Revenue Insurance and Chemical Input Use Rates

by

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Abstract

Using farm level data and a simultaneous probit model we evaluate the input use and environmental effects of revenue insurance. *A priori*, the moral hazard effect on input use is indeterminate and this study empirically assesses the input use impact of the increasingly popular, and federally subsidized, risk management instrument of revenue insurance. We conclude that the moral hazard effect of federally subsidized revenue insurance products induces U.S. wheat farmers to increase expenditures on pesticides and reduce expenditures on fertilizers.

Key Words: Revenue insurance, wheat, input use, and environment.

Revenue Insurance and Chemical Input Use Rates

The 1996 Farm Act dismantled the complex system of deficiency payments and annual supply management programs that were in place since 1973. Without deficiency payments to compensate for commodity price variability, farmers' revenues should be more uncertain. This new source of price risk was compounded by both the new freedom to plant any crop based on price expectations and greater world market integration achieved via increased trade liberalization. Since producers also have greater flexibility in switching crops from year to year, price variability may increase. There is much interest in how, and how well, innovative risk management tools are allowing farmers to adapt to the new risk environment created by the 1996 Farm Act. Significant number of farmers use risk management tools such as diversification, forward contracting, hedging, crop insurance, and reserve lines of credit (Harwood et al.).

Traditional Actual Production History (APH) coverage still accounts for 42% of wheat acres covered by federally subsidized crop insurance, but revenue insurance products are increasingly popular. By 2001 58% of federally insured wheat acres were covered by either Crop Revenue Coverage or Revenue Assurance (Risk Management Agency). Much work has been done regarding the moral hazard effects (i.e. when economic agents alter behavior because they're insured) of yield insurance on input use but little with respect to the newer revenue insurance instruments. Income Protection and Crop Revenue Coverage first became available in selected areas in 1996 and Revenue Assurance in 1997. Group Risk Income Protection and Adjusted Gross Revenue were added in 1999. Conventional wisdom holds that the moral hazard effect will lead to reduced chemical input usage (and hence positive environmental outcomes), but this effect may be weaker with respect to revenue insurance products because there is a second source of outcome variation, i.e. price, over which input use decisions have no effect. Using farm level data, this study examines the relationship between fertilizer and pesticide input use

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decisions and revenue insurance decisions. This work also yields potentially policy relevant insight into the interrelationships between environmental and risk management programs.

Beginning with Pope and Kramer's (1979) work, a considerable theoretical literature has evolved that details the conditions under which risk and risk reduction may increase or decrease input use. *A priori,* the effect is indeterminate, so the empirical results are essential to address the policy question of whether or not there are significant environmental impacts from yield and revenue insurance. The evolving nature of the federally subsidized insurance programs, however, makes the answer a moving target. What was true for yield insurance may or may not hold for revenue insurance. We find that while insurance purchases tend to reduce combined expenditures on fertilizers and pesticides, this masks the countervailing effects of pesticides and fertilizers. By disaggregating the two we find that for U.S. wheat farmers, purchases of revenue insurance is associated with relatively lower expenditures on fertilizers and relatively higher expenditures on pesticides.

Revenue Insurance

Federal crop insurance, first designed in 1938, was developed by the federal government to protect farmers against unexpectedly low yields. Crop insurance provides protection from a broad range of perils that can lead to yield shortfalls. One can argue that until 1995 the U.S. crop insurance program was more like yield insurance than income insurance (revenue insurance). Crop insurance such as the multiple-peril crop insurance (MPCI) protects against yield shortfalls that are due to drought, frost, flooding, plant disease, insect infestation, and other natural hazards beyond a grower's control.

Rapid expansion has occurred in the number of federally backed insurance products offered to farmers since the 1996 farm legislation. Although federally subsidized insurance has been a part of the government's farm program for over fifty years, the 1996 Federal Agriculture Improvement and Reform Act (1996 Farm Act) introduced revenue insurance pilot programs. Revenue insurance products, such as Income Protection Coverage and Crop Revenue Coverage, first became available for a few crops in selected areas for the 1996 crop year, and Revenue Assurance was added in the 1997 crop year. Skees *et al.* point out that revenue insurance offers the possibility of combining existing price and yield guarantee programs into one single program that may be easier to administer and easier for farmers to use.

Crop Revenue Coverage (CRC) determines the protected revenue at either planting or harvest, depending on when crop prices are higher. Revenue Assurance (RA), however, sets the revenue level that is to be protected at the time the crops are planted. With the harvest price option RA will also pay the harvest price if it's higher. Even APH, which is the current variant of the traditional multiple peril yield insurance, does offer some degree of price protection as it will provide indemnity payments based on the selected percentage of expected price at the time of planting, as well as the selected percentage of yield. The newer revenue insurance instruments, however, obviously provide substantially better price protection and they are the focus of this research as they are increasing in popularity and little research has been conducted on their input use implications.

