Evaluating the Effects of Asymmetric Information in a Model of Crop Insurance

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Abstract

Asymmetric information in the form of moral hazard and adverse selection can result in sizeable efficiency losses and program costs for government provided crop insurance plans. We present a methodology and illustrative simulations to show how these two types of information problems interact in way to create program costs for the providers of crop insurance. Our methodology allows us to ascertain the relative contributions to program costs of these two types of phenomena, which is critical for improving the design of such insurance plans at least possible cost as well as for studying general efficiency considerations

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1 Introduction

There has been substantial empirical research into the effects of crop insurance on producer decisions regarding input use and program participation. Of particular concern has been the implications of insurance on the phenomena of moral hazard and adverse selection. This literature is very nicely reviewed in a paper by Knight and Coble (1997) with a particular focus on the Multiple Peril Crop Insurance program established by the 1980 Federal Crop Insurance Act. They note that empirical studies have identified that this insurance program has generated substantial moral hazard and adverse selection effects but that the size or importance of these effects have not been well studied.[1] In this paper we use a model and supporting simulations to illustrate a methodology for analyzing a publicly provided crop insurance program in the presence of both moral hazard and adverse selection. This is a valuable exercise because the implications on program costs and productive efficiency are affected quite differently by each of these phenomena. Either moral hazard or adverse selection complications may on their own create substantial and undesirable program costs for a public insurance program. However, identifying the extent to which these costs are generated by moral hazard or adverse selection is important. The primary concern with moral hazard is that it generally leads to inefficiencies in production decisions while the major impact of adverse selection is creation of inefficiency of the insurance market and risk-bearing costs per se (should good risks exit the market). Moreover, different policies and different approaches to information acquisition are necessary if one is to try to ameliorate these two problems. Lessons learned from the empirical work concerning public crop insurance plans in conjunction with models such as ours which attempt to isolate moral hazard and adverse selection effects should also provide valuable lessons for other public insurance programs.

In this paper we demonstrate that the implications of the two phenomena of moral hazard and adverse selection, when they present themselves jointly, can be compounding in that they create program costs which are super-additive. This implies that efforts by the insurer to overcome either one of the information asymmetries involved (i.e., hidden type or hidden input) may

[1] "Moral hazard and adverse selection effects *(combined ... our addition)* have been less extensively examined. Evidence of both has apparently been found whenever sought; however, only a few studies provide estimates of the magnitude of moral hazard and adverse selection effects on MPCI indemnities." .... Knight and Coble (1997)

provide benefits which far exceed those that would be expected if one were to consider these problems in isolation. Moreover, if it turns out that it isn't terribly important which problem of asymmetry of information is resolved in order to improve efficiency or control program costs, then the insurer may wish to resolve only one of the information problems and of course choose the one which is less costly to correct. Although we do not perform any explicit efficiency analysis in this paper, the welfare implications of our approach are quite evident.

As noted in the paper by Knight and Coble (1997), there is substantial empirical work concerning the implications of crop insurance on producers' decisions, both in terms of their input choices and participation in the program. To a limited extent we design our simulation model to reflect this work. In particular, we pay close attention to the functional form for the distribution of crop yields and the design of the insurance program. Since we are not attempting to reflect precise real world experience for a particular crop, and production of different crops requires quite different specific parameter values, the model should be viewed as providing a general methodological framework rather than a specific example of a particular crop. Nonetheless, our base case scenario is calibrated to reflect a plausible crop insurance scenario as gleaned from a number of empirical studies.

There is a very limited theoretical literature on the implications of hidden effort (moral hazard) and hidden type (adverse selection) both being present in an insurance market setting[2]. As noted by Arnott (1992, p. 355), "Theorists have been deterred by the inherent complexity and messiness of the problem ... with even only two events and two groups..." Possible nonexistence of a Nash equilibrium, even in the presence of adverse selection only,[3] indicates how difficult such an analysis may become. In this paper, however, these complications are substantially eliminated by the fact that we are analyzing a public insurance program and so existence of equilibrium is not a concern. The paper which is perhaps closest in spirit to ours is the simulation study performed by Stewart (1994). He considers the welfare implications of the joint presence of moral hazard and adverse selection problems in a competitive insurance market. His results are very different from ours, however, primarily due to the fact that we are looking at a public insurance program

[2]See, for example, Picard (1987), Hoy (1989), and the few other references given in Arnott (1992).

