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"Pesticides and Production Risk: Theory and Empirical Evidence"

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RISK-REDUCING AND RISK-INCREASING EFFECTS OF PESTICIDES

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This paper examines the issue of uncertainty and pesticide use and, in particular, explores the conditions under which pesticides increase or decrease profit risk. We develop a simple yet versatile model of crop production that can incorporate several sources of uncertainty and that makes clear the conditions under which pesticide use will increase or decrease risk. We show that when the principal source of uncertainty is pest population, pesticides are likely to be risk-reducing, the conventional view. But if crop growth is also random and if pest populations are high primarily when crop growth conditions are good, then pesticides will likely be risk-increasing. The reason is that pesticides then increase output in already good states of nature, thus increasing the variability of harvests. This result provides a convenient vehicle for interpreting several empirical findings.

1. Introduction

Risk is widely believed to be a major determinant of pesticide use. This belief has its origins in the observation by crop scientists that insecticides, in particular, were used in response to the risk of pest infestation, that is, before infestation was observed (see, for example, van den Bosch and Stern, 1962). Numerous other random variables in addition to infestation also affect pesticide productivity, including weather, prices, and biological factors that influence potential output, damage per pest, and pesticide effectiveness. These uncertainties are present for both observable and unobservable infestations. Thus, even when pest infestations are observable, and farmers can respond to observed infestation levels, the true extent of infestation, the damage associated with any given infestation level, and the effectiveness of pesticide applications remain stochastic.

This framework leads naturally to the concept of pesticides as a form of insurance (Carlson and Main, 1976; Norgaard, 1976). Scouting to monitor

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infestations, or other methods of providing information about infestation, could therefore be used to reduce the demand for this insurance function and reduce insecticide use, helping to alleviate environmental problems associated with pesticides (Carlson, 1979; Miranowski, 1974). For the same reasons, taxes aimed at reducing pesticide use for environmental reasons would need to take the risk effects of pesticides into account (Leathers and Quiggin, 1991). New crops for which pest damage is more predictable could also be valuable.

Numerous theoretical and empirical papers have discussed these issues directly and indirectly. The purpose of this paper is to provide a general model and to consider policy prescriptions and findings about pesticides in this light. We reconsider the notion of pesticides as risk-reducing or risk-increasing inputs and show that, in many production contexts, pesticides are more likely to be risk-increasing than risk-reducing.

2. A Model of Input Choice Under Uncertainty

Consider a production technology given by $f(x,\epsilon)$ where x is an input, ϵ a random variable (state of nature) and $f(x,\epsilon)$ crop output. ϵ is usually considered to be an index of random factors affecting production. We assume that states of nature can be ordered from worst to best independent of x, as when ϵ indexes rainfall or, more generally, crop-growth conditions. This assumption implies that $f_\epsilon(x,\epsilon) > 0$, where the subscript denotes the partial derivative. In general we expect the input to raise output in all states of nature, $f_x(x,\epsilon) > 0$, although there may be inputs (e.g. fertiliser) whose marginal product is zero or negative for some values of ϵ. A common example of a production function of this type is the Just-Pope production function, $f(x,\epsilon) = g(x) + s(x)\epsilon$ (Just and Pope, 1979).

Let p be the non-stochastic price per unit of output, w the unit cost of input x, and y yield. State-contingent farm profits are $pf(x,\epsilon) - wx$. Denote the distribution of ϵ as $G(\epsilon)$, defined over a support $(\epsilon_{min},\epsilon_{max})$, and the density function as $g(\epsilon)$. A farmer with utility of profits u chooses x to maximise:

$$\max_{x} \int_{\epsilon_{min}}^{\epsilon_{max}} u(pf(x,\epsilon) - wx)dG(\epsilon) \qquad (1)$$

Where price or product quality are stochastic, we may also model farm profits, denoted $\Pi(x,\epsilon)$, and interpret ϵ accordingly.

Quiggin (1991) has argued that the input x is risk-reducing if $f_{x\epsilon}(x,\epsilon) < 0$, since the input raises production more in bad states of nature than in good states. The input is risk-increasing if $f_{x\epsilon}(x,\epsilon) > 0$. A risk-reducing input can be characterised in three ways (Quiggin): (1) A risk-averse producer would use more of it than a risk-neutral one; (2) the input causes a monotone spread or second stochastic dominance shift in the distribution of output; and (3) a producer with output insurance would use less of the input. The definition is thus more general than those that look only at increases in variance. In the Just-Pope example, $f_{x\epsilon}(x,\epsilon) = s_x(x)$ and the input is risk-increasing precisely when it increases the variance of $f(x,\epsilon)$.

3. Pesticides at Risk-Increasing or Risk-Reducing Inputs

The conventional wisdom is that pesticides are risk-reducing inputs, so that risk-averse farmers apply more of them than risk-neutral farmers would (Carlson, 1979; Robinson and Barry, 1987). This view is due largely to the work of Feder (1979), who analysed pesticide use decisions using a model of expected utility maximisation by a farmer with non-increasing absolute risk aversion. Profit was:

$$\pi = \Pi_0 - C_0 - \delta N[1 - k(x)] - cx \tag{2}$$

where Π_0 and C_0 are constant revenue and non-pesticide production cost, δ is damage per pest, N is pest population size, k(x) is the proportion of the pest population killed by application of a dose of pesticide x and c is the unit cost of the pesticide. Feder considers three sources of randomness: pest population N, damage per pest δ and pesticide effectiveness. He shows that Sandmo-type mean-preserving spreads in δ, N, and, under certain conditions, pest survivorship, $[1 - k(x)]$, lead a risk-averse farmer to apply more pesticides per application x and to treat at a lower pest population threshold N, implying that pesticides are risk reducing.

Robison and Barry (1987, pp. 107-112) derive essentially the same results using this specification of pest damage in a mean-variance model. They note that the model is limited because it considers only one source or risk.

The empirical evidence on the risk effects of pesticides is quite mixed. In particular, several econometric studies obtain results consistent with the notion that pesticides are risk-increasing. Farnsworth and Moffitt (1981) found that pesticides increase yield variability on cotton in California, while Antle (1988) obtained similar results for tomatoes produced for processing in California. Horowitz and Lichtenber (1994) found that Corn Belt farmers who purchased crop insurance used more insecticides and herbicides on corn, which would be expected for a risk-increasing input. In his review of the literature on pesticides and risk, Pannell (1991) cites several simulation studies indicating that higher pesticide use is associated with greater variability of income. He finds no study that shows pesticides as reducing risk in cases where they are applied *ex ante*, i.e. before the realisation of an important random variable.

