for the spatial dimension we distinguish 10 regions (for the 48 contiguous states), according to the USDA breakdown for regional productivity, as in Table 2.

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[26] The significance level is the same, given the multiplicative relationship.

Table 2

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 $\varepsilon_{TC,HL}$ and $\varepsilon_{TC,HR}$ values by decade, presented in Table 3, indicate an upward trend in the proportional agricultural sector marginal-cost-benefits of B_{HL} disposal. But the reverse occurs for B_{HR}, which is consistent with the more general $\varepsilon_{SVk,t}$ estimates, from Table 1.[27] The implications for the associated pesticide costs follow closely;

[27] It is important to present these in proportional (real) terms, $\varepsilon_{TC,Bk} = \partial \ln TC/\partial \ln B_k$ to see these trends, since the nominal trends reflected in the $SV_{Bk} = \partial TC/\partial B_k$ values can be somewhat misleading for comparisons. The tendency for the B_{HL} value to increase is exacerbated if one looks instead at the SV_{Bk} values, and that for B_{HR} appears slightly upward rather than downward as it is when looking at percentage changes.

pesticide-quality-enhancing costs of reducing B_{HL} (represented by $\varepsilon_{P*,HL}=\partial \ln P^*/\partial \ln B_{HL}$) are increasing over time, but are declining for B_{HR} (from $\varepsilon_{P*,HR}$).

For the regional breakdown, note first that the Corn Belt states have a far smaller marginal cost (shadow value) of risk reduction in percentage terms, at least for leaching ($\varepsilon_{TC,HL}$=-0.0007), than is found in other areas. Leaching-risk reductions in the corn states also seem associated with *lower* effective pesticide use; $\varepsilon_{P*,HL}$ is positive, and larger than for any other region (although Northern Plains and Pacific states exhibit similar tendencies). The highest proportional costs of reducing leaching, B_{HL}, appear instead in the Southeast and the Appalachian regions. The implied change in P* follows closely, with the Appalachian and Southeast states requiring the most augmentation of P* to reduce leaching risk, and the Northeast closely following.

By contrast, the costs of reducing *runoff* are significantly larger in the Corn Belt states, where decreases in runoff are strongly linked to increased effective pesticide application. The states with the next highest costs of reducing runoff are in the Lake, Southeast, and Delta areas, which also exhibit some of the greatest corresponding increases in P*. However, the impact of B_{HR} on effective P use, $\varepsilon_{P*,HR}$, is even larger in the Northern Plans and Appalachian regions; the magnitude of $\varepsilon_{P*,HR}$ in these areas is next to the Corn Belt in terms of magnitude, although the implied P* adjustment to reduce runoff risk is less than one-third that for the Corn Belt states.

These patterns embody both quality and quantity components, as exhibited by regional variations in the levels and composition of applied pesticides. They are likely, for example, linked to the more dramatic increases in herbicide use found in the Corn and Southern states than in other regions. This hypothesis seems consistent with the Beach and Carlson finding of a positive relationship of herbicide prices for corn (and soybeans) to productive characteristics of pesticides. By contrast, the Pacific region exhibits virtually no change in effective pesticide use in order to lower runoff, which may reflect the large quantities of non-persistent petroleum oils and sulfur used in California.

To facilitate evaluating the quality and quantity components of the pesticide input relationships, elasticities reflecting the temporal and spatial patterns of SQ_{P*} (P*) and SQ_P (P) demand are reported in Table 4. First note the dramatic difference in the time trends of – and thus the gap between – P* as compared to P. From the 1960s to the 1990s the fitted value of P*, SQ_{P*}, increased by a factor of 5, whereas the average SQ_P doubled by the 1980s and then dropped again. This corresponds to a drop of ADJ_P from 1.3 to 0.26 during this time period, clearly indicating that increases in the shadow quantity of P* have primarily been driven by quality changes. This seems broadly consistent with the finding of Fernandez-Cornejo and Jans that constant quality pesticide use peaked in 1981, and yet expenditures, and thus implicitly quality, continued to increase significantly.