Revenue insurance has been especially popular for growers of corn and soybeans, crops that were the initial focus of the privately developed Revenue Assurance and Crop Revenue Coverage products. Although wheat accounts for a smaller portion of the overall crop revenue insurance business than corn and soybeans, revenue insurance policies cover a considerable

share of wheat acreage in several States. In Kansas, Michigan, and Texas, more than one-quarter of wheat acreage insured above the CAT (short for catastrophic) levels was covered by revenue insurance in 1998.

Literature Review

To understand the input use effects of risk reduction instruments such as crop insurance, it is first necessary to understand the input use effects of risk on risk-averse producers. Pope and Kramer offer one of the first models concentrating on production risk and its effects on input use. They consider a stochastic production function, constant relative risk aversion utility function and allow for inputs to either increase or decrease risk. In the single input case they show that under risk aversion an agent uses more (less) of an input which marginally decreases (increases) risk. In a two-input, competitive model, however, there may be interactions between inputs that make the comparative statics more ambiguous.

Loehman and Nelson extend the Pope and Kramer model to include multiple inputs in which all inputs are either risk-increasing or decreasing and all pairs are classified as either risk substitutes or complements. If the inputs (or pairs of inputs) are risk substitutes and both are risk-increasing (reducing) individually then the use of at least one and maybe both inputs will decrease (increase) with increasing risk aversion. If use of only one input decreases then use of the other will increase. On the other hand, if one input is risk-reducing and the other is risk-increasing, then with increasing risk aversion the use of the risk-reducing input should increase and the use of the risk-increasing input should decrease. If the inputs are risk complements and both are risk-increasing (reducing), then use of both should decrease (increase) with increasing risk aversion.

Production risk distorts input decisions away from their risk neutral levels, but whether the level of inputs used increases or decreases with risk aversion cannot be determined *a priori*. Turning to the risk mitigating effects of crop insurance, Ahsan, Ali, and Kurian argue that private crop insurance has failed because of information asymmetries creating adverse selection. In the context of a one input one output model they show that full coverage crop insurance encourages risk taking and causes farmers to choose inputs as if they were risk neutral. This change in input use increases expected output. Since increased output likely increases social welfare, they argue there is a role for the public provision of crop insurance to improve resource allocation. Nelson and Loehman, however, show that full coverage does not necessarily increase expected output in the multiple input case if some inputs are risk-reducing. In general increased output is not a benefit of insurance. They do, however, show that if an actuarially fair contract dependent on all observable variables, e.g. input use, realized yield, rainfall, etc., were defined then input choices would be made as if the farmer were risk neutral. The above implications of crop insurance assume full coverage and no moral hazard. In the presence of moral hazard effects, they argue that input use is likely to decrease for the risk-averse farmer, but admit it can not be determined *a priori*. Actual input use depends on the relationship between the distribution of the state of nature and the marginal product of the input in each state, which affects the expected indemnity payment. The actual impact is inherently an empirical question. Quiggin developed a model indicating the conditions under which insurance would lead to a reduction in input use because of the moral hazard problem. He concludes that the effect of insurance will be to reduce input use for risk-reducing inputs and those that have no risk effects and increase input use for those that are "strongly" risk-increasing. The effects are more ambiguous for "weakly" risk-increasing inputs.

Horowitz and Lichtenberg modified Quiggin's model of moral hazard and argue that fertilizer and pesticide inputs, are often "strongly" risk-increasing and that crop insurance may encourage input use. After demonstrating the theoretical possibility that the moral hazard effect could lead to increased input use, Horowitz and Lichtenberg empirically test their hypothesis using farm-level data collected by the National Agricultural Statistical Service (NASS) in its 1987 Farm Costs and Returns Survey supplement for corn. The analysis was restricted to the Corn Belt where dryland corn is a major crop. They point out that, contrary to conventional wisdom, chemical usage may often be "strongly" risk-increasing. An input increases risk if it adds relatively more output in good states than bad ones by increasing the discrepancy between the two. Indeed in many cases the marginal product of pesticides will be small in bad states if growing conditions are poor because (i) insect populations and weed growth are apt to be low and (ii) crop yield and thus potential losses from pest infestation are likely to be low. Under such conditions, high pest infestations and therefore high pesticide productivity occur primarily when crop growth conditions are good.