The theoretical underpinning for the notion that pesticides are risk-reducing is not altogether robust, either. As Robison and Barry note, Feder's model ignores important sources of uncertainty such as crop size (potential output) and price. In addition, Feder shows that pesticides are not always risk-reducing: a mean-preserving spread in pest kill k(x) leads a risk-averse farmer to apply less pesticide per application with a higher pest population threshold, suggesting that pesticides can be risk-increasing. Moffitt (1986), using an optimal threshold model, finds that increased uncertainty about infestation or damage results in both a higher dosage and a higher threshold, making it possible that total seasonal pesticide use could be lower. Pannell (1991) notes that greater uncertainty about price or output makes such a result possible as well.

The next section re-examines the issue of uncertainty and pesticide use. We use a more general framework than that used by Feder or Robison and Barry to explore the conditions under which pesticide use increases or decreases risk. We then consider several empirical cases. The possibility that the risk effects of pesticides depend on the source of uncertainty has been remarked on before (see Pannell, 1991, for a comprehensive review of the literature on this topic). One development of our paper is a simple, versatile, and general model that can incorporate several sources of uncertainty and that makes clear the conditions under which pesticide use will increase or decrease risk.

4. Pesticides and Production Risk

Let ϵ be a vector of random factors affecting production. For simplicity, we assume that it consists of two elements, θ and ω, and write the production function as $f(x,\theta,\omega)$, where x is pesticide use, θ is a random factor influencing potential output (crop growth) and ω is a random factor influencing pest damage (pest population). Alternatively, one can think of θ and ω as indices of random factors affecting these two respective components. As before, we scale θ and ω so that a higher realisation of either implies a higher level of output; thus, $f_\theta(x,\theta,\omega) > 0$ and $f_\omega(x,\theta,\omega) > 0$. A higher value of θ thus represents better crop growth conditions (higher rainfall, greater solar radiation) while a higher value of ω represents less pest damage (lower infestation levels, less damaging pests, higher natural predator population levels, higher pesticide effectiveness). Pesticides decrease damage so $f_x(x,\theta,\omega) > 0$ as well.

Lichtenberg and Zilberman (1986) have argued that models of pesticide productivity should define realised output as a combination of potential output and pest damage with the restriction that damage cannot exceed potential output. Our model distinguishes two corresponding potential types of uncertainty: (1) uncertainty due to variability in potential output and (2) uncertainty about fraction of potential output damaged. The former reflects variability in crop growth conditions due to fluctuations in rainfall, solar radiation, temperature and the like. The latter includes the three sources of uncertainty discussed by Feder: variability in infestation level, damage associated with different infestation levels and pesticide effectiveness.

One specification that incorporates this restriction on damage is $f(x,\theta,\omega) = h(\theta)(1 - d(x,\omega))$ where $h(\theta)$ is potential output and $d(x,\omega)$ is the fraction of output damaged. Multiplicative specifications like this have been widely used in simulation studies of pesticide use (Lichtenberg and Zilberman); we will use it to help illustrate our arguments. Pesticides decrease damage, so $d_x(x,\omega) < 0$. A higher value of θ denotes higher yield when $f_\theta(x,\theta,\omega) = h_\theta(\theta)(1 - d(x,\omega))$ is positive, i.e. $h_\theta(\theta) > 0$. A higher value of ω denotes higher yield when $f_\omega(x,\theta,\omega) = -h(\theta)d_\omega(x,\omega)$ is positive, i.e. $d_\omega(x,\omega) < 0$.

We proceed by examining different scenarios about the sources of uncertainty.

Case 1 Uncertainty About Pest Damage Only

Suppose that crop growth conditions are non-random and that there is uncertainty only about damage, because of randomness in pest infestation, damage per pest, or pesticide effectiveness. In our model, this corresponds to an assumption that $f(x,\theta,\omega) = f(x,\theta^*,\omega)$ where θ^* is a constant and ω is the important random variable. The sign of the cross-partial between input x and pest infestation ω, $f_{x\omega}(x,\theta^*,\omega)$, depends on whether marginal damage reduction is higher or lower in better states of nature. If marginal damage reduction is higher during less favourable states of nature, such as periods of high pest infestation or when pests are more damaging, then $f_{x\omega}(x,\theta^*,\omega) < 0$ and pesticides are risk-reducing.

For example, in the multiplicative model we have $f(x,\theta^*,\omega) = h(\theta^*)(1 - d(x,\omega))$ and $f_{x\omega}(x,\theta^*,\omega) = -h(\theta^*)d_{x\omega}(x,\omega)$. Pesticides are risk-reducing if marginal damage reduction is higher in less favourable states of nature, that is, if $-d_{x\omega}(x,\omega) < 0$, which yields $f_{x\omega}(x,\theta^*,\omega) < 0$. That this is reasonable can be seen more readily when damage takes the specific form $d(x,\omega) = d^*(\omega)(1 - m(x))$ where $d^*(\omega)$ is potential damage, which is the level of damage if no pesticide is applied, and m(x) is a mitigation function. The derivatives are $d^*_\omega(\omega) < 0$ and $m_x(x) > 0$. Pest infestation increases potential damage and this damage may be mitigated by pesticides. The cross-partial is $-d_{x\omega}(x,\omega) = d^*_\omega(\omega)(\omega)m_x(x) < 0$.

Case 1 encompasses Feder's model (see equation (2)). Crop damage, $h(\theta^*)d(x,\omega) = \delta N[1 - k(x)]\omega$, is here independent of randomness in potential output: under this specification, Feder finds pesticides to be risk-reducing.

Empirically, this case is likely to correspond to irrigated crop production, particularly in arid areas such as the western United States. Crop growth conditions do not vary much: water availability is controlled by the grower, and factors such as solar radiation and diurnal temperature patterns typically do not fluctuate much during the growing season. Pest infestation and damage are uncertain because they depend on (random) initial pest and predator population levels. One would thus expect pesticide use to be risk-reducing for the large number of fruits, vegetables, cotton, and alfalfa grown under irrigation in arid regions.

Case 2 Uncertainty About Crop Growth Conditions Only

Suppose that the only source of uncertainty is uncertainty about crop growth conditions. In our model, this corresponds to an assumption that $f(x,\theta\omega) = f(x,\theta,\omega^*)$ where ω^* is a constant. One would expect the marginal product of pesticides to be higher when growing conditions are good and there is more crop to be protected. If this is true, then the cross-partial $f_{x\theta}(x,\theta,\omega)$ is positive, and pesticides are risk-increasing. This result is easy to see in the multiplicative model. The cross-partial is $f_{x\theta}(x,\theta,\omega^*) = -h_\theta(\theta)d_x(x,\omega^*) > 0$. Pesticides clearly increase output more in the good state of nature because a given decrease in proportional damage salvages more production.

