Aggregation Issues in Pest Control Economics: A Bioeconomic Approach

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Abstract

Previous research has defined "aggregate pesticide expenditures" as the control variable; however, virtually all managerial recommendations and environmental restrictions target specific pesticides, rates, and crops. A bioeconomic approach considering particular pesticides on specific pests and crops is recommended for managerial-policy applications and testing for increasing returns. Exponential weed control and seven popular yield damage functional forms were estimated for a bioeconomic weed control model for winter wheat in Washington. Concavity with respect to herbicide rate was observed for most popular damage functions at normal weed densities and manufacturers' label rates, but convexity existed outside these ranges and should be checked.

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Introduction

The marginal product of pesticides, the primary damage control input in agriculture, has implications for privately optimal pesticide use and potential environmental risks. If the marginal product of pesticide is increasing over a substantial range, optimal private usage could be much higher than current label recommendations. However, application rates exceeding label rates may not be environmentally safe.

Unfortunately, economists have been frustrated by a number of specification and data issues in attempting to measure the productivity of agricultural pesticides. Our first objective in this paper will be to review several studies which have used pesticide expenditure data to measure pesticide productivity. Pesticide expenditures encompass a multitude of inputs such as insecticides, fungicides, broadleaf herbicides, grass herbicides, and nonselective herbicides. The expenditure data are also collected at various levels of geographic aggregation. This "aggregate pesticide expenditure" approach will be compared to a "bioeconomic" approach using crop and pesticide specific data from experimental sources. We will argue that the latter bioeconomic approach is superior for most policy analysis, managerial recommendations, and testing for the empirical presence of increasing marginal productivity. Our second objective will be to report results regarding increasing marginal productivity using several estimated yield damage functional forms applied to an experimental data set of postemergence herbicide applications on winter wheat.

It will be useful in this discussion to explicitly distinguish between two types of data aggregation. The first is aggregating pesticides with different modes of action, target pests, and environmental externalities into a single "dollar expenditure" variable. The second is aggregation of expenditures or quantities of pesticides to a farm, regional, or other geographic level larger than a single-crop field or experiment. It will be argued that both types of aggregation severely limit policy, managerial, and theoretical conclusions.

In addition to questions of policy-managerial relevance, aggregate data are vulnerable to classical aggregation bias. Available aggregate data describing heterogeneous firms or fields will generally fail to satisfy properties for consistent aggregation (Chambers). This means the aggregate response will fail to equal the sum of the responses of the micro units. While classical aggregation bias is important, our primary concern about aggregation is the loss in policy or managerial relevance which occurs when diverse pesticides on several target pests are aggregated into a single monetary expenditures variable.

To determine the marginal productivity of pesticides, economists have generally used geographically and product aggregated pesticide expenditure data because the cost of the data are low, the data are available, and the regional generality of results may be greater. Theoretically, analysis based on aggregate data can provide expected regional or national impacts from policies which act on undifferentiated pesticide expenditures. For example, impacts of national or regional bans or ad valorem taxes on *all* pesticides could be assessed with the results of these popular studies (Campbell; Carpentier and Weaver; Carrasco-Tauber and Moffitt; Chambers and Lichtenberg; Headley; and Saha, Shumway, and Havenner). Modern industrialized countries, however, rarely if ever have regulated the multitude of agricultural pesticides with such blunt instruments. Instead, they have targeted particular pesticides and use rates on particular target uses. The U.S. Environmental Protection Agency (EPA) permits use of herbicides on turf grasses and ornamentals that are not permitted on fruits and vegetables. Where particular products are banned, such as DDT or methyl bromide, or are under review by the EPA, such as organophosphates, only single products or classes are banned or uses limited because of scientifically documented environmental damage (Schierow, 1996; 1999). The herbicide dinoseb was delicensed for application to field peas and lentils due to toxicity in that environment. The EPA reviewed the triazines (atrazine, cyanazine, and simazine) and considered registration changes because of the high incidence of these chemicals in groundwater (Schierow, 1996).