The authors argue that federally funded crop insurance may actually increase usage of risk-increasing inputs because farmers may be inclined to undertake riskier production practices knowing that the downside risk is greatly reduced. This is the traditional moral hazard problem but inputs are presumed to be risk-increasing rather than risk-decreasing. Horowitz and Lichtenberg assume that the insurance decision was made before the input use decision, and control for selection bias by using a two stage Heckman estimator. Their estimation implies that, for several indicators of chemical usage, the amount used increases with crop insurance. The authors find that those purchasing insurance applied 19% more nitrogen per acre, spent 21% more on pesticides, increased herbicide acre-treatments by 7% and insecticide acre treatments by 63%.

Smith and Goodwin criticize Horowitz and Lichtenberg's findings that multiple peril crop insurance (MPCI) causes farmers to increase chemical input use. They argue that the moral hazard problem probably causes decreased input use. Even if an input is risk-increasing and increases the variance of yields, it will also likely increase the expected yield. The increase in variance increases the likelihood of an indemnity payment but the increase in mean yield decreases it. The net effect may be that the expected indemnity payment increases with input use but Smith and Goodwin doubt it for two reasons. First, chemical inputs increase production costs and lower (increase) the expected profits (losses) when indemnity payments are made. Second, the critical yield that triggers an indemnity payment is determined by the farm's yield history. Thus, using inputs that increase expected yields decreases the expected indemnity payment. Of course, this is only true if the input lowers the probability of a low yield. Thus, the effect of input use on the distribution of yields matters. As Nelson and Loehman note, the effect of input use on the expected indemnity payment depends on the relationship between the distribution of the state of nature and the marginal product of the input in each state because that is what affects the expected indemnity payment.

Smith and Goodwin used survey data of Kansas wheat farmers' production practices in 1990 and 1991. With the data they construct a variable for aggregate chemical use that includes the combined expenditures on fertilizers and pesticides. They do not disaggregate pesticide and fertilizer inputs because they note there was little variation across farms in non-fertilizer input use. To test their hypothesis Smith and Goodwin estimate both a single and simultaneous equation model and employ the Wu-Hausman Specification Test in order to determine whether the insurance purchase and chemical input use decisions are exogenous. In both cases exogeneity is rejected which suggests that they are jointly determined. This sheds doubt on

Horowitz and Lichtenberg's recursive structure in which insurance decisions are made prior to input decisions. Smith and Goodwin find that failure to account for simultaneity creates a positive bias in the crop insurance coefficient that potentially causes the model to indicate that the insurance moral hazard problem encourages farmers to use more chemical inputs. Furthermore, their probit estimation indicates that if a farmer applies more chemicals then the probability he also purchases crop insurance declines. The authors claim that could be because the expected return to crop insurance declines with input use. They estimate that each dollar spent on chemical inputs lowers the probability of insurance purchases by 0.9% to 1.4%. It must be noted that their model is really estimating the impact of crop insurance on fertilizer not pesticide use. The impact of crop insurance on pesticide use could be tested with a sample of wheat farmers with more variability in pesticide use, which may be achievable with a sample expanded beyond Kansas.

Babcock and Hennessy argue that the effect of increased fertilizer use on the probability of low yields primarily determines whether insurance purchases will tend to cause insured farmers to increase or decrease their fertilizer expenditures. Using data from four cooperating Iowa farms growing corn continuously from 1986 to 1991 they conclude that increased fertilizer use, as measured by pounds per acre, sharply decreases the probability of low yields. Using a CARA utility function they simulated the optimal fertilizer application rates given different levels of risk aversion, insurance coverage, and correlation between yields and prices. While the exact results depend on the above parameterization of the model, they find that in general increasing insurance coverage induces decreased fertilizer application rates. The authors note that their results for fertilizer are consistent with Smith and Goodwin's but they do not empirically address pesticide usage.

Model and Estimation Procedure

Let us assume that the farmer is producing a vector of output Y from inputs X, given random

production disturbances (weather, pests and disease) denoted by $\tilde{\Phi}$ with joint density function

$D(\tilde{\Phi})$. Therefore, the realized output is $Y=Y(X, \tilde{\Phi})$, where M is a set or realization of $\tilde{\Phi}$. The

outputs are sold in a competitive market and the farmer faces random output prices $\tilde{P}$, where the

joint density of $\tilde{P}$ is V(P). The total revenue, R, equals $P*Y$. Now let us assume that the farmer

buys revenue insurance. In case of revenue insurance the premiums (insurance costs) are

subtracted and any indemnities received I(R) are added to the net revenue to obtain farmer's

realized net farm income (A), which is defined as

$$A = R + I(R) - WX \tag{1}$$

where W denotes input prices, which are assumed to be nonrandom. The farmer maximizes

expected utility:

$$EU = \int_{R_{MIN}}^{R_{MAX}} U(R + I(R) - \gamma - WX)\,dG(R, X) \tag{2}$$

where $G(R, X)$ is the cumulative conditional distribution of R given X, implied by $Y(X, M)$,

$D(M)$, $V(P)$, R_{MIN} and R_{MAX} are minimum and maximum levels of revenue, and γ is the premium

paid for revenue insurance.

