Is moral hazard good for the environment? Revenue insurance and chemical input use

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Abstract

Using farm level data we evaluate the input use and environmental effects of revenue insurance. A priori, the moral hazard effect on input use is indeterminate. This paper empirically assesses the input use impact of the increasingly popular, and federally subsidized, risk management instrument of revenue insurance and the extent to which its effects on input use may differ from those of the older yield based instruments. We conclude that among winter wheat farmers, those who purchase revenue insurance tend to spend less on fertilizers but do not appreciably alter pesticide expenditures. Thus, any improved environmental outcomes due to crop insurance are likely due to reduced fertilizer not pesticide use. When the environmental indicators included indicated a potential environmental fragility (i.e. high erosion, pesticide leaching or pesticide runoff potential), the input use equation suggested that fertilizer expenditures decreased. Revenue insurance undoubtedly further reduces fertilizer applications on these fields as well, but the marginal environmental benefit of revenue insurance is lessened because the reduction, where it matters most, accrues on land on which fertilizer use has already been curtailed to some degree.

Keywords: Environment; Fertilizer use; Moral hazard; Pesticide use; Probit; Revenue insurance; Sample selection

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 may 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. Furthermore, greater flexibility to switch crops from year to year may contribute to price variability. In response, the US federal government began offering new risk management tools such as revenue insurance. The discussions leading up to the 2002 farm bill once again brought crop insurance, its successes and unintended consequences, to the political fore.

Rapid expansion has occurred in the number of federally backed insurance products offered to farmers since the 1996 farm legislation. Glauber and Collins (2002) examine the history of federal crop insurance programs and review the experience of crop insurance programs. Although federally subsidized insurance has been a part of the government’s farm program for over fifty years, it was not until 1996 that revenue insurance instruments were introduced (Glauber and Collins, 2002). By 1998 three revenue insurance programs (Income Protection (IP), Crop Revenue Coverage (CRC), and Revenue Assurance (RA)) were offered to producers in various locations for selected crops. Numerous studies identify the advantages of a revenue insurance program. Skees et al. (1998) point out that revenue insurance offers the possibility of combining existing price and yield guarantee programs into a single program that may be less expensive to administer and easier for farmers to use. Glauber et al. (1989) point out that the target revenue insurance program was best
at stabilizing per-acre farmer income and market prices. Turvey (1992) compared dollars of public expenditures per dollar of risk reduction and found revenue insurance was the best at promoting self-insurance through diversification. In another study Gray et al. (1994) found revenue insurance alternatives to be less expensive and more effective at supporting farm income than the current farm policy (deficiency payments). Similar results were obtained by Harwood et al. (1999) and Hennessey et al. (1997).

The various revenue insurance policies (IP, CRC, and RA) differ somewhat in the way the indemnity payments are structured but Crop Revenue Coverage (CRC) covers the vast majority of the wheat acres covered under revenue insurance. An indemnity payment will be made if the revenue guarantee exceeds the revenue received from crop sales. The revenue guarantee is the chosen coverage level (usually 65%) of the historical average yield times either the projected price at planting or the spot price at harvest, whichever is greater. The indemnity payment is the difference between the revenue guarantee and the actual revenue realized. 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. On the other hand, with Average Production History (APH) coverage, such as Multiple Peril Crop Insurance, only yield shortfalls trigger indemnity payments. With APH coverage a farmer chooses a particular coverage and price protection level. For instance, the amount of average yield that can be insured ranges from 50 to 75% (in some areas 85%) and the percent of the predicted price that can be insured ranges from 55 to 100% of the price. If the harvest is less than the yield insured, the farmer is paid an indemnity based on the difference. It is worth noting that this does offer some degree of price protection as it will provide indemnity payments if the harvest is less than the yield insured.

The newer revenue insurance instruments, however, 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.

