AGGREGATION ISSUES IN PEST CONTROL ECONOMICS: A BIOECONOMIC APPROACH

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ABSTRACT

Early studies of the productivity of pesticide expenditures determined a very high marginal product. 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 excessively high marginal product of generic pesticide expenditures estimated in some earlier studies are not evident in our analysis of crop and herbicide specific experimental data. Field-level data for winter wheat in south eastern Washington indicate increasing returns to herbicide application are unlikely to occur in typical field application.

I. 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 private marginal product of pesticide is increasing over a substantial

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range, optimal private usage could be much higher than current label recommendations. Also, application rates exceeding label rates may not be environmentally safe.

Economists have been frustrated by a number of specification and data issues in measuring the productivity of agricultural pesticides. Geographical and product aggregated pesticide expenditure data have been used to determine the marginal productivity of pesticides, because the cost of the data is low, the data are available, and the regional generality of results may be greater (Campbell 1976; Carrasco-Tauber and Moffitt 1992; Chambers and Lichtenberg 1994; Headley 1968; Saha, Shumway and Havenner 1997). Policy implications from analysis of aggregate pesticide expenditures though can not take into account the registration process of the Environmental Protection Agency that targets particular pesticides use rates, and specific uses (Schierow 2000).

Early studies of the productivity of pesticide expenditures determined a very high marginal product, indicating that producers under apply pesticides (Headley 1968; Campbell 1976). Lichtenberg and Zilberman (LZ) specify a recursive homothetic separable model that eliminates an upward bias present in the earlier studies. The model follows the established approach used in the pest control sciences for herbicide efficacy (Roberts and Wilson 1961) and yield response to the pests (Cousens 1985; Stern et al. 1959; Talpaz and Frisbie), where: (a) the pesticide reduces the pest population (the "dose response" in biology); and (b) the surviving pest population damages crop yield. The LZ model specifies yield (Q) as a function of a vector of directly productive inputs (*Z*) and a damage abatement or control function (*G(X)*), which is a function of the damage control input vector (X):

$$(1)\quad Q = F[Z, G(X)]$$

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 of

Headley and accepted the LZ specification. 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 a possible explanation for the high marginal product of pesticide estimates of early empirical studies and some conflicting results with the LZ model (Carrasco-Tauber and Moffitt). Fox and Weersink showed that increasing returns are possible under specific conditions using various functional forms for damage and control functions, but none were tested with empirically estimated parameters and observed variable values. 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 assure concavity of the production function in a damage control input.

Models for managerial decision making require greater detail than aggregate pesticide expenditures models can provide. Managers require refined decision rules for application of particular pesticides on specific crops conditional on pests, pest densities, crop, soil moisture conditions, and other state variables (King et al. 1993; Marra and Carlson; Mortensen and Coble; Swinton and King, 1994a, 1994b; Talpaz and Frisbie 1975; Weersink, Deen and Weaver 1991). The biology of dose response (Seefeldt, Jensen and Fuerst 1995), threshold analysis (Stern et al.), weed competition (Black and Dyson 1993; Cousens), and economic optimization requires specific pesticide, crop and field information.

Parallel with the aggregate approaches, there has been a history of biologically precise pest control economics based on pesticide and crop specific field experimental data (Pannel 1990; King et al. 1986; Ethridge et al. 1990; Swinton and King 1994b; Lybecker, Schweizer and King 1986; Kwon et al. 1998). The bioeconomic modelling in this paper has been the product of interdisciplinary cooperation between economists and biological scientists. Optimal interior solutions for the analytical model indicate concavity in the damage control input, but this could have been the result of the specific functional forms (Pannel 1990; Kwon et al.). 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. 1994).

The bioeconomic models described above provide a 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 that have been aggregated across geographic areas and pesticide products. Furthermore, the bioeconomic models maintain a 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.