The goal of this analysis is to determine the effect of revenue insurance on input usage, such as

expenditures on pesticides and fertilizer. Since some inputs, especially for winter wheat, are

applied before the insurance sign-up deadline, input and insurance decisions are best viewed as

being made simultaneously. This means two equations, one for input decisions and the other for

insurance purchase decisions, should be estimated simultaneously. The insurance purchase

decision involves a dependent dichotomous variable and so it will be estimated using probit maximum likelihood with independent variables. Consider the following simultaneous-equation model:

$$y_{1t} = \delta_1 y^*{}_{2t} + \beta_1 X_{1t} + u_{1t}$$
$$y^*{}_{2t} = \delta_2 y_{1t} + \beta_2 X_{2t} + u_{2t}$$

$$(3)$$

where y_{1t} and $y^*{}_{2t}$ represent revenue insurance purchase and input usages, respectively and are endogenously determined, X_t is a vector of exogenous variables that are relevant to the revenue insurance purchase decision and input usage, u_{it}'s are residual error terms that are assumed to be normally distributed with zero mean and constant variance, and δ_1, δ_2 and β_1, β_2 are vectors of parameters to be estimated. The distribution of y_{1t} is discrete such that

$$y_{1t} = \begin{cases} 1 & \text{if } y^*_1 > 0 \\ \\ 0 & \text{otherwise} \end{cases}$$

$$(4)$$

The reduced-form of equations for the above system can be written as

$$y_{1t} = Z_t{}' \Gamma_1 + v_{1t}$$
$$y^*{}_{2t} = Z_t{}' \Gamma_2 + v_{2t}$$

$$(5)$$

where Z_t is an appropriately defined vector of instruments.

In an empirical model, this suggests that observed purchases of revenue insurance and input usages are jointly determined and thus a simultaneous equations estimator should be adopted. Procedures for estimating simultaneous equation models in which one or more of the equations possess one dichotomous endogenous variable have been developed by Amemiya (1974, 1979); Nelson and Olson; Lee *et al.*; Heckman; Newey ; and Vella. Nelson and Olson offer a straightforward approach by suggesting a simple two-stage estimation procedure whereby endogenous variables are replaced by predicted values obtained in a first stage by regression

upon an instrument set. However, as is noted by Amemiya (1979) and Lee *et al.*, Nelson and

Olson's proposed estimator misrepresents the true variances of the parameters in that it ignores

the fact that the reduced form equations were estimated in the first stage. In this analysis, a

jackknife procedure is utilized to obtain consistent estimates of the standard errors of the input

usage equation parameters.

Data

Data collected in the 1998 Agricultural Resource Management Study (ARMS) were used to

examine the effect of crop revenue insurance on input use, specifically on fertilizer and pesticide

use. The ARMS is a collaborative effort between the USDA's Economic Research Service (ERS)

and National Agricultural Statistics Service (NASS) to annually collect and summarize

information on farm resource use and finances. A special version of the 1998 ARMS collected

detailed information about wheat production practices and costs, farm finances, and the use of

crop revenue insurance. Sampling and data collection for the wheat version of the ARMS

consisted of a three-phase process (Kott and Fetter). Phase 1 involved screening a sample of

producers from NASS lists of U.S. farm operations to determine whether or not each farm

produced wheat. For phase 2, production and cost information was collected on a randomly

selected wheat field on each of the farms in the sample of wheat growers. All respondents to the

phase 2 interview subsequently were queried about farm financial information in phase 3.

Respondents in all phases of the 1998 ARMS for wheat included 1457 farms in 17 states.[1] The

target population of this sample is farms planting any wheat with the intention of harvesting

grain. Each sampled farm represents a number of similar farms in the population, as indicated by

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[1] The 17 states include California, Colorado, Georgia, Idaho, Illinois, Kansas, Louisiana, Minnesota, Mississippi, Missouri, Montana, Nebraska, North Carolina, North Dakota, Ohio, Oklahoma, and Oregon.

its expansion factor. The expansion factor, or survey weight, is determined from the selection probability of each farm, and thereby expands the ARMS sample to represent the population of wheat farms. Unlike most previous studies, our dataset allows us to account for other risk management strategies such as participation in the Conservation Reserve or Wetland Reserve Programs that provide a riskless source of income from previously cultivated land. In the case of revenue insurance, the type of marketing arrangement is especially important as it offers another instrument with which to manage price risk.