Traditional, yield-based 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. Although wheat accounts for a smaller portion of the overall crop revenue insurance business than corn and soybeans, revenue insurance policies have covered a considerable share of wheat acreage in several states. From 2000 to 2001 the percentage of federally insured winter wheat acres covered by revenue insurance increased from 17 to 58% (Risk Management Agency, March 2001). Much work has been done regarding the moral hazard effects (i.e. when economic agents alter behavior because they are insured) of the older yield-based insurance instruments on input use but little with respect to the newer revenue insurance instruments. Conventional wisdom holds that the moral hazard effect will lead to reduced chemical input usage (and hence positive environmental outcomes), but with the increasing popularity of revenue insurance there is reason to ask whether the same holds for these newer risk management instruments.

Using farm level data, this study examines the relationship between fertilizer and pesticide input use decisions and revenue insurance decisions. Additionally, the study investigates whether the relationship between revenue insurance and input usage is different across four different regions where winter wheat is grown. The analysis is conducted on a national level with the unique feature of a larger sample than previously analyzed, comprising farms of different sizes and in different regions of the United States. Ceteris paribus, good environmental outcomes are assumed to be ones in which fewer chemical fertilizers and pesticides are used and bad environmental outcomes are ones in which more chemical fertilizers and pesticides are applied. The environmental impact of fertilizers and pesticides differ so this study disaggregates the two. This work yields potentially policy relevant insights into the interrelationships between environmental stewardship and risk management programs.

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. By insuring revenue not yields the link between input use and the expected net indemnity payment may be weakened and so make input use less responsive to revenue insurance purchases. When indemnity payments are made, however, revenue insurance tends to entail larger payments, which may exacerbate the moral hazard effect. Moral hazard in revenue insurance means—revenue insurance can encourage farmers to increase/decrease chemical use because it will increase the likelihood or magnitude of insurance payments they receive. Our empirical work indicates that while insurance purchases tend to reduce combined expenditures on fertilizers and pesticides, this masks the divergent effect of revenue insurance on fertilizers and pesticides. By disaggregating the two we find that for US winter wheat farmers, purchases of revenue insurance are associated with relatively lower expenditures on fertilizers but little change in expenditures on pesticides.

1. Previous studies

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 empirical results are essential to address the policy question of whether or not there are significant environmental impacts from yield and revenue insurance. The risk mitigating effects of crop insurance as described in early work by Ahsan et al. (1982) argue that full coverage crop
insurance encourages risk taking and causes farmers to choose inputs as if they were risk neutral and hence increase output. Since it is very difficult to determine whether an input should be classified as risk increasing or risk decreasing, the effect of insurance on input use remains an essentially empirical question. There are two studies in the literature that evaluate the impact of crop insurance on input use, particularly fertilizers. Horowitz and Lichtenberg (1993) argue that fertilizer and pesticide inputs are often ‘strongly’ risk increasing and that yield insurance may encourage increased input use. They argue that federally funded crop insurance may 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 where inputs are presumed to be risk increasing rather than risk decreasing. The authors find support for their hypothesis using survey data for corn. Their estimation implies that, for several indicators of chemical usage, the amount used increases with crop insurance. Our study builds on Horowitz and Lichtenberg’s (1993) work, and differs in several ways. First, we use winter wheat data instead of corn data. Second, our study uses more soil variables (such as erodability, leaching potential, productivity index, and surface runoff) that are indicators of environmental variables. Third, our study investigates the regional effects of revenue insurance on fertilizer and pesticide use. Finally, unlike Horowitz and Lichtenberg (1993) who used several indicators of chemical usage, this study uses both fertilizer and pesticide use.

Smith and Goodwin (1996) counter Horowitz and Lichtenberg’s (1993) findings that multiple peril crop insurance (MPCI) causes farmers to increase chemical input use. They argue that moral hazard probably induces decreased input use. Applying a slightly different notion of a risk-increasing input, they argue that 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 (1996) 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. For winter wheat, an anonymous referee correctly noted that insurance must be purchased in the fall and some chemicals are applied during the spring. These applications are then made after insurance has been purchased and after new information about the state of nature is revealed, e.g. prices, soil moisture, weed and insect infestations. A limitation of the study (Smith and Goodwin, 1996) is that they do not disaggregate pesticide and fertilizer inputs because there was little variation across farms in non-fertilizer input use. It must be noted that their model is really estimating the impact of crop insurance (MPCI) on fertilizer not pesticide use.