Early studies by Headley and Campbell estimated the productivity of pesticide expenditures by including expenditures as a conventional input in a typical one-stage production function. Their results showed the marginal productivity of pesticides to greatly exceed their marginal costs, implying suboptimal use. Subsequent scholars have focussed on modelling and econometric improvements to reconcile the high marginal productivity estimated by Headley and by Campbell. Following the established approach used in the pest control sciences for herbicide efficacy (Roberts and Wilson) and yield response to the pests (Cousens; Stern et al; Talpaz and Frisbie), Lichtenberg and Zilberman (LZ) specified a two-stage damage control model where: (a) the pesticide reduces the pest population (the "dose response" in the biological and medical science literature), and (b) the surviving pest population damages crop yield. In the LZ two-stage model, yield (Q) is a function of a vector of directly productive inputs ($\boldsymbol{Z}$) and a damage abatement or control function ($G(\boldsymbol{X})$), which is a function of the damage control inputs ($\boldsymbol{X}$):

(1) $$Q = F[\boldsymbol{Z}, G(\boldsymbol{X})]$$

This two-stage approach is consistent with the biology of pests in a production system (Matthews), and facilitates incorporating state variables. The specification in equation (1) has asymmetric roles for the two input classes and assumes homothetic separability in productive inputs, $\boldsymbol{Z}$, and the endogenous damage control inputs, $\boldsymbol{X}$ (Carpentier and Weaver; Saha, Shumway, and Havenner).

Carrasco-Tauber and Moffitt estimated the damage abatement specification of equation (1) using Weibull, logistic and exponential functions with state-level averaged per farm pesticide expenditure data. The similarity of the marginal product of pesticide expenditure between a Cobb-Douglas conventional input specification and equation (1) indicated that high pesticide productivity estimates were due to more than one-stage versus two-stage model specifications.

A dual specification of equation (1) using U.S. aggregate time-series data on pesticide expenditures developed by Chambers and Lichtenberg rejected the conventional input specification as the correct specification. They admitted their model estimates were somewhat conjectural because of the use of aggregated U.S. national agriculture sector data. Carpentier and Weaver noted the asymmetric LZ model was unnecessary with multivariate econometric techniques, and the homothetic separability of productive inputs $\boldsymbol{Z}$ and control inputs $\boldsymbol{X}$ is unrealistic for nonexperimental data. Their fixed effects model using farm-level panel data that took farm heterogeneity into account showed lower marginal products of pesticide expenditures than reported in previous studies using symmetric model specifications. Saha, Shumway, and Havenner employed alternative stochastic specifications using farm-level data on total pesticide expenditures. They concluded proper specification of the stochastic element of the production function precluded overestimating the marginal productivity of pesticide expenditures.

Intrinsic increasing returns to pesticides due to functional form selection is another possible explanation for the high marginal product of pesticide estimates of early empirical studies. Fox and Weersink showed that increasing returns are possible under specific conditions using popular functional forms for damage and control functions. Concavity of the damage and control functions in equation (1) is not sufficient to prevent increasing returns to damage control inputs. Hennessy developed global conditions for the damage and control functions that assures concavity of the production function in a damage control input. The functional forms specified by Fox and Weersink have not been tested on empirical field data to determine whether increasing returns are evident or feasible in the range of data found in field situations. Testing for increasing returns to damage control inputs with various specifications of functional forms would be facilitated by experimental data where other variables can be controlled.

We argue models including aggregate pesticide expenditures as the decision variable are inappropriate for managerial decisions. Managers require refined decision rules for application of particular pesticides on specific crops conditional on pests, pest densities, crop, moisture conditions, and other state variables (King et al., 1993; Marra and Carlson; Mortensen and Coble; Swinton and King, 1994a, 1994b; Talpaz and Frisbie; Weersink, Deen, and Weaver). The biology of dose response (Seefeldt, Jensen, and Fuerst), threshold analysis (Stern et al.), weed competition (Black and Dyson; Cousens), and economic optimization requires the precision of pesticide-crop specific field information, which is not available in the aggregate pesticide expenditure data that many economists have used.