The objective of this study is to determine whether empirical field evidence of pest control supports the contention of increasing returns, or increasing marginal productivity, to pesticide application, or whether returns are decreasing. Like most bioeconomic studies, the approach of estimating separate pest survival (control) and yield damage functions is employed. We use field-level experimental data to estimate negative exponential herbicide-specific weed survival functions and winter wheat yield damage functions based on seven different functional forms. 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 values observed in the field or whether concavity is the result of extrapolating beyond the data used in estimation. 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

The model used in this study is a modified version of the LZ model in equation 1. Weed survival is estimated and then used in the estimation of crop yield. The density of weeds surviving following herbicide treatment is more important in determining yield damage than the proportion of weeds remaining. A subset of production inputs, specifically crop rotation and tillage practice, enter both the weed survival and the yield functions. Crop rotation and tillage practice are assumed separable from the herbicide effects.

Weed Survival

Weed numbers per unit area (m^2) surviving herbicide application are $G(X)$, as in the process model by Blackwell and Pagoulatos. Control as a proportion is central to biologists computing efficacy of a dose, but actual weed density is required to properly estimate crop yield damage. The weed survival model for three weed types is specified as:

$$(2) \quad DS_i = SWD_i e^{-b_{ij} H_j} + d_i DH_N + \sum_{k=1}^{2} a_{ik} TIL_k + \sum_{m=1}^{2} c_{im} CR_m + e_i \quad i=1,\ 2,\ 3$$

where DS_i is the surviving weed density (plants/m^2) at mid-summer; $SWD_i e^{-b_{ij} H_j}$ is the selected negative exponential functional form for weed survival; SWD_i 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_j is the category of herbicide (j=B for post emergence broadleaf, and j=G for post emergence summer and winter annual grasses), j=B when i=3 and $j=G$ when i=1 or 2; DH_N is a binary variable equal to 1 when a nonselective herbicide was applied prior to fall planting of winter wheat[1], otherwise zero; TIL_k are binary variables for the tillage practice compared to moldboard plow (TIL_1=1 for no-till, TIL_2=1 for chisel plow, otherwise 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 zero); b_{ij}, d_i, a_{ik}, and c_{im} are parameters to be estimated; and e is the error term. Especially important in this study is b_{ij}, the coefficient showing the control of weed type i by the herbicide j. We assumed an additive effect of tillage and crop rotation on surviving weed densities. We found no evidence in the literature that crop rotation had a multiplicative influence on the control of weeds present in winter wheat at the time of herbicide application. We selected the negative exponential functional form for weed survival based on its good fit to the data, the sensitivity of its marginal dose response to both dose rate and preexisting weed densities, and its popularity in the weed science literature (Feder 1979; Kwon et al.; Moffit, Hall and Osteen 1984).[2]

The three weed group equations will not be independent because a weed group not only competes with the crop, but also competes with other weed groups in a given year. While each weed type within a plot competes with other types annually, the weed types do not compete across plots. The error components across equations are therefore assumed to be contemporaneously correlated; however, the errors across observations are assumed to be uncorrelated. The seemingly unrelated regression technique is used to accommodate for the absence of independence among the

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[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 did not converge.

three weed survival equations(Judge et al. 1988).

For the negative exponential survival functions, the coefficients bij should be positive for the herbicides specific to control of the appropriate weed category, zero otherwise. Higher rates of the appropriate herbicide, H, should reduce the surviving weed population. The expected sign of d_i is negative because treatment of weeds prior to seeding should reduce weed population the next summer. The sign for a_{ik} should be negative because conservation tillage in the area of study tends to increase weed competition in winter wheat relative to plowing (Young et al. 1994). No prior sign, based on available research, could be assigned to c_{im}.

Yield and Damage Control

A modification to the LZ model in this analysis is the inclusion of site specific variables in both the weed survival and yield functions (Saha, Shumway and Havenner 1997). Yield, Q, is modelled as a function of weed-free yield, the yield damage function caused by weed competition, tillage system, and crop rotation. A Mitscherlich-Baule form was specified for the weed-free yield because it has been found to be superior to quadratic and linear von Liebig forms for showing the relationship between crop yield and biophysical conditions (Frank, Beattie and Embleton 1990). The functional form of the weed-free yield estimation should have a relatively small impact on the yield damage function estimate, and therefore the emphasis in this study is placed on the functional form of the yield damage function. The yield function is specified as:

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

where the terms before the square bracket models weed-free yield of the benchmark winter wheat system; *SM* is percent soil moisture at April 1; and *OM* is percent soil organic matter. The S_i's are estimated parameters. The $g(\cdot)$ function is the yield damage function, where $\hat{TWS}$ is the estimated total weighted weed survival prior to harvest of the three weed categories estimated by the weed survival function. Seven functional forms are estimated for $g(TWS)$: logistic, rectangular hyperbolic, exponential,[3] Weibull, Pareto, linear and square root (Table 1). The general properties of the functions are reported in Fox and Weersink.