[3]See Rothschild and Stiglitz (1976).

which includes subsidization and he is concerned with a competitive, zero profit, insurance market. There are many other differences as well, including the fact that his model has only two states of the world and assumes a difference in production technologies by type in a manner which is more restrictive than our approach.[4]

2 The Basic Model

In this section we develop the basic model to describe the producer's optimal input choice for both cases in which insurance is and is not provided. We illustrate how this model is calibrated to generate our simulations which demonstrate how one can determine the relative impacts on program costs of adverse selection and moral hazard.[5] The simulation results and discussion of them are presented in the following section. Although we choose our functional forms and parameters in order to reflect knowledge gained from some of the previous empirical studies that have analyzed the impact of crop insurance on producer decisions, we keep the model as simple as possible so that we can demonstrate transparently how to determine the relative contributions of moral hazard and adverse selection to program costs. Actual applications of our methodology would require case specific adjustments to our choice of parameters and other modelling assumptions.

We assume output, $\tilde{y}$, is a random variable which depends on a single input chosen, x, the state of nature, ω, and an agent type specific parameter, ϕ. Higher productivity producers will be associated with a higher value of ϕ, which, for example, could reflect higher quality land. The state of nature, ω, which reflects weather and other growing conditions, will be modelled in such a way that higher values represent better growing conditions and,

[4] Given these differences, it is not surprising that the results of Stewart (1994) are different from ours. Most striking is that he obtains a sub-additivity result concerning the welfare implications of the two types of hidden information being present simultaneously while we show program cost, which is also a different characteristic of the insurance implications, may be super-additive.

[5] Comparative static results indicating the effect of changes in various parameters (e.g., output price) on input use have been developed by Leathers and Quiggin (1991), Ramaswami (1993), and others using theoretical models of insurance. Our simulation model is designed explicitly to demonstrate how to measure the size of program costs due to the two problems of moral hazard and adverse selection rather than comparative static effects per se.

hence, higher output. A higher input value, x, is assumed to generate higher output. We can, therefore, describe the production process as a production function

$$\widetilde{y} = f(x, \omega, \phi) \tag{1}$$

with $f_x > 0$, $f_{xx} \leq 0$, $f_\omega > 0$, and $f_\phi > 0$.[6] For the purpose of our simulations, we will adopt the following specific production function.

$$\widetilde{y} = x^\lambda \omega \phi \tag{2}$$

with $\lambda \leq 1$. Thus, production is multiplicative in both the random variable ω and the agent type specific parameter ϕ. The distribution function for output, conditional on a given x and ϕ, will be inherited from the distribution function assumed for ω. In our simulations, we use the beta distribution function for ω because of its flexibility. We assume only one input in order to maintain simplicity in this part of the model and, as noted earlier, to promote transparency regarding the relative effects of adverse selection and moral hazard on input decisions of producers and program costs for the providers of insurance. It would be interesting to allow for a set of inputs, some of which would increase and others which would decrease the riskiness of the production process.[7] We leave such variations to potential future work.

In the absence of insurance the producer chooses the input level, x, to maximized expected utility of profit. We let p be the price of the product[8] and w the input cost. A fixed cost could be included without loss of generality. Thus, profit with no insurance for a producer of type ϕ is:

$$\pi(x, \omega, \phi) = pf(x, \omega, \phi) - wx \tag{3}$$

The producer chooses input x to maximize expected utility of profit. Letting $u(\pi)$ be the elementary von Neumann-Morgenstern utility function, $g(\omega)$ be the probability density function for the random variable ω, and $\underline{\omega}$ and $\overline{\omega}$ the

[6]This production function is similar to the one used by Quiggin, et al.(1993). One can include any constant term within the definition of ϕ as well as the level of any fixed inputs.