The U.S. farm sector consists of a highly diverse set of businesses and farm households committed to living in rural areas and engaging in farm economic activities. Since the early 1900's USDA analysts have sought to identify patterns in U.S. farming that might further the understanding of differences in financial performance of farms. The climatic, soil, water, and typographical base of geographic areas tend to constrain the number and types of crops and livestock that are well adapted. County clusters, based on types of commodities produced, have shown that a select few commodities tend to dominate the production landscape of geographic areas that cut across traditional political boundaries. To more carefully capture differences across farms, information on soil productivity is used as an indicator of a soil's ability to produce crops. Using the Natural Resources Inventory (NRI) data produced by the USDA's Natural Resource Conservation Service (NRCS), a soil productivity index ranging from 0-100 is developed in which 0 is the least and 100 the most productive soil. See Pierce *et al.* for details. The 1992 NRI data points are aggregated to the county level to obtain an average of the soil erodibility index (EI92AVG). In our dataset this ranges from 1.1 to 341, indicating low to high levels of potential erosion. Also produced by NRCS, the SOILS 5 data are linked to the NRI data and aggregated to obtain county averages. The variables LCHAVG and SURFAVG are indices indicating the county average potential for pesticide leaching and runoff, respectively. From low to high

potential for erosion, these variables range from 1, indicating nominal potential for pesticide leaching and runoff, to 3, indicating high potential for pesticide leaching and runoff potential. These variables were then aggregated to the county level by linking them to the NRI data points and using the NRI expansion factors.

Even though weather exhibits a regular pattern, farms face an ever-present threat of crop failure due to drought and flooding. To capture this effect on farm income we specifically use rainfall data. We use average monthly rainfall (1960-1998) in each county in which the farm is located to construct the mean and coefficient of variability of rainfall (RIN_M and RIN_CV). RIN_M captures the agronomic affect rainfall may have on optimal input use in the input expenditures equation and RIN_CV serves as a proxy for weather induced revenue risk. The basic idea underlying the estimation is that variability in weather (shocks to rainfall) will produce exogenous shocks to income.

Another factor that is potentially important in making the decision of whether to buy revenue insurance is the perceived variability in the revenue from wheat. The notion is that variability in revenues and revenue insurance purchases are directly related. We use National Agricultural Statistics Service (NASS) estimates of county wheat prices and quantities to construct revenues. The coefficient of variation in revenues (CV_REV) was created for each county based on its revenue history form 1980 to 1998.

Empirical Results

The equations presented in (5) are estimated jointly with a simultaneous probit model developed by Amemiya and detailed in Maddala. Smith and Goodwin show that insurance purchase and input use decisions are best characterized econometrically as being jointly determined. Building on their approach we disaggregate expenditures on fertilizers from those on pesticides, investigate the link between input expenditures and environmental indicators, and focus on the relatively new, federally subsidized, revenue insurance instruments.

Table 1 describes the variables used, and Tables 2 and 3 present the results of the two-stage estimation procedure in which the predicted values from the probit estimation are substituted into the OLS regression and vice versa. Because of the estimation procedure employed and the complex sample design of the ARMS, the standard errors are calculated using the jackknife approach in which 15 replicate weights are employed.

In the sample of 1457 total observations, there are 674 growers with Basic Catastrophic Insurance, 396 purchasing the Buy-Up Actual Production History (APH) Insurance, 130 observations of revenue insurance and 504 observations of uninsured wheat farmers. Since any individual farmer may purchase different types of insurance for different fields, the combined number of policies issued plus uninsured farmers exceeds the total number of observations in the dataset.

In this paper our interest relates largely to revenue insurance. In order to fully utilize the dataset, the initial estimation compares those purchasing some form of revenue insurance against all other wheat farmers – denoted (a) in Tables 2 and 3. The other farmers include those covered under CAT or the APH as well as uninsured farmers. These results are then compared with results from regressions utilizing data only from growers who purchased either revenue

insurance or who remained uninsured. These results are denoted with a (b). This greatly reduces the degrees of freedom but better isolates the input effects of revenue insurance. The qualitative implications, however, are largely unaffected.

The share of farm income from other government programs (SGOV), such as Conservation Reserve Program, Wetland Reserve Program, Environmental Quality Incentive Program and Agricultural Market Transition Act (CRP, WRP, EQUIP, and AMTA payments) is included in the revenue insurance participation equation because a stream of predictable steady income from other sources may affect risk preferences and hence insurance purchases. As expected, the coefficient on SGOV is negative though insignificant in all models (Table 2). Similarly, the shares of income from livestock/poultry (SLIVE) and crops (SCROPS) variables are included because they may affect risk attitudes. The use of other risk management tools, such as contracts, scouting, and hedging, are included as well. The percentage of crop under contract (PCONTRCT) and the use of private risk management tools such as hedging (PRVT_RISK) both predict a greater likelihood of revenue insurance being purchased. Only PCONTRCT, however, is significant. The percentage of wheat marketed in the cash market (PCASH) has a similar effect. Although only significant in (b), the farmer's debt to asset ratio (D_AST) positively affects insurance purchases. This likely reflects greater risk aversion amongst highly indebted farmers.