Babcock and Hennessy (1996) 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 Iowa State University research farms, in which fertilizer rate was experimentally controlled, 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. The authors note that their results for fertilizer are consistent with Smith and Goodwin’s (1996), but they do not empirically address pesticide usage.

2. Estimation procedure

In our empirical model we estimate the potential impact of revenue insurance on farmers’ input use decisions. The goal of this analysis is to determine the effect of revenue insurance on input usage as measured by expenditures on fertilizers and pesticides. The decision to purchase revenue insurance, according to USDA wheat experts and as one reviewer noted, is made prior to production and some input use decisions. Additionally, purchase of revenue insurance also depends on risk aversion, distribution of prices and yields, and other factors affecting farm profitability. The level of revenue insurance \( Y_i \) desired by the \( i \)th farmer is assumed to be a function of farm, operator and household financial characteristics. The data source, Agricultural Resource Management Survey (ARMS) collected information on revenue insurance as a dichotomous choice. To the extent that \( Y \) is a discrete variable, estimation of the probability of purchasing revenue insurance using ordinary least squares will result in biased regression parameters. To circumvent this outcome, probit regression is used as in

\[
Y^{*}_i = \beta \Omega_i + \epsilon_i, \quad \Phi(\epsilon_i) \sim N(0,1)
\]

\( Y_i = 1 \), if \( Y^{*}_i > 0 \) (operator buys revenue insurance),
\( Y_i = 0 \), if \( Y^{*}_i \leq 0 \) (otherwise),

(1)

where \( \Omega_i \) is a matrix of explanatory variables, and \( \beta \) is a vector of parameters to be estimated. Unlike the random variable \( Y_i \) \((i = 1, \ldots, n)\) which is observable, the variable \( Y^{*}_i \) is unobservable since it is derived from a farm operator’s utility function. The expected value of \( Y \) can be expressed in terms of the probability \( P \) of purchasing revenue insurance as in

\[
E[Y|\Omega_i] = P(Y_i = 1) = P(Y_i^* > 0) = P(-\epsilon_i < \beta \Omega_i)
\]

\[ = \Phi(\beta \Omega_i) = \Phi(\tilde{z}) = \int_{-\infty}^{\tilde{z}} \phi(\mu_i) du_i,
\]

where \( u_i \) (equivalent to \( \epsilon_i \)) is a random variable with mean zero and unit variance, \( \Phi(\cdot) \) and \( \phi(\cdot) \) are the standard cumulative distribution and the probability function of
the standard normal, respectively. The estimated equation will result in the predicted probability of participation in revenue insurance program \((\hat{Y}_i)\). The marginal change in the probability of purchasing revenue insurance with respect to a change in the \(k\)th explanatory variable \(\Omega_k\) is given by:

\[
\frac{\partial E[Y|\Omega_k]}{\partial \Omega_k} = \phi(\cdot)\hat{\beta}_k.
\] (2)

The second objective is to examine the impact of buying revenue insurance on the input use decision. In the case of wheat, following Horowitz and Lichtenberg, the decision on input use \((X_i)\) is made after the revenue insurance contract has been bought. Input use decisions depend on the probability of revenue insurance purchases \((\hat{Y}_i)\) and farm and operator characteristics \((\Omega_2)\).

\[
X_i = \alpha \Omega_2 + \zeta \hat{Y}_i + \mu_i.
\] (3)

In the model defined by Eqs. (1) and (3), while \(\beta\) captures selection effects, \(\zeta\) measures the moral hazard effect. Eq. (3) is estimated using an Ordinary Least Squares (OLS) method.

### 3. Data

Data collected in the 1998 Agricultural Resource Management Survey (ARMS) were used to examine the effect of crop revenue insurance on input use, specifically on fertilizer and pesticide use. 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 and farm finances. Sampling and data collection for the wheat version of ARMS consisted of a three-phase process (Kott and Fetter, 1998). Phase 1 involved screening a sample of producers from NASS lists of US farm operations to determine whether or not each farm produced wheat. In Phase 2, production and cost information was collected for a randomly selected wheat field on each of the farms in the sample of wheat growers. All respondents to the Phase 2 interview were subsequently queried about farm financial information in Phase 3. Thus, these data integrate field level production practices with farm level financial information. Field level input use data is an important advance over previous work in that it provides crop specific input use data for a given field rather than just farm level input use information in which the inputs may have been used for multiple crops.