The survival and yield equations were estimated with SHAZAM (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

TABLE 1. Yield Damage Functions[a]

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

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

[3] For distinction, the (negative) exponential yield damage function is referred to as an "exponential" function and the negative exponential weed survival function is referred to as a "negative exponential" function.

maximum likelihood estimate (MLE) of σ^2, and a calculated R^2 is also reported.

Data

Production and weed control data for winter wheat from a 1986-91 field experiment in southeastern Washington provides an opportunity to test alternative yield damage functions to determine whether increasing returns to pesticides are evident at a given field level (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 plus three levels of weed management (minimum, moderate, and maximum) were imposed across the two crop rotations. There were effectively 18 winter wheat treatments (3 rotation sequence positions for winter wheat, 2 tillage practices, and 3 weed control levels). All rotational positions of a crop were grown each year. With four replicates, the time series and cross sectional data provided 432 observations (Young et al.).

Weed species were grouped into summer annual grasses, winter annual grasses, and broadleaves because growth patterns and weed competition are similar across these broad groups. Several herbicides were used over the six years, with types and rates relative to label 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: nonselective preplant (control all plant growth); postemergence grass (control summer and winter annual grasses); and postemergence broadleaf. Major site-specific determinants of plot wheat yields were soil organic matter and soil moisture, as well as surviving weed density, tillage system, and crop rotation.

Results

The estimates of the negative exponential weed survival equations for the three weed types are reported in Table 2. The calculated pseudo R^2 values, 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 later weed flushes, primarily wild oats, that often

TABLE 2. Estimated coefficients of the negative exponential weed survival 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 pseudo 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, DHN = 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.

occur after spring herbicide application in this region. Indeed, control of all weeds present during spring control was higher than weed counts prior to harvest would indicate because of post-application weed flushes. Nonselective glyphosate herbicide (DH_N) reduced broadleaves but did not have a statistically significant effect on grasses. Soil conserving no-till (TIL_1) and chisel plow (TIL_2) tillage systems resulted in significantly higher weed survival prior to harvest than moldboard plowing, but chisel plowing increased broadleaf weed density by less than 3 plants/m^2. Weed flushes following application of herbicides were more frequent with reduced tillage systems. The preceding crop was not included in the final estimate of weed survival because all these variables were highly insignificant with coefficient values usually less than one. There was little effect on the remaining estimated coefficients, on the log-likelihood function, and on the calculated pseudo R^2 values from excluding the preceding crop variables.

Grass and broadleaf weeds present prior to harvest were aggregated into *TWS* based on biomass. Estimating yield damage with *TWS*, rather than with each of the three weed categories, simplifies estimation and interpretation without loss of information on total weed competitiveness. *TWS* includes weeds surviving control plus those emerging after control. Biomass indicates the competitiveness of the weed categories for nutrients and moisture. Estimated total weighted weed survival is specified as:

$$(4) \quad T\widehat{WS} = 0.92(\widehat{DS}_1) + 1.0(\widehat{DS}_2) + 0.47(\widehat{DS}_3)$$

where the variables are as previously defined and the ^(hat) indicates a predicted value. 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. The weight of 0.47 for broadleaves indicates a broadleaf weed is about one-half as competitive as a grass weed.

Yield damage equations were estimated using the seven functional forms in Table 1 with the results reported in Table 3. Variable definitions are in equations (2) and (3), and in Table 1. Log-likelihood, MLE of σ^2, and calculated R^2 values are similar across all seven equations. The coefficients showing influence of soil properties on weed free yield (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 (u_1 and u_2) and preceding crop (v_1 and v_2) significantly affected crop yield. Conservation tillage and rotating winter wheat with spring wheat and especially the legume spring peas, increased winter wheat yield. The coefficients (n_0 and n_1 in Table 1) for the yield damage function due to weeds are significant for all cases. All variables have expected signs based on agronomic principles. Increased total weighted 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.