The coefficient on per acre premiums (PREMR) is positive and highly significant. This is likely an artifact of the premium rate structure. Based on their ten-year yield history, high-risk farmers are charged higher premiums. The higher premiums, however, may not fully reflect the increased risk and hence the implicit subsidy may be greater for high-risk farmers. The robust and significant, positive coefficient on PREMR provides support for this argument. In other

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words this result indicates an adverse selection problem caused by a rate structure that does not accurately reflect the risk assumed by the insurer.

The most interesting result of the probit estimation is the coefficient on YHAT($). As in Smith and Goodwin, when expenditures on fertilizers and pesticides are combined, the coefficient is negative, which indicates that greater input use leads to a lower probability that revenue insurance will be purchased. Although when the estimation is limited to revenue insurance and the uninsured, i.e. (b), the greatly reduced degrees of freedom generate results that are not significant, the coefficient is negative and highly significant when all the observations are used. This basically reproduces the Smith and Goodwin result using revenue insurance instead of multiple peril crop insurance. On net the moral hazard effect reduces the expenditures on fertilizer and pesticides, so the environmental impact of crop insurance may indeed be positive. The environmental impact of pesticides and fertilizers, however, may vary, so investigation of whether or not the effect of crop insurance is to reduce both individually is warranted. Pesticides and fertilizers may have different risk properties and indeed the regression results seem to suggest that the effect of crop insurance on each is not identical. In both regressions, (a) and (b), the coefficient on YHAT($) is positive for pesticides and negative for fertilizers and everywhere significant except for the case of fertilizer under the limited dataset, (b). This suggests that the more fertilizer a farmer applies, the less likely he is to purchase revenue insurance. Conversely, the more pesticides he applies, the more likely he is to purchase revenue insurance. At $26.11 per acre the average expenditures on fertilizer exceeds the $6.36 per acre spent on pesticides, and on net the fertilizer effect dominates. While combining expenditures on fertilizers and pesticides is useful in determining the aggregate impact, it masks the countervailing effects of fertilizer and pesticide use on revenue insurance purchases.

Similar effects of revenue insurance are indicated by the results of the input use estimation presented in Table 3. Again the dependent variables employed include not only aggregate expenditures on fertilizer and pesticides but each individually for both datasets (a) and (b). Demographic variables of gender, education, occupation, and net worth are found to be poor explanatory variables for input expenditures. The coefficient on mean rainfall (RIN_M) is everywhere negative but only significant in two instances. The coefficient on the proportion of wheat acres that are irrigated (IACRES) is positive and generally significant. This suggests that irrigation is positively correlated with input use.

Three environmental indicators were included in the input use equation estimation. The coefficients on EI92AVG and LCHAVG are significantly negative for the fertilizer and the fertilizer/pesticide aggregation regressions using observation set (a). This suggests that farmers are cognizant of the environmental impacts of chemical inputs and are currently engaged in some abatement. The opposite, however seems to be the case with respect to the coefficient on SURFAVG in the pesticide equation. Since SURFAVG measures the pesticide runoff potential, it may be that to achieve any given level of pest control, farmers are forced to apply more pesticides in areas where more of it is subject to runoff.

Again, the most interesting results relate to the substituted predicted values. In general the greater the probability that a farmer will purchase revenue insurance, the more he spends on pesticides and the less he spends on fertilizer. The net effect, however, is that the combined expenditures on fertilizer and pesticides are reduced by revenue insurance. Although the high degree of statistical significance is lost when the smaller dataset (b) is used, the signs are everywhere consistent with (a). The aggregate effect on expenditures, however, may be specific

to wheat and other crops for which expenditures on fertilizers significantly exceed those on pesticides.

The results from the fertilizer/pesticide aggregation confirm the Smith and Goodwin conclusion, which was also based on wheat production. In their seminal, much-debated work, Horowitz and Lichtenberg concluded just the opposite. The disaggregated estimation results presented above partially reconcile the two because the Smith and Goodwin aggregate result holds even though expenditures on pesticides increase if the farmer is insured. The explanation for the differential effects of crop insurance on pesticide and fertilizer usage, lies in the risk properties of each.