[7]The way we model production implies that an increase in the single input x leads to greater riskiness in production as well as higher expected output. In a multiple input model it is quite plausible that some inputs could reduce both expected yield and riskiness.

[8]For simplicity we assume that price is not random. The possibility of hedging in combination with a crop insurance plan which allows future spot price to be the basis of repayment makes this assumption not so critical to the analysis.

upper and lower limits for ω, the producer's optimization problem becomes:

$$\underset{\{x\}}{Max}\ EU_n(x) = \int_{\underline{\omega}}^{\overline{\omega}} [u(pf(x,\omega,\phi) - wx)]g(\omega)d\omega \tag{4}$$

where EU_n denotes expected utility with no insurance.

We now model how the insurance program is designed and determine the relevant optimization problem for a producer conditional on purchasing insurance. A critical yield is determined by the insurer, which we denote as y_c, and any shortfall below this level determines the indemnity or payout (i.e., $p(y_c - y)$ if actual output $y < y_c$). Since output depends on the input chosen, x, the type specific productivity parameter, ϕ, as well as the random variable ω, if follows that conditional on any pair x, ϕ, and critical level y_c, there is some critical value of ω, which we denote as ω_c, which triggers an insurance payment (i.e., $y < y_c$ whenever $\omega < \omega_c$). Thus, we can write ω_c as a function of x, ϕ, and y_c (i.e., $\omega_c(x, \phi.y_c)$). The probability that an indemnity is received is

$$k(x,\phi,y_c) = \int_{\underline{\omega}}^{\omega_c(x,\phi.y_c)} g(\omega)d\omega \tag{5}$$

with $k_x < 0$, $k_\phi < 0$, and $k_{y_c} > 0$. We let ρ denote the cost of the insurance policy to the producer. The profit function for a producer who purchases insurance is

$$\begin{aligned} \pi(x,\omega,\phi) &= py_c - wx - \rho \text{ , if } y < y_c \\ &= pf(x,\omega,\phi) - wx - \rho \text{ , if } y \geq y_c \end{aligned} \tag{6}$$

The producer's decision problem conditional on purchasing insurance is

$$\begin{aligned} \underset{\{x\}}{Max}\ EU_w(x) &= k(x,\phi,y_c)u(py_c - wx - \rho) \\ &+ \int_{\omega_c(x,\phi,y_c)}^{\overline{\omega}} [u(pf(x,\omega,\phi) - wx - \rho)]g(\omega)d\omega \end{aligned} \tag{7}$$

where $EU_w(x)$ denotes expected utility with insurance. The first term on the right hand side of equation (7) represents the utility conditional on an insurance payout being triggered multiplied by the probability that an insurance payment is in fact triggered. The fact that this term is increasing in y_c and decreasing in the level of input used, x, reflects the moral hazard problem (i.e., the incentive to reduce input in the presence of insurance).

Since $k_\phi < 0$, this term is larger the smaller is the type specific productivity parameter. Thus, as is the case under adverse selection, if lower productivity producers receive the same insurance terms as do high productivity producers, the insurance contract will be more valuable to the lower productivity types. Moreover, since both $k_\phi < 0$ and $u(py_c - wx - \rho)$ is decreasing in x, the incentive to decrease the input level is greater for lower productivity producers. Thus, one can expect a stronger moral hazard effect for low productivity producers under adverse selection. We discuss these effects further in the section describing the simulation results.

We consider three alternative scenarios for the insurance scheme based on what information the insurer has concerning the input levels of the producers and their productivity type. In all cases we assume the insurer chooses a coverage level which is some fraction of the average yields for producers who do not purchase insurance, which in effect represents outcomes in the absence of insurance. The insurer determines a price of insurance which covers the actuarial or expected cost of indemnities based on yields generated in the absence of insurance provision. The purchase of insurance leads to changes in behaviour and so the actual expected costs of providing insurance will generally differ from the computed values. This is, of course, the crux of the problem with publicly provided insurance plans and it is the difference in these costs, which we call program costs, that are the focus of our attention.