The estimated equations for weed survival and yield damage are checked for increasing returns to herbicide rates over observed weed densities and herbicide rates. The negative exponential weed survival is combined with seven yield damage functions. Two approaches of direct examination are used to determine concavity of production in the control for the estimates. The first is 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 direct evaluation of 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 yield damage functions when combined with the estimated negative exponential weed survival function. For the estimated Pareto and Weibull yield damage functions with the negative exponential weed survival function, yield with

TABLE 3. Estimated Coefficients of Yield Damage Response Functions for Selected Models. Exponential

Variable[a]	Logistic	Rectangular Hyperbolic	Exponen -tial	Weibull	Pareto	Linear	Square-root
Intercept	97.764 (15.09)[b]	97.872 (16.69)	93.879 (19.12)	243.61 (21.87)	90.678 (23.58)	91.762 (21.35)	99.346 (17.54)
SM	0.201 (10.95)	0.200 (10.95)	0.199 (10.98)	0.199 (10.62)	0.197 (10.80)	0.197 (11.62)	0.202 (10.87)
OM	0.838 (4.55)	0.826 (4.60)	0.892 (4.58)	1.095 (3.79)	1.133 (3.98)	0.988 (4.45)	0.854 (4.54)
TWS (n_1)	0.089 (2.44)	1.095 (3.13)	0.0041 (5.12)	0.028 (4.05)	0.0224 (3.69)	0.0022 (6.63)	0.039 (9.01)
TWS (n_0)	-2.780 (-2.03)	68.127 (5.55)					
TIL1	20.704 (8.56)	22.525 (7.49)	17.294 (7.53)	15.561 (6.43)	14.374 (6.24)	14.534 (6.98)	20.918 (9.16)
TIL2	15.412 (4.81)	16.021 (4.32)	9.418 (3.06)	3.962 (1.35)	2.315 (0.83)	4.327 (1.78)	13.252 (4.60)
CR1	9.319 (4.19)	9.791 (4.40)	9.688 (4.26)	8.958 (3.73)	8.848 (3.67)	9.313 (4.11)	9.700 (4.51)
CR2	25.844 (11.52)	26.533 (11.74)	25.453 (11.38)	24.057 (10.26)	23.693 (10.22)	24.278 (11.08)	26.092 (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.

respect to herbicide rate was everywhere convex in the positive quadrant and very close to linear. Yield responses with estimated rectangular hyperbolic, logistic, and exponential yield damage functions with the negative exponential weed survival function are neither strictly concave nor convex with respect to herbicide rate. These three yield response 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 was confirmed using both Hennessy's rule and by direct evaluation of the second order derivatives of yield with respect to herbicide rate. The properties of the linear and exponential yield damage functions with the negative exponential weed survival function are consistent with the general derivations provided by Fox and Weersink.

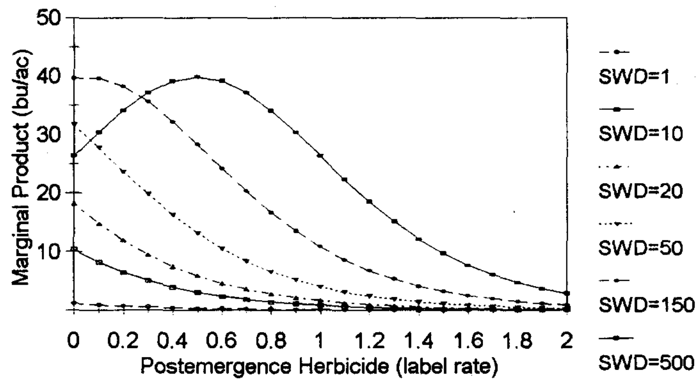
Rectangular hyperbolic yield damage with the negative exponential weed survival function produces a concave production response to herbicide rate when *TWS* is less than 62 plants/m^2. The logistic damage function with the negative exponential weed survival has a concave production response to herbicide rate when *TWS* is less than 38 plants/m^2. Exponential yield damage with negative exponential weed survival produces 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. 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_3) of up to 885, 540, and 3480 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential yield 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/m2 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 $SWD_1 + SWD_2$ up to approximately 120, 80 and 520 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential yield 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 weed densities for concavity to hold 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_3 of broadleaves would have to be less than 225, 135 and 880 plants/m^2, respectively for the rectangular hyperbolic, logistic, and exponential yield damage functions. To maintain concavity for grasses at H_G=0.5, the $SWD_1 + SWD_2$ of grass weeds would have to be less than 85, 60 and 370 plants/m^2, respectively, for the rectangular hyperbolic, logistic, and exponential yield damage functions. The broad range of theoretically appealing concavity for the exponential yield damage function makes this function attractive for empirical use.