Parallel to the aggregate economic analyses, a more biologically precise line of pest control economics proceeded based on pesticide and crop specific field experimental data (Pannel; King et al., 1986; Ethridge et al.; Swinton and King, 1994b; Lybecker, Schweizer and King; Kwon et al.). This work, referred to as bioeconomic modelling, has been published in the pest science literature, as well as in agricultural economics journals. Many of these studies are the product of interdisciplinary cooperation between economists and biological scientists. Dynamic models are generally appropriate for insects, but the cost of collecting soil seed bank data is often too costly for dynamic weed control decision models (King et al., 1986). Multiple weed types have been included in some models (Kwon et al.; Lybecker, Schweizer, and King; Swinton et al.).

Bioeconomic pesticide application rate studies have generally implied decreasing returns to herbicide rate (Pannell; Kwon et al.). Pannell determined optimal herbicide rates for the control of one weed species. His optimal interior solution indicated concavity in the damage control input. Kwon et al. developed a field-level profit maximization model for postemergence herbicide rates for broadleaf and two grass weed types in winter wheat. The resulting profit function had interior solutions over a range of weed densities, prices, and costs. None of the field-level bioeconomic studies reviewed utilized the specific functional forms which Fox and Weersink showed were associated with ranges of increasing returns.

The bioeconomic models described above provide a much sharper instrument to examine impacts of realistic policies because they examine the impacts of specific herbicides that might be regulated on specific crops for which the herbicides are legally registered and technically feasible. The bioeconomic approach avoids using "aggregate pesticide expenditures" as the control variable. Furthermore, the bioeconomic models maintain a much closer fit to the biological logic underlying equation (1); consequently, they provide a less ambiguous means of testing for increasing returns to pesticide rates over realistic data ranges for particular pesticides and crops.

Our second objective is to report empirical results regarding increasing marginal productivity of herbicides. We use field-level experimental data to estimate herbicide-specific weed control and winter wheat yield damage functions for several functional forms. Like most bioeconomic studies, we employ the two-stage approach pioneered by biological scientists. Where concavity of the production and profit function with respect to herbicide rate is restricted to certain weed densities or other state variable levels, the levels will be evaluated to determine if they are within reasonable values likely to be observed in the field. Field data permit specification of pest densities, soil properties, and ancillary management practices that are critical to precise pest control recommendations.

Model and Data

Model

A modified version of equation (1) is used. Actual weed numbers per unit area (m^2) surviving herbicide application are used for $G(\mathbf{X})$, as in the process model by Blackwell and Pagoulatos. Proportions are central to biologists computing efficacy of a dose, but actual weed density is required to properly estimate yield damage. The weed survival model for three weed types is specified as:

$$\textbf{(2)} \qquad DS_i = SWD_i e^{-b_i H_j} + dDH_N + \sum_{k=1}^{2} a_k TIL_k + \sum_{m=1}^{2} c_m CR_m + e_i \qquad i = 1, 2, 3$$

where DS is the surviving weed density (plants/m^2) at mid-summer; SWD is the weed seedling density (plants/m^2) in the spring prior to postemergence herbicide application; (i = 1 for summer annual grasses, i = 2 for winter annual grasses, and i = 3 for broadleaves); H is the category of herbicide (j = N for nonselective, j = B for post emergence broadleaf, and j = G for post emergence grass); DH_N is a binary variable equal to 1 for the application of a nonselective herbicide prior to fall planting of winter wheat[1]; TIL_k are binary variables for the tillage practice compared to plow (TIL_1 = 1 for no-till, TIL_2 = 1 for chisel plow, otherwise the values are zero); CR_m are binary variables for the crop preceding winter wheat compared to winter wheat (CR_1 = 1 for spring wheat, CR_2 = 1 for spring pea, otherwise the values are zero); and e is the error term. Binary variables are additive in this model because the production system, tillage, and crop rotation affects the efficacy of control, the competitiveness of the crop, and subsequent weed flushes. The terms d, $a_{k,}$, c_m are the parameters to be estimated. Each of the three weed groups not only competes with the crop, but with the other weed groups. To accommodate the correlation among the error terms of the three weed survival equations, the seemingly unrelated regression technique is used.