Respondents in all phases of the 1998 ARMS for wheat included 1457 farms in 17 states from which there are 865 usable observations for winter wheat.\(^2\) The target population for 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 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 winter wheat farms.

In this paper our interest relates largely to revenue insurance and whether the dramatic shift by wheat farmers away from APH coverage (MPCI) toward revenue insurance products (CRC and RA) altered input use. The revenue insurance results compare the 99 observations with revenue insurance against 766 without revenue insurance. Those observations reporting only purchases of other insurance products such as multiple peril crop insurance or some other non-revenue insurance products were not included in the dataset. This generates a total of 865 observations.

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. To account for the use of diversification as one way to reduce risk, we employ an entropy index (i.e. the proportion of revenue from each enterprise in the total value of farm production) to measure farm diversification (FM_DIVERS). The index\(^3\) takes a value approaching 1 when a farm is fully diversified and 0 when a farm is specialized (Theil, 1972). Specifically, an entropy measure of farm diversification considers the number of enterprises in which a farm participates and the relative importance of each enterprise to the farm. An operation with many enterprises, but with one predominant enterprise, would have a lower number on the diversification index. Higher index numbers go to the operations that distribute their production more equally among several enterprises.

The climatic, soil, water, and topographical 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 input use 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 county level average soil productivity index is...
developed in which 0 is the least and 100 the most productive soil (see Pierce et al. (1983), for details). Soil productivity likely affects input use, especially fertilizer. How much, if any, manure has been applied to the field (MANURE) may matter as well because manure applications may be indicative of the level of soil nutrients and hence the marginal product of chemical fertilizer. Also, manure applications may not be reflected in the fertilizer expenditure data if it came from on-farm livestock operations.

Environmental characteristics of the field, such as potential for erosion, leaching, and runoff, affect the impact of fertilizer and pesticide applications. For that reason three environmental indicators were incorporated into the input use equation to determine if input use tended to increase or decrease when the environment was more susceptible to harm from them. The SOILS 5 data (also known as the Soil Interpretation Records), produced by NRCS, provides two environmental indicators. The variables LCHA VG and SURFAVG are indices that represent 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. These variables were aggregated to the county level by linking them to the NRI data points and expansion factors and then matched to individual farms by county. Third, ARMS reports whether or not USDA’s Natural Resource Conservation Service (NRCS) has indicated that the field was highly erodible (HEL). Since this is a field specific indicator, which is rare in the literature, it is perhaps the most reliable of the three environmental indicators. Wu in his study of Central Nebraska farmers found that farmer who bought crop insurance shifted production from hay and pasture to corn. This adjustment in crop mix increased soil erosion and chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin. Because the extensive margin effects dominates the effect of crop insurance on the chemical use at the extensive margin.

One would also expect other risk management strategies such as hedging (PRVT_RISK), contracting (MCONTRCT), irrigation (IACRES), and the portion of acres rented that were paid in the form of a share of the proceeds from crop sales (SHARE) to be important. Other factors that would be expected to affect insurance purchase decisions include whether or not the farmer farms full time (OCCUP) and hence potentially more dependent on farm income. The premium (PREM) paid for the insurance is another important factor that determines farmers participation in insurance programs (Smith and Goodwin, 1996; Goodwin, 1993). Goodwin (1993) in his study used county level premium rates for Iowa farmers. In our study, because of data limitations, we use state premium rates. Further, since revenue insurance was in its infancy, there were numerous counties in 1998 in which there were no purchases of revenue insurance. The size of the farm (VPRODTOT) may indicate to some degree the production technology used and hence partially explain input expenditures but may also be indicative of the demand for insurance if the risk attitudes vary by farm size. Similarly, age (AGE) and education level of the farmer (OPEDUC) may affect production technology and the demand for insurance, especially the relatively new revenue insurance products. The mean for each of the variables utilized in the analysis is presented in Table 1.