An example is Pannell (1990), who suggests for ryegrass weeds in wheat that ω and θ are uncorrelated, since weed density depends primarily on weed seed production in the previous season and cultural practices at the start of the current season. These factors are much less important in determining potential crop yield than weather conditions while the crop is growing; in our framework, this suggests $\omega = \omega^*$.†

An identical argument applies when output price is the sole source of uncertainty. Let profits be $\Pi(x,\theta,\omega^*) = p(\theta)f^*(x,\omega^*) - wx$, where $p_\theta(\theta) > 0$ and θ represents better market conditions and $f^*(x,\omega^*)$ is output. Then $\Pi_{x\theta}(x,\theta,\omega^*) = p_\theta(\theta)f^*_x(x,\omega^*) > 0$.

The set-up is similar when pesticides are used to protect product quality or appearance and pest 'pressure' is relatively constant. Let $f(x,\theta\omega^*) = \pi(x,\omega^*)Q(\theta)$ be high quality output, where $Q(\theta)$ is total output and $\pi(x,\omega^*)$ is the proportion that is of high quality, with $\pi_x(x,\omega^*) > 0$. Then $f_{x\theta}(x,\theta,\omega^*) = \pi_x(x,\omega^*)Q_\theta(\theta) > 0$. The marginal product of pesticides is higher under more favourable growing conditions and thus pesticides will be risk-increasing. To allow multiple quality levels, let p_h be the price of high quality output, and let $p_l < p_h$ be the price of low quality output. Revenue is $[\pi(x,\omega^*)p_h + (1 - \pi(x,\omega^*))p_l]Q(\theta)$ and the cross-partial for profits is $\Pi_{x\theta}(x,\theta,\omega^*) = \pi_x(x,\omega^*)[p_h - p_l]Q_\theta(\theta) > 0$.

Babcock, Lichtenberg and Zilberman's (1992) study of pesticide use on apples provides an empirical example. They find that insecticide use does not affect output but does reduce damage, and that damage reduces the proportion of the crop sold on the higher-price fresh market. Among stochastic factors

† We thank an anonymous referee for detailed comments on this general issue.

rainfall increases output and reduces damage, while freezes have the opposite effect. Letting $\Pi(x,\theta,\omega)$ denote profits, their regression equations imply $\Pi_{x\theta}(x,\theta,\omega^*) > 0$, i.e. pesticides are risk-increasing.

Case 3 Uncertainty About Both Crop Growth Conditions and Damage

Suppose that both crop growth conditions and pest damage are subject to random influences, so that the production function is $f(x,\theta,\omega)$, with both θ and ω variable.

We consider the case where crop growth conditions and damage are highly correlated. Ecological principles suggest that potential yield and damage would often be highly correlated, since a field constitutes an ecosystem systematically skewed towards growth of certain crop plants. Therefore, factors that promote crop growth would likely also encourage growth of any plants that compete well with the crop (weeds) or rely on the crop for food (insect pests) or other sustenance (diseases). Within a given producing region, an improvement in crop growth conditions will tend to lead to greater pest infestations, and one might expect a high negative correlation between the random variables θ and ω.

As in Case 1, we assume that the marginal product of pesticides is higher when pest infestation levels are higher, $f_{x\omega}(x,\theta,\omega) < 0$. Similarly, we assume as in Case 2 that marginal (proportional) damage reduction is greater when crop growth conditions are more favourable, because there is more crop to protect from losses, or $f_{x\theta}(x,\theta,\omega) > 0$.

Consider perfect correlation, $\omega = -\rho\theta$, so that the production function can be written $f(x,\theta,-\rho\theta)$ where ρ is a scale parameter. The random variable θ can be used as an index for production if and only if $f_\theta(x,\theta,-\rho\theta) > 0$. In other words, as crop growth conditions improve, pest damage cannot become so large that realised output actually decreases. The problem becomes significantly more complicated when this condition fails and θ cannot be suitably reordered.

The cross-partial between the input x and the random state of nature θ is $f_{x\theta}(x,\theta,-\rho\theta) = f_{x\theta}(x,\theta,\omega) + f_{x\omega}(x,\theta,\omega)\,[d\omega/d\theta] = f_{x\theta}(x,\theta,\omega) - \rho f_{x\omega}(x,\theta,\omega) > 0$. Thus, when crop growth conditions and pest damage are perfectly negatively correlated, we expect pesticides to be risk-increasing. If θ and ω are negatively but not perfectly correlated, the intuition for these results remains valid.

To see this more clearly, consider the multiplicative case, where the assumption that θ and ω are perfectly negatively correlated implies that the production function is $f(x,\theta,-\rho\theta) = h(\theta)(1 - d(x,-\rho\theta))$, with $d_x(x,\theta) < 0$ and $d_\theta(x,-\rho\theta) > 0$. For our approach to be reasonable, the random variable θ must satisfy $f_\theta(x,\theta,-\rho\theta) = h_\theta(\theta)(1 - d(x,-\rho\theta)) - h(\theta)d_\theta(x,-\rho\theta) > 0$, which means:

$$\frac{h_\theta(\theta)}{h(\theta)} > \frac{d_\theta(x,-\rho\theta)}{1 - d(x,-\rho\theta)} \tag{3}$$

This will hold if the proportional increase in potential yield $h(\theta)$ is greater than the proportional increase in damage reduction, $1 - d(x,-\rho\theta)$.

The assumption that marginal damage reduction is greater when pest infestation levels are higher, damage per pest is higher, or pesticide effectiveness is higher implies that $d_{x\theta}(x,-\rho\theta) < 0$. When crop growth condition and pest infestation are perfectly negatively correlated, then $f_{x\theta}(x,\theta,-\rho\theta) = -h_\theta(\theta)d_x(x,-\rho\theta) - h(\theta)d_{x\theta}(x,-\rho\theta) > 0$, so that pesticides are risk-increasing. Again, pesticides make the distribution of output more risky by increasing yield in already good states of nature.

Possible corroborating evidence for the case of weeds comes from Horowitz and Lichtenberg, who found that farmers with insurance use more herbicides on corn in the Midwest United States; other possible explanations for their finding are discussed there. In the case of insects, high nitrogen applications have been found to be positively correlated with high insect pest populations in a number of cases (for a survey see Dale, 1988). When growing conditions are good, both yield and insect population size will be high, and vice versa. If damage is positively related to pest population size, then insecticide use would be increasing in these cases as well.

There may, of course, be situations where crop growth conditions and pest damage are uncorrelated, or even negatively correlated. Many pests are well established within crop ecosystems and do damage regardless of how well the crop is doing; apple maggot and some weeds are examples. Some pests may do more damage when growing conditions for the crop are poor. For example, drought conditions in Illinois in 1988 favoured explosive populations of two spotted spider mites which are not normally a pest of economic importance.