The expected sign on the coefficient b will be positive because higher rates of the appropriate herbicide, H, should reduce the surviving weed population. The expected sign of d is negative because treatment of weeds prior to seeding should reduce weed population the next summer. The sign for a_k should be negative because conservation tillage tends to increase weed competition over plowing in the area of study (Young et al.) No prior sign can be assigned to c_m based on available research.

Yield, Q, is modelled as a function of weed-free yield, the level of surviving weed competition, and other endogenous and exogenous factors of production. Weed survival is incorporated into a yield function for winter wheat as follows:

(3) $$Q = s_1(1 - e^{-s_2 SM})(1 - e^{-s_3 OM})[g(T\hat{W}S)] + \sum_{k=1}^{2} u_k TIL_k + \sum_{m=1}^{2} v_m CR_m + \varepsilon$$

where the terms before the square bracket models weed free yield of the benchmark winter wheat system as a Mitscherlich-Baule function, where SM is percent soil moisture and OM is percent soil organic matter at April 1. The s_i are estimated parameters. $T\hat{W}S$ is the mid-summer total estimated weighted weed survival of the three weed categories estimated by equation (2). The *g(•)* function is the yield damage function. Seven functional forms are estimated for *g(TWS)* in this paper: logistic, rectangular hyperbolic, exponential, Weibull, Pareto, linear and square root (table 1). The properties of the functions are reported in Fox and Weersink.

Grass and broadleaf weeds surviving treatment are combined into a mid-summer total weighted weed survival density. The total weighted weed survival density in winter wheat was determined from predicted mid-summer weed densities and weighted by mid-summer weed biomass, an indicator of the competitiveness of the weed categories for nutrients and moisture, and is specified as:

$$T\hat{W}S = 0.92(\hat{D}S_1) + 1.0(\hat{D}S_2) + 0.47(\hat{D}S_3) \tag{4}$$

A competition index of 1.0 was assigned to winter annual grasses and the weights assigned to summer annual grasses and broadleaves were proportional to the frequency weighted average biomass of winter annual grasses.

We estimated the survival and yield equations with the SHAZAM econometric program (White). Convergence for the nonlinear models is not guaranteed for any given set of starting values. Though a global optimum is not assured, solved models were reestimated with different starting points to give high probability to identifying the optimum. Two measures of goodness of fit were used to select the yield responses reported: the log-likelihood function and the maximum likelihood estimate (MLE) of σ^2, and a calculated R^2 is also reported.

Data

The experiment from which the field data are obtained was conducted in southeastern Washington from 1986 through 1991 (Young et al.). The experiment had two crop rotations: winter wheat-winter wheat-spring wheat and winter wheat-spring barley-spring pea. Conventional and conservation tillage were combined with three levels of weed management: minimum, moderate, and maximum on both rotations. All rotational positions of a crop were grown each year. There were four replicates and the data set provided 432 observations for winter wheat over the six years. Several herbicides were used on winter wheat over the six years, with types and rates changing with the treatment and weeds present. Because of the numerous herbicides used, the application rate was expressed as a proportion of the label rate. Herbicides were grouped into three subgroups for winter wheat: nonselective preplant, postemergence grass and postemergence broadleaf.

Results

Weed survival and yield damage equations were estimated using all functional forms in table 1. The exponential weed survival function was selected throughout because of its popularity in the literature, its goodness of fit to our data, and its sensitivity of marginal dose response to both dose rate and preexisting weed densities.[2] The results of the seemingly unrelated regression weed survival equations for the three weed types are reported in table 2. The calculated R^2 values in table 2, while relatively low, are reasonable for cross sectional data of this type. Postemergence grass (H_G) and broadleaf (H_B) herbicides significantly reduced weed survival of grasses and broadleaves, respectively, for this data set. At the label rate for broadleaves (H_B=1), broadleaf control was 93% ($1-e^{-2.659}$). The lower estimated coefficient for summer annual grasses reflects weed flushes, primarily wild oats, that often occur after spring herbicide application in this region. Indeed, control of all weeds present during spring control was likely much higher than weed counts at mid-summer would indicate because of post-application weed flushes. Nonselective glyphosate herbicide (DH_N) reduced broadleaves the following mid-summer but did not have a statistically significant effect on grasses. Soil conserving no-till (TIL_1) and chisel plow (TIL_2) tillage systems permitted significantly higher weed survival, but chisel plowing increased broadleaf weed density by less than 3 plants/m^2. The higher weed survival with conservation tillage is consistent with common farmer practice in this region of boosting herbicide use to control higher weed escapes when tillage is reduced. The preceding crop was not included in the final estimate of weed survival because all variables were highly insignificant, coefficient values were mostly less than one, and there was no affect on the log-likelihood function and calculated R^2 values.