4. Empirical results

Using SAS we estimate the insurance purchase decision and the input use decision equations. Building on Horowitz and Lichtenberg’s (1993) 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 and whether their impact on input use differs from that of the older MPCI. Because of the estimation procedure employed and the complex sample design of ARMS, the standard errors are calculated using the delete-a-group jackknife technique with 15 replicate weights. Further, because of potential endogeneity problem between revenue insurance and input use decisions, as pointed out by Smith and Goodwin (1996) and one of the reviewers, we first estimated the probability of participation in revenue insurance programs (Eq. (1)) by a farmer and then used the predicted value (estimated probability of participation) into the input usage equation (Eq. (3)).

The maximum likelihood estimates of the probit model (Eq. (1)) are presented in Table 2. The McFadden $R^2$, which is defined as 1 minus the ratio of the unrestricted to restricted log-likelihood function, was 0.144. This measure of goodness-of-fit (McFadden $R^2$) indicates that the probit model performed quite reasonably, considering the cross-sectional nature of the data. The results show that some of the demographic characteristics of farmers
along with some farm specific variables do play an important role in the decision to purchase revenue insurance. Specifically, the coefficient on operator’s age (AGE) has the expected sign and is statistically significant at the 1% level. The marginal effect (= 0.0144) suggests that an additional year of age increases the probability of purchasing revenue insurance by approximately 1.4%. On the other hand, the coefficient on AGESQ is negative and statistically significant at the 1% level. The negative coefficient implies an inverted-U shape in the age and revenue insurance purchase decision profile of farmers. This indicates that, other things constant, older farm operators are less likely than younger farmers to purchase revenue insurance. However, the marginal effect is small. One explanation is that an older farm operator may have more wealth and less debt providing greater potential to self-insure. This is consistent with some of the technology adoption literature (El-Osta and Morehart, 1999; Lin, 1991; and others) and insurance literature (Mishra and Goodwin, 2003; Smith and Baquet, 1996; Just and Calvin, 1990).

Participation in marketing contracts (MCONTRACT), such as wheat marketed through a basis contract or a fixed price contract, is another risk management strategy used by farmers. Contracting assures farmers of an outlet for their produce at a given price (Paul et al., 1985). The coefficient on MCONTRACT is positive and statistically significant at the 10% level of significance. However, the marginal effect (= 0.0004) is very small. Results indicate that farmers who participate in marketing contracts are more likely to buy revenue insurance. Perhaps, this result demonstrates that farm operators who are risk averse adopt other risk management strategies as well and that revenue insurance and marketing contracts are complements.

Farm diversification (FM_DIVERS) is another way to spread risk and stabilize income. Since diversification itself is a form of insurance, farms with greater diversification are less likely to purchase revenue insurance. The coefficient on farm diversification (FM_DIVERS) is negative and statistically significant at the 1% level of significance. As expected, producers who spread their risk through farm diversification are less likely to purchase revenue insurance. The marginal effect (= -0.1912) suggests that as the index of farm diversification increases, operators are less likely to purchase revenue insurance, ceteris paribus. Thus, diversification and revenue insurance are substitute risk reduction strategies. The use of other risk-management tools, such as hedging (PRVT_RISK), were included in the analysis but were insignificant. The coefficient on soil productivity...
log likelihood, restricted

Superscripts *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively. Sample size

Table 3 presents the OLS estimation of the input expenditure equation (3). The dependent variables employed include not only aggregate expenditures on fertilizers and pesticides but each individually. Based on the $R^2$ the fertilizer and pesticide and fertilizer only model performed reasonably well, considering the cross-sectional nature of the data. The probability of revenue insurance purchase decision ($Y_{HAT}$) has a negative, statistically significant, and significant effect for fertilizer and pesticide and fertilizer only expenditures. Results suggest that the per acre cost of fertilizer and pesticide by farmers with revenue insurance tend to be, on average, $21 lower than the corresponding costs for those with no insurance. The decrease in fertilizer and pesticide expenditures seems to be driven entirely by reduced expenditures on fertilizers (when estimating the fertilizer equation alone). These results are consistent with the findings of Smith and Goodwin. The effect of revenue insurance purchases on pesticide use is negligible. Unfortunately, our data does not allow a meaningful analogous estimation of yield based instruments because we are unable to separate out observations of Multiple Peril Crop Insurance (MPCI) from those of the Group Risk Plan (GRP).