5. Conclusion

The risk effects of pesticides are important in a number of contexts. For example, crop insurance has been proposed as a means of reducing pesticide use; this proposal is based on a belief that pesticide use is positively correlated with production risk (Carlson, 1979; Miranowski, 1974). Risk is likely to be important in determining the adoption of new crop varieties, which are often developed to have less variable yields, and the use of pesticides associated with them. A recent paper by Leathers and Quiggin (1991) suggests that farmers' responses to policies such as pesticide taxes will depend on the risk effects of pesticides.

Pesticides are widely believed to reduce production risk, but the theoretical analyses that provide the underpinning for this belief have been based on a limited view of production that assumes that pest damage is independent of other factors affecting output. As Lichtenberg and Zilberman have argued, this view is implausible because damage is limited by potential output. Thus, pesticide productivity depends on other factors affecting output.

Taking a more general view of production that incorporates this interdependence between pesticides and other factors, we examine the condition under which pesticides are likely to be risk-reducing or risk-increasing. We show that pesticides may be risk-increasing in a wide variety of circumstances, a result consistent with numerous empirical studies. Future research on pest management under risk would likely benefit from explicitly recognising multiple sources of uncertainty and investigating their mutual effects on crop production.

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Insurance, Moral Hazard, and Chemical Use in Agriculture

John K. Horowitz and Erik Lichtenberg

This paper examines how crop insurance affects corn farmers' fertilizer and pesticide use in the U.S. Midwest. Crop insurance might be expected to affect chemical use because of "moral hazard"; insured farmers may undertake riskier production than do uninsured farmers. Results suggest that insurance exerts considerable influence on corn farmers' chemical use decisions. Those purchasing insurance applied significantly more nitrogen per acre (19%), spent more on pesticides (21%), and treated more acreage with both herbicides and insecticides (7% and 63%) than did those not purchasing insurance. These results suggest that both fertilizer and pesticides may be risk-increasing inputs.

Key words: crop insurance, fertilizer use, moral hazard, pesticide use, risk.

Deteriorating quality of the rural environment and agricultural resource base has become a growing source of concern in the United States. Environmental problems include leaching of nitrate and pesticides into groundwater, surface water pollution from soil erosion and nutrients and pesticides in runoff, pesticide drift, and residues on foods. All of these arise as spillovers from agriculture and are widely perceived as problems of increasing gravity.

There has been further concern that farm commodity programs, favorable tax treatment of agricultural investment, and other agricultural policies have exacerbated these problems (National Research Council). One program that could potentially influence agricultural chemical use is federal crop insurance. Agriculture is widely believed to be an industry in which risk plays a substantial role in production decisions, including decisions such as chemical use, cultivation practices, and cropping patterns which have potentially significant environmental effects. It seems likely that crop insurance, which is aimed specifically at affecting risk, could affect environmental quality both through direct changes in input use decisions on existing crop land and indirectly through changes in cropping patterns. Crop insurance has been specifically proposed as a means for encouraging reductions in pesticide use, and its potential in this regard has been investigated on general conceptual grounds (Carlson 1979) and through simulation (Miranowski et al.). However, the issue of whether crop insurance actually affects agricultural chemical use has not been investigated empirically.

Crop insurance might be expected to affect chemical use because of opportunities for "moral hazard," i.e., the possibility that insured people take fewer precautions against harm (Arrow, Holmstrom). Moral hazard has been identified as a major reason for the absence of private insurance markets for most agricultural risks (Chambers).

The present paper estimates the effect of insurance coverage on chemical use by corn-growers in the U.S. Midwest. Moral hazard plays an important role in many theoretical economic models, but it has rarely been measured and there is often little more than anecdotal evidence of its importance. Estimation has been difficult because insurance may induce only small, hard-to-measure changes in behavior if contracts are written to minimize moral hazard; in cases where significant moral hazard effects are present, it may be difficult to observe either agents' precautionary actions, the costs of those actions, or their effects on the distribution of returns. If the insurance contract is complex, it may also be

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difficult to determine what the optimal actions are for the insured parties and therefore how to interpret estimation results (Newhouse, Phelps, and Marquis). Separation of moral hazard and adverse selection effects has also been a problem (Manning et al.).

Measuring the moral hazard effects of crop insurance should be less problematical for a number of reasons. Agricultural production conforms fairly closely to the neoclassical model and much is known already, at least qualitatively, about the production relationships that are necessary for understanding moral hazard. Production is relatively risky because of its dependence on weather, pest population growth, and other stochastic factors. Federal crop insurance is designed in a way that permits moral hazard (Chambers).

We consider only the effects of insurance on land currently planted to corn. As noted above, an important effect of crop insurance may be to alter cropping patterns, which may in turn cause changes in chemical use because of differences in climate, soils, and other factors affecting the productivity of chemicals. Our study does not deal with such effects.

A Model of Insurance and Input Choice

Let the production technology be given by $f(x, \omega)$, where x is an input, ω is a random state of nature, and $f(\cdot)$ is output. We assume states of nature ω can be ordered from worst to best independently of x, which would be appropriate if ω were rainfall, for example. This assumption is strong but not unreasonable in some cases. In terms of our notation, it means $f_2(x, \omega) > 0 \ \forall \ x$, where $f_i(x, \omega)$ is the partial derivative of output with respect to the ith argument. In general, we expect inputs to raise output in all states of the world, *i.e.*, $f_1(x, \omega) \geq 0$, although there may be cases for which $f_1(x, \omega) < 0$ for some values of ω. Such an input may be said to be strongly risk-increasing (Quiggin). For example, nitrogen fertilizer is widely believed to cause burning and reduce yields when there is low rainfall. Denote the distribution of ω as $G(\omega)$, defined over a support $[\omega_{\min}, \omega_{\max}]$, and the density function as $g(\omega)$.

Let p be the nonstochastic price per unit of output, w the unit cost of input x, and y yield. State-contingent farm profits in the absence of insurance are $pf(x, \omega) - wx$. We consider an insurance contract that guarantees to the firm revenues of at least py^*, where p and the insured yield level y^* are assumed to be determined exogenously and $f(x, \omega)$ is observable by the insurer. If yield falls below y^*, the farmer receives a payment equal to $p[y^* - f(x, \omega)]$. This is a commonly observed form of insurance contract even outside of agriculture.

Under such a contract, there exists a trigger state $\omega^* = \omega^*(x, y^*)$, defined by the implicit function $f(x, \omega^*) = y^*$, such that the insurer pays out to the firm whenever ω falls below ω^*. Because ω^* is a function of x, the insurer's expected payout is determined by the firm's choice of x. This moral hazard possibility will be important to the players if the insurer cannot perfectly observe ω or write a contract contingent on x. There may also be adverse selection if there exists a parameter of functions $f(\cdot)$ or $g(\cdot)$ that is known by the firm prior to choice of x but is not known by the insurer.