The estimated yield damage for the seven functional forms are reported in table 3. Variable definitions are in equation (3) and in table 1. Estimating yield damage with the total biomass weighted weed survival, rather than the three weed categories, simplifies estimation and interpretation. Log-likelihood, MLE of σ^2, and calculated R^2 values are similar across all equations. The weed free yield coefficients (s_1, s_2, and s_3) are all highly significant as expected. Spring soil moisture and soil organic matter are primary determinants of site productivity in this dryland farming region. Tillage (a_1 and a_2) and preceding crop (c_1 and c_2) significantly affected crop yield. Conservation tillage and rotating winter wheat with spring wheat and especially spring peas increased winter wheat yield. The coefficients for the damage functions (n_0 and n_1) are significant for all cases. All variables have expected signs based on agronomic principles. Increased total weed survival depresses winter wheat yield. Note the Weibull function reduces to a constant and the Pareto function is undefined if *TWS* equals zero. Our experimental site, like most fields, did not contain observations with zero weed density.

Increasing Returns

The estimated equations for weed survival and damage are tested for increasing returns to herbicide rates over observed weed densities and herbicide rates. Two approaches are used to determine concavity of production in the control for our estimates. The first is to use the rule specified by Hennessy where the ratio of the second to the first derivative of the inverse survival function with respect to the pest must be less than the ratio of the second to the first derivative of the damage function with respect to the pest. The second approach is to directly evaluate the second order derivatives for production with respect to herbicide rate.

Hennessy's rule for global concavity held for the estimated linear and square root damage functions when combined with the estimated exponential survival function. For the estimated Pareto and Weibull damage functions with the exponential survival function, yield with respect to control was everywhere convex in the positive quadrant and very close to linear. The estimated rectangular hyperbolic, logistic, and exponential damage functions with the exponential survival function are neither strictly concave or convex with respect to herbicide rate. These three functions are concave at low surviving weed levels and higher herbicide rates, and convex at high surviving weed levels and low herbicide rates. The changing concavity for these three functions were confirmed using both Hennessy's rule and by directly evaluating the second order derivatives of yield with respect to herbicide rate. The properties of the linear and exponential damage functions with the exponential survival function are consistent with the general derivations provided by Fox and Weersink.

The rectangular hyperbolic damage function with the exponential survival produces a concave production response to herbicide rate when *TWS* is less than 62 plants/m^2. The logistic damage function with the exponential survival has a concave production response to herbicide rate when *TWS* is less than 38 plants/m^2. The exponential damage and survival functions have a concave production response to herbicide rate when *TWS* is less the 244 plants/m^2. Precontrol weed densities corresponding to the above *TWS* levels will depend on the weed type and the herbicide type and rate. For controls with high efficacy, such as broadleaf herbicides, production will be concave with application at the label rate (H_B=1) and precontrol spring weed densities (*SWD*) of up to 885, 540, and 3480 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential damage functions. These are high infestation levels that were not observed in the field data used in this analysis but rare occurrences of broadleaf densities of up to 2200 plants/m^2 have been observed in farmers' fields in the region (Hall). Grasses are generally more difficult to control in wheat and some species can not be controlled because they genetically resemble wheat. Production will be concave for summer annual grasses at the label rate (H_G=1) with *SWD* up to approximately 120, 80 and 520 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential damage functions. Field observations of summer annual grass weeds in winter wheat in the study region have densities below these levels, but higher densities can occur (Hall).