The revenue insurance results from the fertilizer/pesticide aggregation confirm Smith and Goodwin’s (1996)
conclusion for MPCI. In their seminal, much-debated work, Horowitz and Lichtenberg, however, concluded just the opposite. The disaggregated estimation results presented above offer a third explanation because Smith and Goodwin (1996) aggregate result holds even though expenditures on pesticides vary little between insured and uninsured farmers. Since the environmental impact of pesticides and fertilizers are not identical, disaggregating the two is warranted. Pesticides and fertilizers may have different risk properties and indeed the regression results suggest that the effect of crop insurance on each is not identical. The explanation for the differential effects of crop insurance on the use of fertilizers and pesticides may be that fertilizer expenditures dominate pesticide expenditures in wheat production such that there is little variation in pesticide expenditures even in a national survey. Amongst winter wheat producers pest pressure tends to be low so that at $4.71 per acre, pesticide expenditures are small relative to the $28 per acre spent on fertilizer in our sample. Further, wheat crop as such do not use significant amount pesticides. Since the study cannot control for field level pest pressures, the insignificant result may simply be a result of excessive white noise in pesticide expenditures.

Following Horowitz and Lichtenberg (1993) argument, if pesticides are risk increasing or if pesticides do not do much to reduce a grower’s expected indemnity payment by decreasing the probability of low yields, once they are insured, risk-averse farmers are likely to increase their use of risk-increasing pesticides. Working against this effect is the fact that pesticides are not free and any pesticide expenditures would reduce the expected net indemnity payment. The end result then may be that there is little change in pesticide use amongst wheat farmers as seems to be indicated in Table 2. It may also be that farmers are hesitant to reduce pesticide applications for fear of large yield reductions from failure to achieve a given level of pest control. In our sample only 45% of farmers applied any pesticides at all. It could even be that pesticides are only ‘weakly’ risk-increasing inputs for which Quiggin (1992) argues the impact of moral hazard effect on input use is ambiguous. In any case there is reason to suspect that the risk properties of pesticides and fertilizers are distinct enough that revenue insurance purchases impact their use differently. Nonetheless, for winter wheat the major environmental effect of revenue insurance almost certainly lies with fertilizer applications as so much more is utilized.

Horowitz and Lichtenberg (1993) 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 evidence 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 and their expense lowers expected profits when an indemnity payment is made. This combined effect almost certainly creates an incentive for insured farmers to reduce fertilizer expenditures. The significantly negative coefficient of Y_HAT in the fertilizers expenditure equation corroborates this result.

As expected, the coefficient on the productivity index (MEAN_PI) is negative and statistically significant at the 1% level of significance for both fertilizers and pesticides and fertilizer alone. The results indicate that an increase in the productivity of soils, leads to a reduction in expenditures on fertilizers and pesticides. This is because the marginal product of fertilizer is lower in areas where the soil is inherently fertile. The MANURE variable is significantly positive for fertilizers and pesticides and fertilizer alone. Despite the conventional wisdom that manure and fertilizers are substitutes there are situations where they can be complements. For example, additional fertilizer may be applied to winter wheat used for winter grazing by livestock to provide more vegetative growth (forage for the livestock). Further, soils that could benefit from manure applications may benefit from chemical fertilizer as well because they are of lower inherent fertility. Interestingly, larger farms appear to spend more on fertilizers and pesticides combined but not pesticides alone. This suggests that larger farms may utilize somewhat different production technology than smaller farms or perhaps are less likely to suffer from a liquidity constraint.