In the first scenario that we model, we assume the insurer can observe the productivity type of each producer and bases the price of insurance on that information. Thus, high and low productivity types pay different prices for insurance and the probability of an insurance payment being triggered also depends on the producer's type. This scenario is referred to as *moral hazard only.* We then consider the operation of the insurance plan on the basis of inputs being observed but productivity type not known by the insurer. We call this an environment of *adverse selection only*, although this is something of a misnomer as explained below. The insurer in this scenario is presumed to have observed the average input level employed in the absence of insurance and then uses this level as the input requirement for those who do purchase insurance. Since productivity type is not observable, it wouldn't make sense to assume that the actual input levels of each productivity type were observable. Thus, there is a sense in which moral hazard is not entirely eliminated in this scenario even though the average input level that producers used in the absence of insurance is known and this input level is observable and enforced once insurance is purchased. The problem is that there remains the issue that the 'appropriate' input level depends on the productivity type and this isn't enforceable. However, the extent to which a producer can engage in moral hazard by reducing the input level is of course limited in this environment as it cannot fall below the average input level that was used by producers in the absence of insurance.

The final scenario investigated is that in which the insurer can observe neither the input level chosen by producers nor their productivity type. The coverage level for insurance and its price is based on the pooled experience of the various productivity types in the absence of insurance. The insurer cannot determine the type of the producers who do buy insurance and also cannot observe their input levels. Thus, we refer to this scenario as one of *moral hazard and adverse selection.*

In our simulations we compare the program costs, which are defined as the difference between expected insurance payouts and premium revenue collected for each scenario. In this way we can see the relative importance of moral hazard and adverse selection in generating these costs. Alternatively, the premium levels could be adjusted upwards in order to offset these costs, either fully or partially, and so our calculations also indicate the extent to which this would be required. Of course, increasing the costs of the insurance premiums could affect the selection of insureds, with higher productivity types more likely to view insurance as unattractive, thus exacerbating the impact of adverse selection, possibly leading to even more losses for the insurance plan.

3 Description of the Simulation Model

In this section we describe the basic model and associated assumptions for the simulations used to generate our results. We preform a number of sensitivity analyses by varying the value of key parameters, most notably for the utility function, $u(.)$, and the density function, $g(\omega)$. These are described below and in the following section along with the results of the simulation exercises. First we describe the base model and compare to assumptions and empirical results in the literature on crop production and insurance. As noted in the introduction, we design our simulation model to reflect these results, although we are not trying to replicate any particular crop setting. In particular, we pay close attention to the functional form for the distribution of crop yields and the design of the insurance program since these are critically important factors in determining the moral hazard and adverse selection effects of the program.

Profit from crop production is as indicated in equation (3) with the production function, $\widetilde{y} = x^{\lambda}\omega\phi$, as given in equation (2). We use the parameter value $\lambda = 0.96$ for our base case and also adopt a range of values in our simulations.[9] The use of a beta distribution function is used for our random variable ω in the base case, and a truncated normal is also adopted for the purpose of sensitivity analysis. The particular beta distribution adopted is the one with parameter values $\alpha = 2.5$ and $\beta = 2$, which determines the density function as indicated below.

$$g(\omega) = \frac{\omega^{\alpha-1}(1-\omega)^{\beta-1}}{\int_{\underline{\omega}}^{\overline{\omega}} t^{\alpha-1}(1-t)^{\beta-1}dt} \tag{8}$$