The precontrol densities for concavity will be lower than those indicated above if control rates are less than label rates. To maintain concavity at H_B=0.5, the *SWD* of broadleaves would have to be less than 225, 135 and 880 plants/m^2, respectively for the rectangular hyperbolic, logistic, and exponential damage functions. To maintain concavity for grasses at H_G=0.5, the *SWD* of grass weeds would have to be less than 85, 60 and 370 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential damage functions. The broader range of theoretically appealing concavity for the exponential yield damage function makes this function attractive for empirical use.

With the three functions that have most frequently been used to estimate damage control (hyperbolic, logistic, and exponential), convexity and increasing returns to control will likely only be present when precontrol weed densities are exceptionally high and control rates are much less than label rate. Furthermore, caution is required when extrapolating to the region where concavity does not exist as these values are beyond the data used to estimate our functions. The region of increasing returns in the functions may be due to extrapolation rather than actual increasing returns in the data.

The presence of increasing returns only when weed densities are high and application rates are below label conforms with the biology of control and the registration process for a pesticide. Prior to registering a pesticide, extensive tests are undertaken to determine the efficacy of the pesticide. A herbicide manufacturer is unlikely to select a label rate where weed survival is high and crop yield is increasing at an increasing rate with the herbicide rate. Profit incentives will likely motivate the company to set a relatively high label rate where the marginal product of the herbicide is ‘small’, assuming the rate is environmentally safe. The higher label rate will enhance marketability and reduce liability for nonperformance.

Of the damage control functions considered in the analysis, the rectangular hyperbolic is the most commonly used function in weed control research. The function has many properties that conform to the biology of weed control (Cousens). The function also conforms over typical ranges to economic properties desirable in a damage function. However, our results indicate that when this damage formulation is combined with the popular exponential survival function, the estimated functions should always be checked for production concavity in the feasible data range.

The marginal product of control will depend upon the level of the particular pesticide, the host crop, initial pest infestation, other state variables, and the functional form. The model formulation can ensure a positive marginal product, but no generalization can be made about the magnitude. For a range of precontrol weed densities, the marginal product of broadleaf herbicide is illustrated for our estimated exponential weed survival with rectangular hyperbolic damage functions in figure 1. The marginal product is monotonically declining over all herbicide rates for

SWD less than 151. The current price of wheat ($2.60/bu) and label rate cost of broadleaf herbicides ($11.00/ac) will require the marginal product to exceed 4.2 bu/ac for herbicide application to be profitable. Unreported results indicated the marginal product for grasses must exceed 9.2 bu/ac for profitable control because of higher grass herbicide costs.

Optimal proportions of label rate for the rectangular hyperbolic, logistic, and exponential damage functions for the above input to output price ratio were similar across all functions and precontrol spring weed densities (table 4). For broadleaf weeds, spring weed density needed to be above 10 plants/m^2 to justify profitable control for all three damage functions. Optimal rates were less than label rate for densities up to about 120 plants/m^2. The three functions deviated slightly in recommendations at high spring weed densities, with the rectangular hyperbolic recommending rates about 30 percent higher than either the logistic or the exponential. The results indicate there is an economic benefit to applying less than label rates in most situations. Producers apply less than label rates in many situations, but in so doing they forfeit recourse with the herbicide manufacturer if herbicide performance is substandard.

The "excessively high" marginal product of generic "pesticide expenditures" estimated in some earlier studies (Headley; Campbell; Carraco-Tauber and Moffitt) are not evident in our analysis of crop and herbicide specific experimental data. At the label rate, the ratio of the marginal value product to the cost of herbicides exceeded 1.0 only if weed densities were extremely high.

Conclusions

Analysis of agricultural pesticide productivity and price response using aggregate pesticide expenditures data can provide national or regional impacts for policies directed to undifferentiated "pesticide expenditures." Aggregate models, if properly specified, can also avoid overestimation of the marginal product of pesticides that occurred in early studies using aggregate data. Aggregate analysis based on pesticide expenditures, however, provides little managerial or policy guidance in real world situations where pesticide-crop specific information are required. The pesticide registration process generally approves pesticides and rates by product and by crop. Furthermore, in rare cases where pesticides are banned, the restrictions apply to particular products.