Following the Horowitz and Lichtenberg argument, in many regions it is likely to be the case that when crop growth conditions are poor, insect and weed populations are likely to be low as well. As such, pesticides may not appreciably decrease the probability of low yields and expected indemnity payments. Furthermore, the potential losses from pest infestation are small because of the low yields in bad weather. In good growing conditions the opposite is likely to hold because pest populations are apt to be larger. Larger pest populations and greater yields imply that the marginal product of pesticides may be quite large. By increasing the upside potential much more than decreasing the downside risk, pesticides are risk-increasing inputs and only marginally affect the expected indemnity payment. As long as they don't decrease their expected indemnity payment by decreasing their probability of low yields, risk-averse farmers are likely to increase their use of risk-increasing inputs, such as pesticides, once they are insured. This Horowitz and Lichtenberg result for pesticides is corroborated in the results presented in Tables 2 and 3.

Horowitz and Lichtenberg make the argument that fertilizers are risk increasing as well, and so their use should increase with insurance purchases. Equally important, however, is the input's effect on the probability of low yields because that is what determines the expected indemnity payment. While pesticides may not appreciably affect the probability of low yields, Babcock and Hennessy subsequently show that fertilizers do. Although they believe pesticides are likely to reduce the probability of low yields as well, they only offer econometric results that fertilizers actually do. If so, the moral hazard effect is likely to lead to less intensive use of fertilizers because their use significantly lowers the insured farmer's expected indemnity payment. In the presence of a substantial reduction in the probability of low yields, this effect is likely to hold even if fertilizers are risk-increasing inputs. The significantly negative coefficients on YHAT and YHAT($) presented in Tables 2 and 3 affirm this hypothesis.

Summary and Conclusions

Following the 1994 Federal Crop Insurance Reform Act and the 1996 FAIR Act, the USDA Risk Management Agency conducted pilot tests of revenue insurance as an alternative to multiple-peril crop insurance (MPCI). The Agricultural Resource Management Study (ARMS) survey of 1998 collected data on the revenue insurance pilot program. Using farm-level data, this work is the first to examine the impact of revenue insurance on fertilizer and pesticide input decisions.

Our conclusion is that pesticides and fertilizers may affect risk in significantly different ways and a one-size-fits-all explanation is not appropriate. The effect of revenue insurance amongst wheat farmers appears to be that it tends to reduce expenditures on fertilizers and increase expenditures on pesticides. It has even been suggested that different pesticides may have varied risk properties, but that is left to future research. The differential effect on fertilizer and pesticides

makes the environmental impact of revenue insurance somewhat ambiguous or at least location

specific in that it is dependent on the nature of the local environmental conditions.

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Table 1. Description of Variables

Variable Name	Variable Description
YHAT ($)	Predicted value from input expenditure equation.
SGOV	Share of farm income from conservation reserve and wetland reserve programs, environmental quality incentive program and agricultural market transition act.
PREMR	The per acre insurance premium.
CV_REV	The coefficient of variation of revenue (state price*county yield), 1980-1997.
D_AST	Debt to asset ratio.
CV_RAIN	Coefficient of variation of rainfall by county.
SLIVE	Share of gross farm cash income from livestock and poultry.
SCROPS	Share of gross farm income from crop sales.
PRVT_RISK	A zero-one discrete variable set to 1 if a private risk tool was used - either a put option purchase, a futures hedge, or a hedge-to-arrive contract.
SCOUT	A zero-one discrete variable set to 1 the field was scouted for weeds, insects, or diseases.
PCONTRCT	Percentage of crop that was marketed under a basis contract, fixed price contract for deferred delivery, deferred or delayed contract, and minimum price contract.
PCCC	Percentage of crop that was marketed using a CCC loan.
PCASH	Percentage of crop that was marketed through a cash sale.

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Variable Name	Variable Description
YHAT (Prob)	Predicted value from the revenue insurance participation probit equation.
IACRES	The proportion of acres that were irrigated.
VPRODT	The value of the total farm product.
RAIN_M	Mean rainfall in the county.
MEAN_PI	Mean productivity index of soil in the county.
EI92AVG	Average erosion index by county, 1992 NRI data.
LCHAVG	Average pesticide leaching potential index by county, Soils 5 data.
SURFAVG	Average pesticide surface runoff potential index by county, Soils 5 data.
NETW	Net Worth of farmer.
OCCUP	A zero-one discrete variable set to one if the operator's major occupation farm or ranch work or a hired manager.
EDUC	Index of operator's educational level (1=less than high school, 5=graduate school)
GEND	A zero-one discrete variable set to one if the operator is male.