If the firm is risk averse, it chooses x to maximize the expected utility of profits:

$$(1)\quad \int_{\omega^*}^{\omega_{\max}} u(pf(x, \omega) - wx)g(\omega)d\omega + u(py^* - wx)G(\omega^*).$$

The arguments of $\omega^*(x, y^*)$ are omitted for ease of notation. Let $\pi(\omega) = pf(x, \omega) - wx$ and $\pi^* = \pi(\omega^*) = py^* - wx$. The first order condition is

$$(2)\quad \int_{\omega^*}^{\omega_{\max}} u'(\pi(\omega))[pf_1(x, \omega) - w]g(\omega)d\omega - wu'(\pi^*)G(\omega^*) = 0,$$

where u' is the partial derivative of utility with respect to profit.

To see the general moral hazard effect of insurance, differentiate the first order condition to obtain[1]

$$(3)\quad \frac{dx}{dy^*} = \frac{u'(\pi^*)pf_1(x, \omega^*)g(\omega^*)}{\Delta}\frac{d\omega^*}{dy^*} + \frac{wu''(\pi^*)pG(\omega^*)}{\Delta},$$

where $\Delta < 0$ is the second derivative of the objective function with respect to x. Equation (3) shows that the resulting change in input use de-

[1] Without further restrictions on $f(x, \omega)$, there may be multiple solutions to equation (2) and therefore the optimal x may not be continuous in y^*. See Grossman and Hart or Arnott and Stiglitz.

pends primarily on the shape of the production function at ω^*.[2]

The first term on the right hand side of equation (3) is the effect on input use x of a change in the trigger state ω^* holding y^* constant. This effect depends on $f_1(x, \omega^*)$, multiplied by the rate of change $d\omega^*/dy^*$ in the trigger state; by assumption, $d\omega^*/dy^* = 1/f_2(x, \omega^*)$ is always positive. The second term measures the direct effect on x of a change in y^* holding ω^* constant, i.e., with no change in the trigger state.

Consider first the case where the agent is risk neutral,[3] so that the second term on the right hand side of (3) is zero. The moral hazard effect is determined by the sign of $f_1(x, \omega^*)$. If $f_1(x, \omega^*) > 0$, increased insurance coverage will result in lower input use because there is a larger set of states of nature in which the input has no effect on revenue. The firm thus has less incentive to purchase the input, the typical moral hazard effect. If the input is strongly risk increasing so that $f_1(x, \omega^*) < 0$, increased insurance coverage will result in higher input use.

If the agent is risk averse, the second term on the right hand side of (3) is positive: an increase in y^* lowers the marginal utility of income by increasing income in all states below the trigger state, making the agent more willing to increase spending on the input. The more risk averse the agent is, the larger this effect will be.

The sign of dx/dy^* depends on the balance between the two terms. Note that for any given level of risk aversion, dx/dy^* is decreasing in $f_1(x, \omega s^*)$.

Crop Insurance

Empirical analysis of this model is based on insurance offered by the federal government, which has chosen to become the principal provider of multiple-peril crop insurance in the absence of insurance from private providers (for all perils except hail). Federal crop insurance specifies coverage y^* in terms of a proportion θ of the farm's historic average yield $E(y)$, with $y^* = \theta E(y)$. Farmers who purchase insurance can select θ (from among three possible choices) and a guaranteed price p^* (also from among three possible choices) for a premium that depends on θ, p^*, and the farmer's region. If yield falls below y^*, the farmer receives a payment equal to $p^*[y^* - f(x, \omega)]$; this is the contract modeled above for $p^* = p$.

The government's aims in providing such insurance are complex. At one time, it was argued that insurance could be a cost-effective substitute for price supports as an income stabilization measure (Chambers). More recently, crop insurance has been viewed as a less costly alternative to ad hoc disaster relief (Commission for the Improvement of the Federal Crop Insurance Program). At least one of the government's aims has been maximizing participation, and premiums are indeed subsidized; but it is not clear why the government has not designed contracts to minimize moral hazard opportunities, as discussed in Miranda. Note that for any of these goals, and for almost any information structure, the contract $\{p^*[y^* - f(x, \omega)]$ if $f(x, \omega) < y^*$; 0 otherwise$\}$ will almost surely not be optimal from the insurer's standpoint.

Estimation

Estimation of the relationship between insurance purchases and input use must take account of the fact that both are choice variables. In other words, it is necessary to separate moral hazard effects from (adverse) selection effects.

The decision to purchase insurance is made prior to production and is conditioned on the distribution of prices and yields (conditional on input use), risk aversion, and other factors affecting profitability and risk. The level of coverage I_i^* desired by the ith farmer is assumed to be a function of farm characteristics Z_{1i} and a white noise error u_i:

$$I_i^* = \alpha' Z_{1i} + u_i. \tag{4}$$

Because the data we use do not include direct observations on FCIC coverage, we model crop insurance decisions as a dichotomous choice.[4]

[2] More generally, the difference between input use with and without insurance is

$$x(y^*) - x(0) = \int_0^{y^*} \frac{\partial x}{\partial y} dy$$

which depends on $f_1(x, \omega)$ over all states of the world $\omega \leq \omega^*$; it also depends on the degree of risk aversion, the cost of the input, and the density function.

[3] A risk neutral agent might still buy federal crop insurance because it is subsidized.

[4] Our data include observations on each farm's total annual expenditures on insurance from federal and private sources. Private insurance includes hail and (crop) fire insurance. Hail and fire insurance reimburse farmers for actual yield losses incurred from these two specific causes and should not induce moral hazard effects in chemical use. Thus, including them in the dependent variable should add noise but should not otherwise affect the results. Private insurance also includes livestock insurance, the moral hazard effects of which are not clear. However, any bias introduced by livestock insurance is likely to be small since only 10% of the insurance purchasers in our sample had 90% or more of their revenue from livestock sales.

Let the indicator variable I take the value 1 if $I^* > 0$ (so the firm chooses to purchase insurance) and 0 if $I^* \leq 0$ (so that the firm does not purchase insurance). If error term u_i is distributed normally, then (4) can be estimated efficiently as a probit equation using maximum likelihood methods. The estimated coefficients are denoted $\hat{\alpha}$ and the predicted probability that insurance is purchased is $\Phi(\hat{\alpha}'Z_1)$, where Φ is cumulative density of a standard normal distribution.

Input use decisions x_i are made at the beginning of and during the production season, after the insurance contract has been selected. Such decisions depend on farm characteristics Z_{2i} and insurance coverage I_i:

$$x_i = \beta' Z_{2i} + \gamma I_i + v_i. \tag{5}$$

In this model, α captures selection effects while γ measures the moral hazard effect.[5]

The sequential nature of the decision process implies that (4) and (5) might plausibly be treated as a recursive system in which errors u_i and v_i are uncorrelated. However, if there are unobserved variables affecting either the farm's riskiness or the farmer's risk aversion, there is likely to be correlation between errors in the decisions made in different stages. To correct for this problem, we follow an approach used often in the labor literature and due to Heckman (1976, 1979; see also Greene, pp. 747–48).