In terms of regions, the largest quality gap appears in the Southern Plains, followed by the Mountain States (that also exhibit very low pesticide use overall), and the Delta region. In terms of levels, the Corn Belt states show the highest P* demand, with the Pacific region, which has many pesticide-intensive crops, the second in line. However, in the Corn Belt the ADJ_P measure on average actually suggests a low level of pesticide quality (along with the Lake and Southeast states, with the Northern Plains next), whereas the Pacific states are above average in terms of quality levels. Note also that although some of these regions exhibit ADJ_P levels that exceed one, the (implicitly weighted) SQ_P/SQ_{P*} ratios all fall short of one, and of the associated ADJ_P averages, thus supporting again the predominance of quality- to quantity-attributes driving demand.

Overall, costs of risk attenuation, and pesticide use/quality patterns, have differed dramatically in both temporal and spatial dimensions. This has important implications about where risk reductions are likely to be the most prevalent without direct regulation. It also indicates how and where agricultural producers are likely to be the hardest-hit in terms of costs, if regulations requiring reductions in risk from leaching and runoff were to be implemented.

Concluding Remarks

This study uses a detailed model of the production structure in U.S. agriculture, and comprehensive data on outputs and inputs – including effective (quality-adjusted) pesticide quantities, and risk from leaching and runoff – to address issues of pesticide use and its benefits and costs to agricultural producers. In particular, we focus on measuring the potential costs to producers of reducing human risk from leaching and runoff associated with pesticide use. We find that changes in production plans to accommodate risk reductions result in significant costs (shadow values), that in turn involve clear output and input composition adaptations.

In particular, these costs are directly associated with substantive increases in effective pesticide quantities (as opposed to simple poundage), which implies induced innovation to augment pesticide quality. This quality is embodied in the pesticides via R&D and associated technological change, and has risen considerably over the sample period, and especially since the mid-1980s. More generally, in terms of netput composition changes, lowering risk from pesticide use involves more materials and less land use, greater capital and labor intensity (perhaps though additional monitoring, or more careful application), and a potential shift from crop to animal commodity production. The costs incurred by agricultural producers to make such adjustments (in addition to the augmentation of pesticide quality) have increased over time, vary widely by region, and differ for reductions in risk from leaching as compared to runoff.

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Appendix

Total pesticide use in terms of pounds of active ingredients in U.S. agriculture increased by more than 3 percent per year from 1960 through the late 1970s/early 1980s, and then stabilized, while expenditures continued to increase.[28] The mix of characteristics, such as application rate, leachability, and toxicity, also changed significantly during this period, as agricultural producers changed their production processes, including a major move toward herbicide as compared to insecticide use.

To adapt the base measures of pesticide prices and quantities for these quality changes, Nehring and Grube regressed the prices of a broad range of pesticides on physical characteristics related to their actual or perceived quality. The productive and environmental characteristics incorporated in the analysis include pesticide applications rates as a proxy for pesticide potency,[29] LD50 scores as a proxy for toxicity,[30] and persistence dummies based on solubility, vapor, sorption, and half lives.[31] Time dummies also imbedded in the regressions were converted to hedonic price indexes, or virtual price indexes for pesticides that capture price effects not connected with quality. The effective or quality-adjusted quantity indexes, P*, were then computed implicitly by dividing total expenditures on each pesticide by their adjusted price index, w_P*.

Although consistent with Fernandez-Cornejo and Jans, and Beach and Carlson, this treatment involves a much more detailed representation of the quality characteristics, and

[28] The growth in quantity and costs of the pesticide inputs used, that far exceeded that for any other input, reflected a shift from labor-intensive production methods to more capital- and chemical-intensive methods due to changes in technology, production processes, prices, and regulatory policies.
[29] A low rate is assumed to be consistent with a more effective pesticide.
[30] LD50 scores indicate the amount of toxicant necessary to effect a 50% kill of the pest being tested. Dummy variable divide pesticides into those with high (>500) or low toxicity scores.

their differential spatial and temporal patterns, of the pesticides. In particular, the earlier studies relied on limited survey information, number of crops and chemicals, and information on variability. The Nehring and Grube study instead catalogued pesticides by chemical, crop, year, and location (from Doane and NASS surveys), incorporating information on close to twenty crops and 200 chemicals. Thus, this pesticide data provides a particularly appropriate basis for our state-level analysis.[32]

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[31] Dummy variables represent half lives of more than 65 days (following Fernandez-Cornejo and Jans), and above-mean values of solubility, vapor, and sorption.

[32] Empirical implementation of our model using these data also suggested that the Nehring-Grube adaptations of the data were carried out in a manner consistent with economic theory. Our use of Shephard's lemma based on the w_P* measure is supported by both appropriate (in terms of 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.