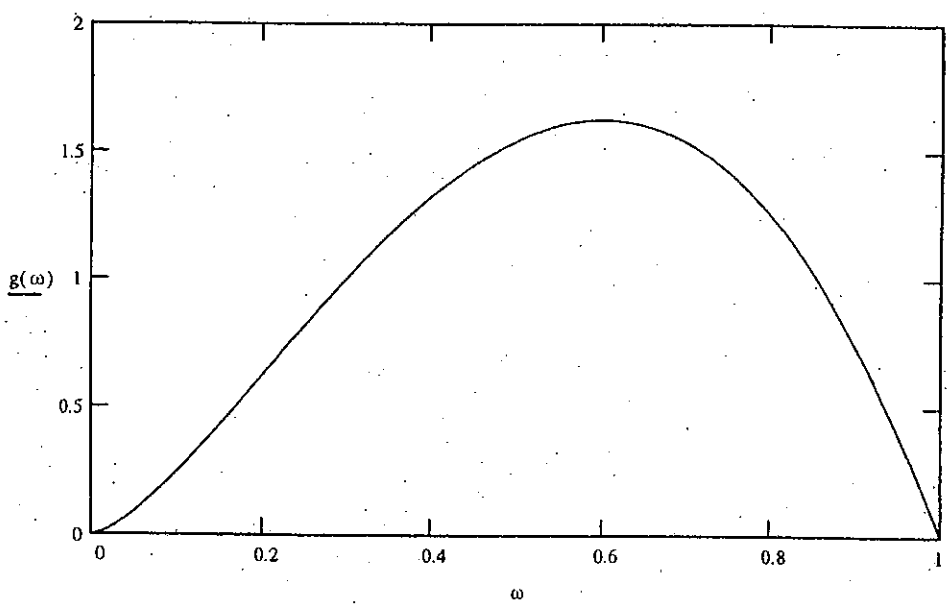

Figure 1

Units of measurement can be defined arbitrarily in the sense, for example, that the variable y could be defined in terms of bushels or tonnes per acre or

[9]Quiggin, et al. (1993) find that for a heterogeneous collection of grain farmers, one cannot reject the null hypothesis of constant returns to scale.

per hundred acres, etc. Moreover, the assumption of a single input is made to keep the analysis simple and this input reflects an index of a variety of inputs. Thus, x is not meant to be representative of any particular input for any particular crop. What is quite important, however, is the shape of the distribution function for the random variable ω and the resulting distribution of y which is inherited from it. The reason this is important is that the shape of the distribution function, in conjunction with the coverage level y_c, determine in relative terms: (i) all of the parameters of the insurance program, (ii) the incentive to purchase insurance, and (iii) the optimal input level conditional on insurance being purchased. [10] Of course, the particular shape of the distribution function is likely to vary by type of crop, region, etc In our simulations we adopt the beta distribution and use several different sets of parameter values in our sensitivity analysis. This allows us to compare outcomes when the distribution is symmetric, asymmetric, more or less peaked, etc.

Note that the production function is multiplicative in ω, and so the input is risk increasing (i.e., an increase in x leads to an increase in the variance of crop yields). The literature on crop insurance has addressed the question of the impact of insurance on input use for cases of multiple inputs, with some being risk increasing and others risk reducing. Use of a multiple input model with both types of inputs would increase the complexity of our model beyond what is required to demonstrate the basic issues that we are analyzing. Nonetheless, since the impact of insurance on input use may well be qualitatively different for these different types of inputs, this is an interesting consideration for future work.[11]

We assume in our base model that risk preferences are summarized by the exponential utility function $u(\pi) = -e^{-\gamma\pi}$, where π is profit from producing the crop. This utility function implies constant absolute risk aversion of degree γ. We adopt a range of values of $\gamma > 0$ in our simulations. A

[10]The beta distribution and normal distribution have been used extensively in the empirical literature. See Babcock and Hennessy (1996) for an example of use of the beta distribution and Just and Weninger (1999) for an example of the use of the normal distribution. Ker and Coble (2002) provide a comprehensive review and critique of the empirical methods used to choose between these two distributional approaches. Nonparametric methods have also been used (e.g., Ker and Goodwin (2000).