Define $\Lambda = \phi(\alpha' Z_1)[I/\Phi(\alpha' Z_1) + (1 - I)/(1 - \Phi(\alpha' Z_1)]$, where ϕ is the density function of the standard normal distribution, and define $\hat{\Lambda}$ similarly, replacing α with its estimate $\hat{\phi}$. Then estimates of γ can be derived from OLS estimation of

$$x_i = \beta' Z_{2i} + \gamma I_i + \sigma \hat{\Lambda}_i + \eta_i \tag{6}$$

where σ is the covariance between errors u and v. Λ is constructed so that error η is uncorrelated with the insurance variable I. Van de Ven shows that estimates of γ derived in this way are consistent.

In a different context, Griffiths and Anderson discuss cross-section, time-series estimation of $f(x, \omega)$ when $f_1(x, \omega)$ may depend on ω and no adverse selection effects exist; see also Just and Pope.

[5] Goodness of fit has been a major concern in the literature on medical expenditures (Manning et al., Duan et al.) because of the skewed distribution of expenditures: Health expenditures are zero for a large proportion of the population and extremely large for a small proportion. Differences in the demand for different kinds of health care services also pose a problem. Neither of these issues is important in the situations we investigate.

Data

Our estimation is based on three data sets. Most of the analysis relies on cross-section, farm-level data collected by the National Agricultural Statistical Service (NASS) in its Farm Costs and Returns Survey (FCRS) 1987 supplement for corn. Information on historic (county average) production and current (county level) precipitation was obtained from the Federal Crop Insurance Commission and the National Climatic Data Center, respectively.

The FCRS is a survey of farmers in the United States who reported some corn acreage in 1987. We restrict our attention to a subsample of farmers in 10 states constituting most of the Corn Belt. All counties in Indiana, Illinois, and Iowa were included, plus selected counties in Kansas, Michigan, Minnesota, Missouri, Nebraska, South Dakota, and Wisconsin, where dryland (non-irrigated) corn is a major crop. A total of 433 farms were sampled by the FCRS, of which 376 are used in our regressions. The data set contains expenditures, input use, farm debts and assets, and income in 1987. It contains no information on prices. The FCRS is based on a complex sample design, and in the analysis below, all observations are weighted by expansion factors provided by NASS.

The FCRS data include total annual expenditure on each farm for both private and FCIC insurance on both crops and livestock, possibly from more than one insurance company, but not on motor vehicles or buildings. Coverage is converted to a dummy variable that takes the value 1 if there are any expenditures and 0 otherwise. Roughly 48% of farmers reported some insurance expenditures. We do not have direct information on the extent to which our coverage variable is determined by FCIC insurance purchases. However in 1988, 93% of cash grain farmers (farmers earning 50% or more of their total revenue from grain sales) in the six major Corn Belt States purchasing some form of insurance were covered by FCIC insurance.[6] Sixty-seven percent of the farmers with insurance coverage in our sample were cash grain farmers. Assuming FCIC coverage changed little over that one year, at least 62% of those in our sample with insurance coverage appear to have purchased FCIC insurance. Many farmers earning less than 50% of total revenue from grain sales

[6] We thank Linda Calvin of the Economic Research Service, U.S. Department of Agriculture for making this information available to us.

and purchasing insurance will also have purchased FCIC insurance.

Inputs studied were the three principal corn nutrients (nitrogen, phosphorus, and potassium), herbicides, insecticides, and overall pesticide use. The quantity of each nutrient applied to corn is the product of application rate in tons per acre and the number of acres treated. The measures of pesticide use were the number of corn acres treated with herbicides and the number of corn acres treated with insecticides; an acre treated twice counts as two acres. These numbers were converted to acre-treatments per acre, a standard measure of pesticide use, by dividing by total corn acreage. Per-acre expenditures on corn pesticides was also used as a measure of overall pesticide use. If, as theory suggests, the price of a compound is positively correlated with its effectiveness, expenditures should be a better aggregate indicator of pesticide use than is a measure such as total pounds of materials applied, which does not adjust for effectiveness.

The FCRS data were supplemented by county-level data on historic average yields and yield variability (Federal Crop Insurance Commission), and by data on actual 1987 precipitation at county weather stations (National Climatic Data Center, U.S. Department of Commerce). Precipitation data were converted to county-level monthly amounts by averaging across all weather stations in each county.

Explanatory variables were restricted to those that were predetermined or exogenous. For insurance choice equation (4), the explanatory variables were county-level mean yields per acre of corn and various alternative crops (grains, sorghum, soybeans), a weighted-average coefficient of variation of crop yields per acre, and the expected "return" to crop insurance, which is a proxy for the price of insurance. This last variable is, roughly speaking, the county historical mean percentage excess of payouts over premia for Federal crop insurance. See Just and Calvin or Gardner and Kramer for derivation of this variable.

For input equation (6), farm-level explanatory variables include the total number of acres planted in corn, the fraction of total acres planted in each of the major crops, and the fraction of total acreage under reduced tillage. The fraction of acres planted in each of the major crops captures important information about production, including types of rotations in use and the current year's crop diversification. Both are risk management tools.

FCRS measured most financial variables at the end of 1987, while the theory and econometric models are based on values at the beginning of the crop year. A few assets, such as the value of livestock and crops in storage, were reported at the beginning of the year as well as at the end. We constructed an asset measure as the sum of the value of buildings and machinery at the end of 1987 and crops in storage and livestock at the beginning of 1987; this variable will not lead to biased estimates if changes in the value of buildings and machinery were small. Debts were measured as of the end of 1987. Because the latter measurement does not reflect the farm's debt position during the time at which insurance and chemical decisions were being made, we did not use the debts measure. The percentage of assets in livestock was another measure of farm diversification.

Tenure arrangements also can have a substantial effect on the riskiness of production. A dummy variable indicates whether any operated acres were rented for cash (as opposed to a share of the crop). We also measured the percent of total operated acres that were rented for a share of the crop. Measures of nonfarming opportunities include a dummy variable indicating whether the operator had any off-farm wages during 1987 or operated an off-farm business. Operator age was also included as an indicator of human capital.

Results

We estimated equation (4) as a probit. Estimated coefficients are given in table 1. Virtually all coefficients are significantly different from zero and have the expected signs. Insurance purchase is more likely in areas with higher corn yields, possibly because the size of potential loss is greater and possibly because premium subsidies are greater in those regions. Insurance purchase is less likely in areas where yields from alternative crops such as soybeans and wheat are higher, signifying that crop diversification is likely to be more profitable.[7] The positive coefficient on the coefficient of variation of all crops suggests that insurance purchases are more likely in riskier areas, the standard adverse selection effect. The negative coefficient on pre-plant (January-March) precipitation reflects the effect

[7] Sorghum is grown mainly in areas with lower rainfall where corn production is marginal. Thus, sorghum may not provide much of an opportunity to diversify away from corn.