Table 1: Shadow Value and Elasticity Measures, overall averages

measure	***estimate***	***t-statistic***	***measure***	***estimate***	***t-statistic***	***measure***	***estimate***	***t-statistic***
			$\varepsilon_{P*,HL}$	**-0.0243**	*-1.887*	SQ_{P*}	**0.0884**	*1.955*
SV_{HL}	**-0.0164**	*-2.118*	$\varepsilon_{P*,HR}$	**-0.0644**	*-2.472*	SQ_{P}	**0.0620**	*3.816*
SV_{HR}	**-0.0004**	*-1.951*				ADJ_{P}	**0.8820**	
$\varepsilon_{TC,HL}$	**-0.0090**	*-2.118*	$\varepsilon_{F,HL}$	**0.0035**	*0.175*			
$\varepsilon_{TC,HR}$	**-0.0077**	*-1.951*	$\varepsilon_{F,HR}$	**-0.0151**	*-1.273*	$\varepsilon_{P*,t}$	**1.2795**	*5.162*
			$\varepsilon_{LD,HL}$	**0.0086**	*2.157*	$\varepsilon_{P*,DF}$	**-0.2121**	*-0.981*
$\varepsilon_{SVHL,t}$	**0.0175**	*1.058*	$\varepsilon_{LD,HR}$	**0.0107**	*2.348*	$\varepsilon_{P*,DP}$	**2.4116**	*-3.881*
$\varepsilon_{SVHR,t}$	**-0.0104**	*-0.556*	$\varepsilon_{L,HL}$	**-0.0205**	*-1.867*	$\varepsilon_{P*,DCT}$	**0.8004**	*7.724*
$\varepsilon_{SVHL,DF}$	**0.0155**	*0.926*	$\varepsilon_{L,HR}$	**0.0144**	*1.961*	$\varepsilon_{P*,DCN}$	**0.8274**	*8.269*
$\varepsilon_{SVHL,DP}$	**-0.0030**	*-0.640*	$\varepsilon_{K,HL}$	**-0.0017**	*-1.063*	$\varepsilon_{P*,A}$	**0.2769**	*2.441*
$\varepsilon_{SVHR,DF}$	**0.0132**	*0.406*	$\varepsilon_{K,HR}$	**-0.0074**	*-2.563*	$\varepsilon_{P*,C}$	**2.7145**	*23.472*
$\varepsilon_{SVHR,DP}$	**0.0145**	*1.196*	$\varepsilon_{M,HL}$	**-0.0141**	*-1.850*			
			$\varepsilon_{M,HR}$	**-0.0255**	*-2.875*	$\varepsilon_{P,t}$	**0.3750**	*5.162*
						$\varepsilon_{P,DF}$	**-0.0650**	*-0.981*
			$\varepsilon_{MCA,HL}$	**0.0039**	*1.731*	$\varepsilon_{P,DP}$	**0.6482**	*-3.881*
			$\varepsilon_{MCA,HR}$	**0.0053**	*1.884*	$\varepsilon_{P,DCT}$	**1.0128**	*7.724*
			$\varepsilon_{MCC,HL}$	**0.0055**	*1.295*	$\varepsilon_{P,DCN}$	**0.9902**	*8.269*
			$\varepsilon_{MCC,HR}$	**-0.0001**	*-1.943*	$\varepsilon_{P,A}$	**0.4591**	*2.441*
						$\varepsilon_{P,C}$	**1.5444**	*23.472*

Table 3: Bad Output Measures, temporal and spatial

overall average		*1960s*		*1970s*		*1980s*		*1990s*	
$\varepsilon_{TC,HL}$	**-0.0090**	$\varepsilon_{TC,HL}$	**-0.0033**	$\varepsilon_{TC,HL}$	**-0.0099**	$\varepsilon_{TC,HL}$	**-0.0092**	$\varepsilon_{TC,HL}$	**-0.0148**
$\varepsilon_{TC,HR}$	**-0.0077**	$\varepsilon_{TC,HR}$	**-0.0131**	$\varepsilon_{TC,HR}$	**-0.0084**	$\varepsilon_{TC,HR}$	**-0.0047**	$\varepsilon_{TC,HR}$	**-0.0039**
$\varepsilon_{P^*,HL}$	**-0.0243**	$\varepsilon_{P^*,HL}$	**-0.0073**	$\varepsilon_{P^*,HL}$	**-0.0294**	$\varepsilon_{P^*,HL}$	**-0.0299**	$\varepsilon_{P^*,HL}$	**-0.0312**
$\varepsilon_{P^*,HR}$	**-0.0644**	$\varepsilon_{P^*,HR}$	**-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 4: P*, P and ADJP measures, temporal and spatial