With the three most frequently used yield damage functions (hyperbolic, logistic, and exponential), convexity and increasing returns to control can 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 these results to the region where concavity does not exist as these values are beyond the data used to estimate the functions in this study. The region of increasing returns in the functions may be due to extrapolation rather than actual increasing returns in pest control.

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

FIGURE 1. Herbicide Rate Marginal Product for Negative Exponential Weed Survival with Rectangular Hyperbolic Damage Function and Five Spring Weed Densities.



marketability and reduce liability for nonperformance.

Of the yield damage control functions considered here, the rectangular hyperbolic is the most commonly used in weed control research. Cousens argues that the rectangular hyperbolic conforms to the biology of weed control. Nonetheless, our results indicate that when this damage formulation is combined with the popular negative exponential weed survival function, production response should always be checked for 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 negative exponential weed survival and rectangular hyperbolic yield damage functions in Figure 1. The marginal product is monotonically declining over all herbicide rates for SWD_3 less than 151. With a price of wheat of \$2.60/bu and cost of broadleaf herbicides of \$11.36/label rate per acre, the marginal product must exceed 4.4

bu/ac for herbicide application to be profitable. Additional calculations indicated the marginal product for grasses must exceed 9.2 bu/ac for profitable control because of higher grass herbicide costs of $23.85/label rate per acre.

Profit maximizing herbicide rates for the rectangular hyperbolic, logistic, and exponential yield 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 must exceed 10 plants/m^2 to justify profitable control for all three damage functions.

TABLE 4. Application Rates Equating the Marginal Value Product with Herbicide Cost for Three Yield Damage Functional Forms.[a]

Spring Weed Density	Broadleaf Weeds			Grass Weeds		
	Rectangular Hyberbolic	Logistic	Exponential	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
130	1.3	1.0	1.0	1.0	0.7	0.7
500	1.8	1.4	1.4	1.5	1.1	1.1

[a] Assuming a wheat price of $2.60/bu(average price received by eastern Washington farmers in 2000), broadleaf herbicide price of $11.36/label rate per acre, and broadleaf herbicide price of $23.85/label rate per acre(major pesticide price paid by eastern Washington farmers in 2000).

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 in the study region do 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 1968; Campbell 1976; Carraco-Tauber and Moffitt 1992) 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

Bioeconomic modelling of pest control incorporates specific crop, pest, product, and site information required by production managers. Bioeconomic models also 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 specific pesticide and its target pests. Bioeconomic studies have tended not to show increasing returns to pesticide application.

For the winter wheat field experiment data in this analysis, an estimated negative exponential weed survival function was combined with seven yield damage functions. With Pareto and Weibull yield damage functions, increasing returns with respect to herbicide rate was observed throughout the herbicide rate and weed density range. The estimated linear and square root yield damage function produced globally concave production response. Estimated rectangular hyperbolic, logistic, and exponential yield damage functions were locally concave over the range of our data, but did have regions of convexity. This convexity occurred under conditions of extremely high weed densities and low rates of herbicide application. These regions were beyond the field data used in estimation.

Field-level data for winter wheat in south eastern Washington indicate increasing returns to herbicide application are unlikely to occur in typical field applications. 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 production convexity is not precluded by the functional forms, researchers should always check for convexity with respect to pesticide rate over the feasible range of their data.

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