[11]See, for example, Quiggin, et al. (1993) who note that "Pesticides are generally viewed as a risk-reducing input and fertilizer as a risk-increasing input." For their study, however, they go on to note that "testing revealed no significant loss in power from aggregating the two inputs.

substantial literature has developed trying to measure the risk preferences of individuals.[12] The most popular functional forms used in empirical estimation of $u(.)$ have been those representing constant absolute and constant relative risk aversion preferences. Empirical estimates of the degree of risk aversion vary widely. Choi and Menezes (1992) note that, for those studies employing a constant relative risk aversion utility function, the range of the degree of risk aversion has been from 0.05 to more than 1000. Some of the empirical research has tried to determine which functional form - constant absolute risk aversion or constant relative risk aversion or neither - is most appropriate. Saha (1993) proposed a flexible form of utility function which allows for a combination of properties concerning absolute and relative risk aversion. There have also been a number of studies found for risk preferences specifically for farmers.[13] These have also found a wide range of results. Thus, there is no obvious choice for a specific functional form to model risk preferences, let alone a specific parameter value which accurately reflects the degree of risk aversion. This problem is exacerbated in our model since we are only considering one aspect (i.e., decisions with respect to a single crop) of a producer's portfolio of assets and production streams.[14] Of particular relevance to our choice is the recent paper of Guiso and Paiela (2004) that measured the parameter of absolute risk aversion from revealed preferences over a hypothetical lottery question. They found a wide range of values within the population surveyed, with the 10th percentile most risk averese having a degree of absolute risk aversion equal to 0.08 while the 90th percentile most risk averse had a value of 0.20. We choose a variety of parameter values in our simulations, with the constant absolute risk aversion utility function with degree $\gamma = 0.10$ for our base case.

4 Simulation Results

In this section we present our simulation results. As noted above, the specific parameter values used in our base case were based broadly on empirical

[12]See, for example, Blake (1996) who refers to much of this literature.

[13]See references in Saha (1993).

[14]Our objective function reflects an attitude towards risk for a given crop decision and so the parameter value chosen may not reflect at all the overall risk preferences of the producer. Bar-Shira, et al. (1997), for example, found that the degree of risk aversion varied across crops and other aspects of farmers' decisions.

studies of crop production and insurance. In particular, the base case parameter assumptions and outcomes are consistent with the empirical estimation by Babcock and Hennessy (1996) for corn production from a group of Iowa farms. As in their model, we adopt a scale assumption reflecting a single acre of corn.[15] We use an output price of $p = 2.2$, as do they. Our production function does differ from their's, although our base case has yields distributed according to the beta distribution, which is the same functional form that they use. One major difference, however, is that our input, x, is intended to reflect an index of various inputs and our production function is Cobb-Douglas and multiplicative in the random variable ω. Thus, we choose our input price, which doesn't represent the price of any particular type of input, to generate similar results to their model. By choice of $w = 0.075$, we generate an average yield for our high productivity type of producer of $Ey = 138$ (in the absence of insurance), which is a plausible expected yield for corn (i.e., bushels per acre). It is important to note that since choice of units can be made arbitrarily, one should not put too much importance on the particular values of prices or quantities. Nonetheless, having chosen a base case which generates 'sensible' results for some particular crop (corn) is helpful from the point of view of interpretation of the model. Moreover, the implications of our changes in parameter values is more understandable and potential applicability of the methodology to real world scenarios is also made more transparent by taking some care with our calibration approach.

One aspect of the simulations differs from the theoretical model outlined above and represents a constraint on the producer's decisions. It turns out, at least in our models, that it is often optimal for producers to choose a zero input level when offered insurance. By doing so, the producer receives a payoff equal to the value of the guaranteed output level, which is a substantial fraction of the average output that would have been generated if the producer had employed an input level equal to that used in the absence of insurance. The net value from this decision is generally very high since zero input costs are incurred and the revenue, which is substantial, is received with certainty.[16] In the real world it seems unlikely that such extreme moral hazard would

[15] See Babcock and Hennessy (1996) for detailed explanations of these assumptions.