overall average		***1960s***		***1970s***		***1980s***		***1990s***	
SQ_{P*}	**0.0884**	SQ_{P*}	**0.0333**	SQ_{P*}	**0.0737**	SQ_{P*}	**0.1162**	SQ_{P*}	**0.1407**
SQ_{P}	**0.0620**	SQ_{P}	**0.0418**	SQ_{P}	**0.0825**	SQ_{P}	**0.0817**	SQ_{P}	**0.0303**
ADJ_{P}	**0.8820**	ADJ_{P}	**1.3110**	ADJ_{P}	**1.1294**	ADJ_{P}	**0.6833**	ADJ_{P}	**0.2625**

Northeast		***Corn Belt***		***Lake States***		***Northern Plains***		***Appalachian***	
SQ_{P*}	**0.0227**	SQ_{P*}	**0.2043**	SQ_{P*}	**0.1361**	SQ_{P*}	**0.1088**	SQ_{P*}	**0.0490**
SQ_{P}	**0.0168**	SQ_{P}	**0.1614**	SQ_{P}	**0.0977**	SQ_{P}	**0.0731**	SQ_{P}	**0.0388**
ADJ_{P}	**0.8786**	ADJ_{P}	**1.0825**	ADJ_{P}	**1.0917**	ADJ_{P}	**1.0284**	ADJ_{P}	**0.9182**

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}	**0.0793**	SQ_{P}	**0.0790**	SQ_{P}	**0.0741**	SQ_{P}	**0.0180**	SQ_{P}	**0.1190**
ADJ_{P}	**1.0717**	ADJ_{P}	**0.7611**	ADJ_{P}	**0.5429**	ADJ_{P}	**0.6493**	ADJ_{P}	**0.8190**

Appendix Table A1: Coefficient Estimates

	Estimate	*t-statistic*
α_{F1}	**-0.139**	*-5.74*
o_{P1}	**-0.190**	*-6.32*
α_{LDL}	**-0.013**	*-2.09*
α_{LDK}	**0.082**	*8.12*
α_{LDF}	**-0.004**	*-0.91*
α_{LDDF}	**0.012**	*3.61*
α_{LDFCT}	**-0.025**	*-3.48*
α_{LDFCN}	**-0.007**	*-0.97*
α_{LDM}	**-0.034**	*-3.74*
α_{LDP}	**0.006**	*1.19*
α_{LDDP}	**-0.012**	*-3.21*
α_{LDPCT}	**0.001**	*0.09*
α_{LDPCN}	**0.013**	*1.50*
α_{LK}	**0.012**	*1.65*
α_{LF}	**-0.022**	*-1.93*
α_{LDF}	**0.013**	*1.30*
α_{LFCT}	**0.026**	*1.47*
α_{LFCN}	**0.075**	*4.46*
α_{LM}	**0.234**	*8.70*
α_{LP}	**0.016**	*2.30*
α_{LDP}	**-0.001**	*-0.15*
α_{LPCT}	**0.014**	*1.21*
α_{LPCN}	**-0.0004**	*-0.04*
α_{KF}	**0.019**	*3.40*
α_{KDF}	**0.034**	*10.25*
α_{KFCT}	**0.024**	*2.08*
α_{KFCN}	**0.016**	*1.30*
α_{KM}	**-0.066**	*-5.01*
α_{KP}	**0.031**	*3.90*
α_{KDP}	**0.018**	*4.09*
α_{KPCT}	**0.028**	*1.68*
α_{KPCN}	**-0.004**	*-0.20*
α_{FM}	**0.047**	*4.07*
α_{MDF}	**0.0004**	*0.03*
α_{MFCT}	**0.161**	*6.27*
α_{MFCN}	**0.169**	*6.16*
α_{MP}	**-0.019**	*-2.16*
α_{MDP}	**0.043**	*4.15*
α_{MPCT}	**0.088**	*4.46*
α_{MPCN}	**0.042**	*1.87*
α_{FP}	**0.008**	*2.25*
α_{PDF}	**0.013**	*3.38*
α_{PFCT}	**0.007**	*0.79*