Three environmental indicators were included in the input use equation estimation because the environmental characteristics of the land may have agronomic implications as well. The coefficient on HEL indicates that fertilizer expenditures decline in the presence of highly erodible land. Results suggest that in the presence of highly erodible land farmers tend to you less fertilizers and pesticides. This is contrary to the findings of Wu (1999). One may think that farmers know the quality of land and tend to apply chemicals prudently. On the other hand, in the presence of highly erodible land (HEL) and a high potential for pesticide runoff (SURFAVG), expenditures on pesticides tend to increase. This suggests something fundamentally different about the properties of fertilizers and pesticides. It may be that there is a fairly linear, positive relationship between yield and fertilizer applications. As such, in the presence of highly erodible land the marginal product of fertilizer may diminish as less of it reaches the plant and so less is applied in the first place. This is confirmed by a negative and statistically significant coefficient on HEL in the fertilizer only equation. However, HEL is not significant in the fertilizers and pesticides equation as the effects of fertilizer and pesticide expenditures tend to counteract each other.

In the case of pesticides, however, there may be a more nonlinear or discontinuous relationship between yields
and pesticide applications in that unless one achieves a given level of pest control, a significant reduction in yield is likely. As such, the failure to achieve that threshold of control comes at great cost. The presence of highly erodible land or high potential for pesticide leaching or runoff diminishes the effectiveness of pesticides and hence increases the amount that must be applied to achieve a given level of pest control. The empirical results are consistent with such an explanation. The coefficient on SURFAVG in the pesticide equation is positive and statistically significant. This suggests that in the presence of diminished pesticide efficacy that farmers apply more pesticides not less for fear of a dramatic reduction in yields due to uncontrolled weeds, insects, or diseases. Interestingly, despite the insignificance of Y_HAT, other coefficients in the pesticide equation, such as those for SCOUT and SURFAVG, are significant. This result suggests that it is not a lack of variation in the pesticide expenditures that is driving the insignificance of the impact of insurance on pesticide expenditures (as was reported in the more localized dataset used by Smith and Goodwin, 1996), so perhaps it is the risk properties of pesticides themselves driving this phenomenon. Nonetheless, empirical confirmation or refutation of this conclusion awaits future studies of more pesticide intensive crops.

Operators’ education play an important role in production (crop and livestock) and adoption of technology (Welch, 1970; Huffman, 1977; Rahm and Huffman, 1984). Khaldi (1975) concludes that education enhances allocative efficiency. In addition, Huffman (1977) points out that education improves the allocative performance of farmers by increasing the acrality with which they respond to changes in economic conditions. The coefficient on operator’s education (OPEDUC) is positive and statistically significant at the 5% or lower level of significance in all three equations (fertilizers and pesticides, fertilizers only, and pesticides only). Results indicate operators with more education spend more on fertilizers and pesticides. This is consistent with an expectation that better educated operators are more adept at acquiring and processing information that is available from various sources, and then adopting and implementing recommendations and solutions that are relevant to their specific problem. In addition, operators with more education are more likely to adopt and exploit new technologies that are designed to improve problem identification and to encourage more efficient use of production inputs.

5. 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 Survey (ARMS) 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 the newer revenue insurance instruments tend to result in a reduction in aggregate fertilizer and pesticide input use for winter wheat, as Smith and Goodwin (1996) earlier indicated was true for MPCI. Furthermore, the effect is entirely driven by reductions in fertilizer expenditures and the environmental benefits of reduced input use, at least for winter wheat, are confined to those attributable to reduced fertilizer applications. When the included environmental indicators indicated a potential environmental fragility (i.e. high erosion potential, high pesticide leaching potential or high pesticide runoff potential) the input use equation suggested that pesticide expenditures increased. Revenue insurance probably does little to offset the pesticide driven environmental problems. On the other hand, fertilizer use appears to decline on fields designated as highly erodible or subject to a high potential for pesticide leaching. Revenue insurance undoubtedly further reduces fertilizer applications on these fields as well, but the marginal environmental benefit of revenue insurance is lessened because the reduction, where it matters most, accrues on land on which fertilizer use has already been curtailed to some degree. Nonetheless, reduced fertilizer expenditures appear to be an outcome of revenue insurance instruments just as they are under MPCI. The exact value of this benefit, however, poses a question for future research.

References