Bioeconomic modelling of pest control incorporates specific crop, pest, product, and site information required by production managers. Bioeconomic models offer a more controlled laboratory to test for increasing returns because they conform more closely to the biological logic of separable control and damage functions for a pesticide and its target pests. Bioeconomic studies have tended not to show increasing returns to pesticide application.

For the field experiment data for winter wheat production used in this analysis, an estimated exponential weed survival function with Pareto and Weibull damage functions resulted in an increasing rate of production with respect to herbicide rate throughout the herbicide rate and weed density range. Estimated exponential survival with linear and square root damage functions were globally concave, indicating that production increased at a decreasing rate with respect to herbicide rate. Estimated exponential survival with rectangular hyperbolic, logistic, and exponential damage functions were locally concave over the range of our data. They were convex only in situations of extremely high weed densities and low rates of herbicide application.

Field-level data for winter wheat in eastern Washington indicate increasing returns to herbicide application are unlikely to occur. Further empirical bioeconomic work is required to determine how applicable these results are to other regions, crops, and pesticides. The extensive preregistration procedures for pesticides, and commercial incentives, would suggest that chemical companies may set label rates where marginal products are diminishing. However, crop competitiveness, climate, herbicide resistance, and other dynamic factors could alter this expectation. Where concavity is not precluded by the functional form, researchers should always check for concavity of their yield function with respect to pesticide rate within the feasible range of their data.

Notes

[1] Early fall application of nonselective herbicide occurs only when sufficient rainfall generates a "flush" of weeds prior to seeding winter wheat.

[2] Other estimated functional forms for weed survival were deemed unsuitable. Linear and square root functions had low significance and a low R^2, logistic had theoretically incorrect signs, and the rectangular hyperbolic, Pareto, and Weibull did not converge.

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Table 1. Damage Functions

Logistic	$1 - \frac{c}{1 + e^{-(n_0 + n_1 TWS)}}$
Rectangular Hyperbola	$1 - \frac{n_1 TWS}{100\left(1 + \left\| \frac{n_1 TWS}{n_0} \right\|\right)}$
Exponential	$e^{-n_1 TWS}$
Weibull	$e^{-TWS^{n_1}}$
Pareto	$\left\| \frac{K}{TWS} \right\|^{n_1}$
Linear	$1 - n_1 TWS$
Square Root	$1 - n_1 \sqrt{TWS}$

TWS is total weed survival, c and K are constants, and n_0 and n_1 are parameters to be estimated.

Table 2. Estimated coefficients of exponential mid-summer weed density functions for three weed subgroups in winter wheat using seemingly unrelated regression.

Variable[a]	DS_1	DS_2	DS_3
H_B	[b]		2.659 (35.20) [c]
H_G	0.670 (6.75)	2.986 (20.34)	
DH_N	-2.451 (-0.43)	0.560 (0.11)	-7.050 (-4.31)
TIL_1	13.267 (3.05)	9.325 (2.46)	9.640 (7.24)
TIL_2	18.778 (4.25)	16.269 (4.16)	2.770 (2.37)
Calculated R^2	0.35	0.28	0.36
Log-likelihood function	-6080.93		
Number of observations	432		

[a] H_B = postemergence broadleaf herbicide, H_G = postemergence grass herbicide, DH_N = discrete variable for preplant nonselective herbicide ($DH_N = 1$ for application, $DH_N = 0$ for no application), TIL_i = discrete variables for tillage ($TIL_1 = 1$ and $TIL_2 = 0$ for no-till, $TIL_1 = 0$ and $TIL_2 = 1$ for chisel plow, otherwise $TIL_1 = TIL_2 = 0$ for moldboard plow.). Weeds (plants/m^2) were categorized as summer annual grasses (DS_1), winter annual grasses (DS_2), and broadleaves (DS_3).

[b] Blank entries indicate that the variable was excluded because it was not relevant to the particular weed type.

[c] , t-statistics are in parentheses.