	Estimate	*t-statistic*
α_{PFCN}	**0.036**	*3.55*
α_{FDP}	**-0.002**	*-0.83*
o_{LDA}	**-0.971**	*-76.43*
o_{LA}	**-0.921**	*-54.45*
o_{KA}	**-0.900**	*-66.55*
o_{FA}	**-0.905**	*-58.76*
o_{ADF}	**0.015**	*4.90*
o_{PA}	**-0.931**	*-65.03*
o_{ADP}	**-0.001**	*-0.56*
o_{APCT}	**0.026**	*2.43*
o_{APCN}	**-0.014**	*-1.29*
o_{AFCT}	**-0.013**	*-1.07*
o_{AFCN}	**-0.029**	*-2.44*
o_{LDC}	**-0.623**	*-87.22*
o_{LC}	**-0.584**	*-55.48*
o_{KC}	**-0.576**	*-88.39*
o_{FC}	**-0.571**	*-69.82*
o_{CDF}	**0.004**	*2.00*
o_{PC}	**-0.613**	*-84.63*
o_{CDP}	**-0.001**	*-0.49*
o_{CPCT}	**0.021**	*4.48*
o_{CPCN}	**0.009**	*2.43*
o_{CFCT}	**-0.011**	*-1.81*
o_{CFCN}	**-0.006**	*-1.23*
o_{LDt}	**0.004**	*5.67*
o_{Lt}	**-0.009**	*-10.71*
o_{Kt}	**-0.013**	*-9.63*
o_{Ft}	**-0.003**	*-4.17*
o_{tDF}	**0.005**	*4.62*
o_{Mt}	**-0.023**	*-8.54*
o_{Pt}	**0.003**	*2.29*
o_{tDP}	**0.005**	*4.22*
o_{tPCT}	**0.010**	*4.84*
o_{tPCN}	**0.022**	*10.52*
o_{tFCT}	**0.004**	*4.75*
o_{tFCN}	**0.007**	*8.89*
o_{LDHL}	**0.002**	*1.18*
o_{LHL}	**-0.009**	*-3.52*
o_{KHL}	**-0.002**	*-1.14*
o_{FHL}	**0.0001**	*0.06*
o_{HLDF}	**-0.001**	*-1.60*
o_{MHL}	**-0.012**	*-2.56*
o_{PHL}	**-0.002**	*-1.85*

	Estimate	*t-statistic*
o_{HLDP}	**0.0005**	*0.77*
o_{LDHR}	**0.00004**	*1.68*
o_{LHR}	**0.0001**	*3.08*
o_{KHR}	**-0.0001**	*-5.42*
o_{FHR}	**-0.0001**	*-2.88*
o_{HRDF}	**-0.00001**	*-0.89*
o_{MHR}	**-0.0006**	*-8.24*
o_{PHR}	**-0.0001**	*-3.61*
o_{HLDP}	**-0.00003**	*-2.18*
γ_{AA}	**-0.0003**	*-0.43*
γ_{CC}	**-0.0011**	*-3.13*
γ_{HLHL}	**0.00003**	*1.86*
γ_{HRHR}	**0.00000001**	*1.41*
γ_{At}	**-0.0018**	*-26.53*
γ_{Ct}	**-0.0018**	*-28.78*
γ_{HLt}	**-0.0001**	*-1.54*
γ_{HRt}	**0.000001**	*1.27*
γ_{AHL}	**0.0003**	*2.20*
γ_{CHL}	**0.0005**	*3.62*
γ_{HLHR}	**0.000005**	*2.20*
γ_{AHR}	**0.00001**	*2.43*
γ_{CHR}	**-0.00001**	*-2.85*
γ_{AC}	**-0.0016**	*-2.60*
ρ	**0.835**	*85.77*
ρ_{L}	**0.607**	*54.85*
ρ_{F}	**0.786**	*59.89*
ρ_{M}	**0.883**	*114.40*
ρ_{P}	**0.967**	*294.84*
ρ_{LD}	**0.896**	*108.39*
ρ_{K}	**0.954**	*284.05*

Equation:	R-squared
TC	**0.989**
L	**0.974**
F	**0.932**
M	**0.970**
P*	**0.966**
LD	**0.999**
K*	**0.996**
MC_{A}	**0.942**
MC_{C}	**0.920**