Table 1. Probit Regression to Estimate the Probability of a Farmer Purchasing Any Crop Insurance

Intercept	−0.33* 15.0
Mean return to FCIC insurance[a]	−0.005 1.32
County mean yield/acre corn	0.0015* 73.5
County mean yield/acre soybeans[b]	−0.24* 58.7
County mean yield/acre wheat[b]	−0.22* 74.7
County mean yield/acre sorghum[b]	0.13* 23.5
Coefficient of variation of yield/acre, all crops[a]	0.20* 21.8
January-March precipitation	−0.0018* 67.4
Total acres operated	0.0005* 54.1
Operated off-farm business in 1987? (1 if yes)	−0.12* 14.2

* Significant at 99% level of confidence. Absolute values of the ratio of coefficient estimate to its standard error are reported below the coefficient estimates. Percentage of correct predictions is 64.1%. Sample size is 376. The weighted mean of the dependent variable is 0.48.
[a] See authors for derivation.
[b] Measured as categorical variables. See authors for derivation.

of the reduced risk that comes from having high soil moisture in the initial stages of crop growth. Farmers operating more acreage may have higher (farm-level) yield variances and perhaps, as a consequence, are more likely to purchase crop insurance. Off-farm income provides income diversification, making insurance purchase less likely.

The coefficient on the return to crop insurance is negative but insignificant; we expected it to be positive. A likely explanation is that this particular variable is a poor measure of the value an individual farmer would expect to get from crop insurance. The insignificance of the return to insurance and the lack of variability in Λ, calculated from the results in table 1, may be a consequence of the data's relatively poor ability to predict insurance purchases. The poor ability to predict insurance is common in studies of crop insurance purchase decisions (Just and Calvin) but it should not affect analysis of moral hazard effects.

Chemical Use and Insurance

Estimated coefficients of the chemical use equation (6) are shown in table 2. These are based on the three hundred seventy-six observations for which chemical use data are available.

Insurance has a positive, statistically significant, and numerically large effect for nitrogen use, pesticide expenditures, and insecticide and herbicide acre-treatments. The results suggest that providing the typical insurance contract to the average farmer (from among farmers who do not currently have insurance) will increase nitrogen application per acre by 18.4 pounds, roughly 19%; pesticide expenditures per acre by \$3.70, roughly 21%; herbicide acre-treatments by 0.06, or 7%; and insecticide acre-treatments by 0.17, or 63%.

The positive effect of insurance on nitrogen is predicted by the many studies that find that the marginal product of nitrogen, $f_1(x, \omega)$ is low or negative at low rainfall levels (in particular, see Just and Pope and the papers in Anderson and Hazell).[8] Our moral hazard model suggests that insurance can increase use of inputs for which this is the case.[9] Insurance has a negative but statistically insignificant effect on phosphorus and potassium use, which would be the case if these nutrients have positive effects on yields in unfavorable states of nature. The presumption that such nutrients have small positive effects on yield under poor growing conditions is consistent with agronomic knowledge in that neither has phytotoxic effects.

Like nitrogen, pesticide use is substantially higher among farmers who have insurance. This is true whether pesticide use is measured as total expenditures or as the fraction of acreage treated with herbicides or the fraction treated with insecticides. Higher pesticide use may seem surprising given the widely held belief that pesticides are risk reducing and therefore a substitute for insurance. We would argue, however, that in many circumstances pesticides are more likely to be risk increasing than risk reducing.

The essential argument is as follows. In intuitive terms, an input reduces risk if it adds more to output in bad states of nature than in good states of nature, since this makes output (and profit) in each state of nature more uniform and

[8] Feinerman et al. present evidence suggesting that preplant soil moisture and nitrogen are substitutes rather than complements on corn in Iowa. This might seem to contradict the notion that water and nitrogen are complements, as our results indicate. However, the production function estimated by Feinerman et al. says nothing about the relationship between nitrogen and in-season rainfall, which should be a major component of the random element in our model.

[9] An alternative explanation is that lenders required borrowers to purchase FCIC insurance and that borrowers tended to use more inputs. We thank an anonymous reviewer for pointing out this possibility.

Table 2. Chemical Use Regressions

	Nitrogen per acre	Phosphorus per acre	Potassium per acre	Herbicide acre-treatments per acre	Insecticide acre-treatments per acre	Pesticide expenditure per corn acre
Intercept	−80.17	−33.40	−0.14	0.81	0.86	39.92
	1.60	0.81	0.003	3.73	2.40	3.51
Insurance dummy	**18.40**	**−2.62**	**−7.27**	**0.06**	**0.17**	**3.70**
	3.01	**0.52**	**1.25**	**2.16**	**3.98**	**2.67**
$\hat{\lambda}$	56.79	64.78	38.50	−0.02	0.21	−0.58
	1.71	2.38	1.22	0.11	0.86	0.08
Total corn acres	0.01	−0.02	0.0003	≈0.00	≈0.00	−0.01
	0.51	1.00	0.01	0.90	0.75	1.03
County mean corn yield/acre	0.14	0.04	0.03	≈0.00	0.00	−0.01
	4.21	1.61	0.88	0.25	0.35	0.67
Coefficient variation corn yield/acre	29.78	7.94	−7.60	−0.22	−0.33	−19.05
	1.07	0.34	0.29	1.81	1.68	3.00
% acreage in soybeans	34.06	100.85	99.44	0.67	−1.35	−8.56
	0.75	2.72	2.31	3.41	4.14	0.83
% acreage in soybeans^2	−9.40	−116.65	−85.82	−0.73	0.73	19.44
	0.14	2.09	1.33	2.46	1.50	1.25
% acreage in small grains	13.55	15.53	9.53	0.09	−0.37	−0.10
	0.84	1.18	0.62	1.30	3.22	0.08
% acreage in pasture	−2.29	−11.50	−15.71	0.005	−0.26	0.79
	0.11	0.65	0.77	0.05	1.66	1.99
% acreage under low tillage	−1.90	−4.21	−14.30	0.04	−0.06	0.89
	0.20	0.55	1.61	1.01	0.90	0.42
January-March precipitation	0.04	0.01	−0.02	≈0.00	0.0003	−0.01
	2.11	0.93	1.00	0.79	2.12	2.91
April precipitation	−0.03	0.10	0.08	2.8×10^{-4}	≈0.00	−0.02
	0.70	2.85	2.08	−1.57	0.18	1.76
Assets ($100,000)	2.84	1.34	1.75	0.01	2.4×10^{-3}	0.49
	2.79	1.60	1.80	2.18	0.23	2.13
% assets that are livestock	−13.75	−4.32	−32.18	0.21	0.05	3.31
	0.51	0.19	1.25	1.77	0.25	0.54
% acres operated for share of crop	20.99	−3.82	27.70	0.06	−0.07	−1.85
	1.97	0.39	2.74	1.31	0.88	0.76
Any acres rented for cash? (1 if yes)	12.86	−12.87	5.70	0.02	0.03	2.60
	1.67	0.93	0.78	0.57	0.59	1.48
Age of operator	−0.24	−0.08	−0.001	0.001	−0.002	−0.03
	0.94	0.38	0.006	1.31	1.14	0.46
Any off-farm wages?	6.06	0.12	7.38	0.02	−0.04	−1.66
(1 if yes)	1.01	0.02	1.29	0.85	0.90	1.22
R^2	0.31	0.18	0.20	0.14	0.24	0.16
F	8.22	4.07	4.63	3.08	5.94	3.62