Table 3. Estimated coefficients of yield damage response functions for selected models.

Variable[a]	Logistic	Rectangular hyperbolic	Expo- nential	Weibull	Pareto	Linear	Square- root
Intercept	97.764	97.872	93.879	243.61	90.678	91.762	99.346
	(15.09)[b]	(16.69)	(19.12)	(21.87)	(23.58)	(21.35)	(17.54)
SM	0.201	0.200	0.199	0.199	0.197	0.197	0.202
	(10.95)	(10.95)	(10.98)	(10.62)	(10.80)	(11.62)	(10.87)
OM	0.838	0.826	0.892	1.095	1.133	0.988	0.854
	(4.55)	(4.60)	(4.58)	(3.79)	(3.98)	(4.45)	(4.54)
TWS (n_1)	0.089	1.095	0.0041	0.028	0.0224	0.0022	0.039
	(2.44)	(3.13)	(5.12)	(4.05)	(3.69)	(6.63)	(9.01)
TWS (n_0)	-2.780	68.127					
	(-2.03)	(5.55)					
TIL_1	20.704	22.525	17.294	15.561	14.374	14.534	20.918
	(8.56)	(7.49)	(7.53)	(6.43)	(6.24)	(6.98)	(9.16)
TIL_2	15.412	16.021	9.418	3.962	2.315	4.327	13.252
	(4.81)	(4.32)	(3.06)	(1.35)	(0.83)	(1.78)	(4.60)
CR_1	9.319	9.791	9.688	8.958	8.848	9.313	9.700
	(4.19)	(4.40)	(4.26)	(3.73)	(3.67)	(4.11)	(4.51)
CR_2	25.844	26.533	25.453	24.057	23.693	24.278	26.092
	(11.52)	(11.74)	(11.38)	(10.26)	(10.22)	(11.08)	(12.22)
Calculated R^2	0.53	0.54	0.53	0.49	0.49	0.52	0.54
Log-likelihood	-1818	-1817	-1821	-1838	-1840	-1825	-1816
MLE of σ^2	265.3	263.7	268.7	291.1	293.0	273.6	263.3

[a]SM = soil moisture, OM = organic matter, TWS = total weed survival (n_0 and n_1 are defined in table 1 for each of the functions), TIL_k is a discrete variable for tillage (TIL_1 = 1 and TIL_2 = 0 for no-till, TIL_1 = 0 and TIL_2 = 1 for chisel plow, otherwise TIL_1 = TIL_2 = 0 for moldboard plow), and CR_m is a discrete variable for preceding crop (CR_1 = 1 and CR_2 = 0 for spring wheat, CR_1 = 0 and CR_2 = 1 for spring pea, otherwise CR_1 = CR_2 = 0 for winter wheat).
[b] t-statistics are in the parentheses.

Table 4. Application rates equating the marginal value product with herbicide cost for three functional forms.

Spring Weed Density	Broadleaf Weeds			Grass Weeds		
	Rectangular Hyberbolic	Logistic	Exponentia l	Rectangular Hyberbolic	Logistic	Exponential
1	0	0	0	0	0	0
10	0	0	0.1	0	0	0
20	0.3	0.3	0.2	0	0	0
30	0.4	0.4	0.4	0.1	0.1	0.1
40	0.5	0.5	0.5	0.2	0.2	0.2
50	0.6	0.6	0.6	0.3	0.3	0.3
60	0.7	0.7	0.7	0.4	0.4	0.4
70	0.7	0.7	0.7	0.4	0.4	0.4
80	0.8	0.8	0.8	0.5	0.5	0.5
90	0.8	0.8	0.8	0.5	0.5	0.5
100	0.9	0.9	0.9	0.6	0.6	0.6
110	0.9	0.9	0.9	0.6	0.6	0.6
120	0.9	0.9	0.9	0.6	0.6	0.6
150	1.3	0.9	1.0	1.0	0.7	0.7
500	1.8	1.3	1.4	1.5	1.1	1.1

Figure 1. Herbicide rate marginal product for exponential weed survival with rectangular hyperbolic damage and five spring weed densities.