[16] Mathematically, this is represented by the fact that the first term of equation (7) evalutated at $x = 0$, which is the insurance payment, dominates the second term which would be profit under $x \neq 0$ conditional on an insurance payment not being triggered. The need and implications of a minimal input requirement are investigated in detail in another paper (Turvey, Islam, Hoy, 2002).

be feasible since it would reflect the situation in which the producer does not even til the soil or plant any seed, let alone use any amount of fertilizer whatsoever. It seems plausible that it would not be very costly for an insurer to monitor at least partially some such minimal level of input usage. Thus, we assume the insurer can successfully (and at low cost) verify that the producer uses at least some minimal fraction of the input level that would be chosen under the scenario of no insurance. This fraction is assumed to be $t = 0.25$ (i.e., one quarter of the input level used without insurance) for our base case.[17] Given this amount, it turns out that an interior optimum with an input level substantially more than 25% of the input level used with no insurance applies, as described by the graph in figure 2. The higher the level of insurance coverage, the more tempting it is for insurers to adopt the extreme moral hazard decision (i.e., $x = 0$).

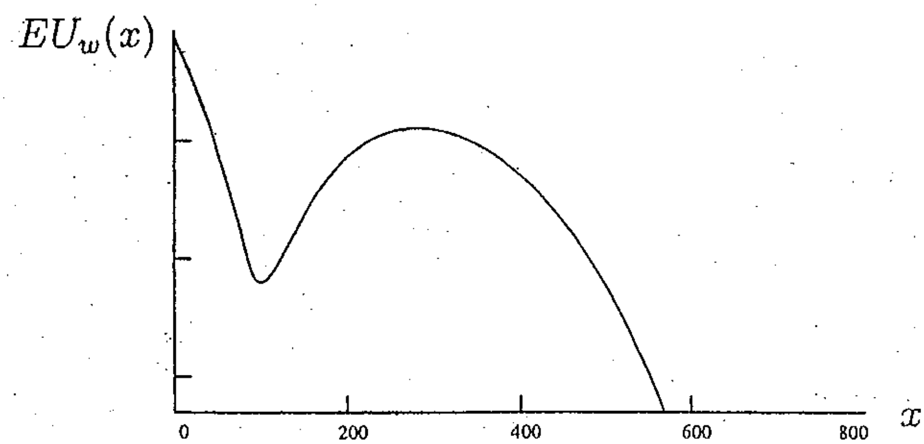

Figure 2

Returning to our base case simulation, the other parameter values chosen are: (i) $\phi_h = 1$, $\phi_l = 0.8$, which reflect the differences in productivity of the high and low productivity types, (ii) a coverage level for insurance of $r = 0.5$, which implies a trigger or guaranteed production level of 50% of average yields achieved in the absence of insurance, and, as described earlier, (iii) $\lambda = 0.96$ (base production function parameter), and (iv) $\alpha = 2.5$, $\beta = 2$ (parameters of the beta distribution). The insurance coverage level in the

[17]In scenarios when producer type is not observable, we adopt the more conservative assumption that the fraction t applies to the input level chosen by low productivity types.

base case is quite low in comparison to real world coverage levels. However, we wanted to start with such a low value to illustrate what happens as we increase that value. In particular, at $r = 0.5$, a minimal input requirement of $t = 0.25$ is sufficient to guarantee interior optima in all scenarios. As the level of insurance coverage rises, however, the minimal input requirement must increase to insure an interior optimum in all cases. For all subsequent simulations, we use $t = 0.5$ as our minimal input requirement and indicate in which cases this turns out to be binding. If we were to relax this constraint by choosing a smaller value of t, the qualitative nature of our results would be maintained but the impact of moral hazard and adverse selection would be magnified. The results of our base case, which are explained in detail below, are provided in the first row of results in Tables 1A, 1B, and 1C. In each table the results of one particular scenario are given as are the production outcomes when insurance is not provided. This facilitates seeing the impact of the incentive effects created by the insurance program for each scenario.

In what follows, when a calculation refers to a high productivity type we use subscript h and when it refers to a low productivity type we use subscript l. In our base case and when only moral hazard is present the two producer types (low and high) receive insurance contracts based on the past experience of producers of their own type when insurance coverage is not in force. With no insurance, the optimal input levels are $x_h = 313$ and $x_l = 310$ for high and low productivity types, respectively, with expected output levels of $Ey_h = 138$ and $Ey_l = 110$ for high and low productivity types, respectively. The trigger value (or coverage level) for the two types is 50% of their risk type specific expected yields (i.e., $y_{ch} = 69$ and $y_{cl} = 55$). Using these trigger values and the type specific yield distributions which apply under the no insurance scenario, the expected indemnities, and hence premiums, are $\rho_h = 5.23$ and $\rho_l = 4.15$.