Absolute values of t-statistics are reported below the coefficients. Sample size = 376.

decreases yield variability. An input increases risk if it adds relatively more to output in good states than in bad ones, since that increases the discrepancy among states. In regions and/or crops where high pest infestations occur primarily when crop growth conditions are good, pesticides work by increasing output in good states of nature and are thus likely to be risk-increasing.

Suppose ω represents an index of "growing conditions." In many cases the marginal product of pesticides will be small 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 (a sentiment reflected in Carlson 1989). Under such conditions, high pest infestations and therefore high pesticide productivity occur primarily when crop growth conditions are good. When such an association prevails, pesticides increase output in good states of nature more than in bad states and are thus likely to be risk-increasing.[10] This conclusion differs from the conventional wisdom because it

[10] In terms of our formal theoretical model, this argument suggests that the first term on the right hand side of (3) will be small and that the second term (the reduction in the marginal utility of income) will dominate, leading to increased pesticide use under insurance.

includes output uncertainty rather than concentrating solely on uncertainty about pest infestation (see, for example, Feder).

The possibility that pesticide use is risk increasing rather than risk reducing has been remarked on before. In his survey on pesticides and risk, Pannell notes that pesticides are likely to be risk increasing when output uncertainty is the dominant source of randomness. He cites several empirical studies, both simulation and econometric, indicating that pesticides are risk increasing in some contexts. In fact, he cites no studies showing pesticides to be risk reducing in cases where they are applied *ex ante*, that is, before the realization of an important random variable.

Our discussion has so far ignored specification issues other than selection effects. The insurance purchase decision has been studied in more detail elsewhere (Gardner and Kramer, Just and Calvin); we are interested in it only to construct $\hat{\Lambda}$. Since there does not appear to be significant correlation between the errors in (4) and (5), $\hat{\Lambda}$ has not played much of a role in our analysis. The estimated coefficients in table 2 do not change much when variables are dropped from the regression. We have used a quadratic functional form for soybean acreages only because soybeans are frequently in rotation with corn.[11] We have not considered possible cross-equation restrictions that might be developed if returns from inputs are correlated.

Other Factors Affecting Chemical Use

The regression results also provide evidence about other risk management issues in agriculture. First, it is often asserted that farmers paying share rent should apply less of variable inputs than cash renters or owner-operators. Yet nitrogen and potassium use per acre grew as the proportion of land operated under share rental increased. The relationship between tenancy and input use deserves further study.

Second, farmers with more assets tend to apply more inputs per acre. Higher input use likely reflects wealthier farmers' enhanced ability to receive credit, or possibly higher machinery ownership, which lowers the cost of application. It is possible, of course, that if nitrogen and pesticides are risk-increasing, increases in their use comes from the lower risk aversion of wealthier farmers.

Overall, the regression results are in accord with standard agronomic knowledge. For example, a larger share of acreage in soybeans is associated with higher phosphorus, potassium, and herbicide use but reduced insecticide use. Many farmers believe soybeans deplete soil phosphorus and potassium, and apply additional amounts of these nutrients on corn when corn follows soybeans. Fields rotated from soybeans or small grains to corn have greater weed problems but reduced infestations of corn rootworm, the principal corn insect pest (Lazarus and Swanson). Fertilizer and insecticide use are higher when precipitation is higher, reflecting increases in plant uptake of nitrogen and in insect population growth under humid conditions.

Discussion

We have examined how insurance affects corn farmers' fertilizer and pesticide use in the midwest. Our results suggest that insurance exerts considerable influence on corn farmers' chemical use decisions. Those purchasing insurance applied significantly more nitrogen per acre (19%), spent more on pesticides (21%), and treated more acreage with both herbicides and insecticides (7% and 63%, respectively). Whether such effects occur in other crops, exactly how much they might affect insurers' payouts and whether they are substantial enough to explain the lack of privately-provided multiple peril insurance, remain to be determined.

There has been growing concern over problems such as ground and surface water contamination, wildlife kills, and a variety of health and safety hazards, all of which are closely associated with agricultural chemical use (National Research Council). Insurance has been proposed as an instrument for addressing these problems by providing a substitute for additional pesticide applications (Carlson 1979; Miranowski). Results obtained here imply that federal crop insurance tends if anything to promote chemical use, rather than the reverse. To be a substitute for pesticide application, insurance contracts would have to be restricted to certifiable pest damage, a factor difficult to verify (Carlson 1979). An alternative would be to adjust the critical states of nature to correspond to those in which pesticides are effective. The lat-

[11] If relative prices are stationary, the proportions of the farmer's land planted to corn and soybeans will indicate the rotation period. Other things equal, a farm that is 50% corn and 50% soybeans will be relying on rotation more than a farm that is, say, 10% in one crop and 90% in the other. We use the quadratic functional form to allow measurement of the extent of diversification in this way.

ter probably would require guaranteeing an extremely high percentage of average yield, for example 95%, and is thus likely to be excessively costly (Miranowski et al.). Overall, our empirical findings confirm the pessimism of previous conceptual studies on this issue.

A major limitation of this study is that data allowed examination of insurance purchases only as an all-or-nothing decision. One would expect the level of coverage selected to influence input use decisions. It would be worthwhile to collect information for a more detailed analysis of insurance purchases and their effects on chemical use.

We have concentrated on the effect of crop insurance on total amounts of agricultural chemicals applied. Other important moral hazard possibilities include the timing of planting and of chemical application, both of which may affect the insurer's payouts but which are unlikely to have substantial environmental effects. Crop insurance may also affect crop choice and land use decisions such as whether to cultivate low-productivity land, decisions that one would expect to have significant environmental consequences. As we noted earlier, we have not addressed these effects. Because, however, such decisions are more easily observable by the insurer, it should be easier to structure contracts to alleviate these kinds of moral hazard if the insurer is so inclined.

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