Table 2. Probit Model of Insurance Purchase Decision

Probit	Intercept	YHAT ($)	SGOV	PREMR	CV_R	D_AST	RIN_CV	SLIVE	SCROPS	PVT_RISK	SCOUT	PCONTRCT	PCCC	PCASH
Fert&Pest														
(a) Rev Insur.	-1.11	-0.021	-0.86	0.05	-0.13	0.07	0.08	-0.13	-0.107	0.32	0.002	0.006	0.004	0.003
	1.56	2.01**	0.86	2.92***	0.103	0.1118	0.0776	0.334	0.35	1.118	0.014	2.943***	1.144	1.66*
(b) RI obs.	-2.7	0.000008	-0.53	0.11	1.35	1.01	0.42	-0.31	-0.504	0.25	-0.09	0.01	0.006	0.009
	2.14**	0.00068	0.315	5.31***	0.6413	2.27**	0.234	0.458	1.207	0.591	0.6908	2.56**	0.9687	2.25**
Pesticide														
(a) Rev. Insur.	-3.49	0.15	-0.89	0.05	1.47	0.07	-0.95	0.07	-0.07	0.33	0.01	0.007	0.005	0.004
	3.78***	4.027***	0.826	2.95***	0.928	0.099	0.557	0.159	0.2176	1.094	0.092	3.139***	1.43	1.82*
(b) RI obs.	-4.81	0.15	-0.63	0.11	3.74	1.28	-0.95	-0.29	-0.42	0.206	0.003	0.02	0.008	0.01
	2.68***	3.15***	0.373	4.922***	1.35	2.802***	0.387	0.422	1.14	0.45	0.0159	2.78***	1.24	2.38**
Fertilizer														
(a) Rev. Insur.	-0.84	-0.04	-0.79	0.05	-0.12	0.07	-0.02	-0.19	-0.11	0.304	-3E-05	0.007	0.005	0.004
	1.22	3.25***	0.805	2.93***	0.0946	0.1105	0.023	0.466	0.367	1.09	0.0002	3.393***	1.235	1.908*
(b) RI obs.	-1.8	-0.02	-0.65	0.11	0.56	1.05	0.81	-0.36	-0.507	0.24	-0.12	0.019	0.006	0.01
	1.44	1.579	0.394	5.42***	0.261	2.469**	0.4699	0.54	1.18	0.61	1.01	2.65***	1.14	2.5**

The absolute value of the t-statistics are reported below the parameter coefficients. Single, double, and triple asterisks indicate statistical significance at the alpha = 0.10, 0.05, and 0.01 levels, respectively.

Table 3. OLS Model of Input Use Decisions

		Dependent Variable =Input Expenditures ($)											
		Prob(Y=1)											
OLS	Intercept	YHAT	IACRES	VPRODT	RIN_M	MEAN_PI	EI92AVG	LCHAVG	SURFAVG	NETW	OCCUP	EDUC	GEND
Fert&Pest													
(a) Rev. Insur.	77.75	-40.81	22.64	0.0000001	-0.001	-0.14	-0.05	-14.04	-1.16	-1.44	-0.16	1.02	-5.29
(0.14)	6.78***	3.3***	5.6***	0.047	0.28	1.47	2.23**	2.05**	0.35	1.1	0.04	0.95	0.668
(b) RI obs.	67.62	-0.26	11.88	-3.21	-0.01	-0.34	-0.07	-0.65	5.1	2.7	-3.13	0.96	-0.79
(0.15)	3.27***	0.036	2.65***	0.075	3.06***	3.24***	1.36	0.19	1.21	0.17	1.07	1.01	0.047
Pesticide													
(a) Rev Insur.	0.05	24.6	6.53	-0.000002	-0.0008	0.02	0.004	-0.41	2.34	5.13	0.201	-0.15	0.59
(0.08)	0.01	3.25***	3.7***	1.83*	0.47	0.685	0.37	0.26	1.94*	1.16	0.148	0.5003	0.205
(b) RI obs.	0.569	10.07	6.21	-0.000003	-0.003	-0.01	-0.002	1.28	4.39	0.000001	-0.02	0.02	-0.02
(0.12)	0.05	1.57	2.17**	2.62***	1.35	0.244	0.11	0.64	1.82*	1.94*	0.009	0.06	0.0037
Fertilizer													
(a) Rev. Insur.	76.43	-62.4	15.7	0.000002	-0.001	-0.16	-0.06	-13.2	-3.47	-0.000001	-0.4	1.13	-5.85
(0.17)	10.22***	5.55***	4.77***	0.69	0.18	2.33***	2.44**	2.38**	1.18	1.93*	0.107	1.1009	0.849
(b) RI obs.	67.2	-10.96	5.57	0.000003	-0.008	-0.33	-0.07	-1.94	0.61	-1.72	-3.08	0.94	-0.8
(0.14)	4.1***	1.547	0.906	0.802	2.296**	3.293***	1.35	0.66	0.117	1.15	0.729	0.816	0.07

The absolute value of the t-statistics are reported below the parameter coefficients. Single, double, and triple asterisks indicate statistical significance at the alpha = 0.10, 0.05, and 0.01 levels, respectively. The numbers in parenthesis are the R square values.