With these insurance policies, the producers reduce their input use to $x_h = 280$ and $x_l = 279$.[18] With these reduced input levels, expected output levels fall to $Ey_h = 124$ and $Ey_l = 100$ and the average indemnities, at $EI_h = 6.7$ and $EI_l = 5.25$, turn out to be higher than the premiums charged, which were based on yields of producers who did not purchase insurance. The implications of this moral hazard problem are that claims exceed revenues

[18] Due to the flatness of the marginal product of input ($\lambda = 0.96$ implying *almost* constant returns to scale), it is not surprising that the optimal input choices for the two types do not vary much. The different productivity parameters, however, do imply significantly different levels for expected yields, in the ratio of ϕ_h/ϕ_l.

collected in the amounts of 26.6% for low productivity types and 28.0% for high productivity types.[19] The fact that these losses are approximately equal for the two productivity types is not surprising since type specific calculations are used for the insurance premiums and similar input choices by the two types, in conjunction with output being multiplicative in the random variable ω, means the problems are very similar for the two producer types. Different methods of modeling the differences in productivity types, which include quite different relative variances in the yield distributions by type, could lead to qualitatively different outcomes. Our goal, however, is to investigate the differences in overall program costs under different information scenarios (i.e., moral hazard only, adverse selection only, and both combined) and so we do not focus on altering our assumptions to create divergent outcomes for the two productivity types.

Next we model the implications of adverse selection only. That is, we assume the insurer can monitor and enforce any specific level of input desired and so chooses the average input level that the two types of producers use in the absence of insurance. The fact that the insurer cannot distinguish between producer types, however, means that modeling the implications of adverse selection in the absence of moral hazard is somewhat artificial, as discussed in the previous section. This follows because any inefficiency or program costs created by not requiring different input requirements for the two types will be inevitable in this scenario and so program costs induced by insurance will correspond not just to selection problems but also to "inappropriate" input use, which is generally considered a moral hazard problem. Since in our base simulation production is *almost* linear in input and the optimal choices of input level for the two productivity types turn out to be almost identical, it turns out that requiring the two types to use the average input level chosen in the absence of insurance is not problematic per se. Under these conditions, major complications in terms of program costs arise from adverse selection only when high productivity types drop out of the insurance market. Our range of simulations, however, cover various issues associated with adverse selection costs for a public insurance program.

If the insurer is not able to identify which producer is of which type, the insurer's observations of production across producers in the absence of

[19] In the tables we report the probability that insurance is triggered (k_l and k_h) to indicate the relative impact of insurance on producers' decisions on inputs and how these decisions affect the probability of collecting insurance.

insurance represents a mixed probability distribution of the two types. In our base simulation we assume the population of producers is made up of 50% of each type. The result is that expected output in the absence of insurance is the average expected output across types ($Ey_a = 0.5Ey_h + 0.5Ey_l = 124$) and so the trigger value of yield is $y_{ca} = 62$. The expected indemnity, and hence the premium charged using the mixed probability distribution, turns out to be $\rho_a = 4.92$. Once insurance is introduced, the input required of each producer is the average observed in the population (i.e., $x_a = 0.5x_h + 0.5x_l = 311.5$). This means the high productivity types end up using less than what is used in the absence of insurance, while the low productivity types use more. The low productivity types are more likely to make an insurance claim since their probability density function is essentially to the left of that of the high productivity types. It turns out that the high productivity types make a claim with probability $k_h = .09$ while the low productivity types make a claim with probability $k_l = 0.15$ and the average indemnities are $EI_h = 3.67$ and $EI_l = 6.16$. Since both types pay the same premium for insurance and the input level of each type is constrained to be the same as the average input level without insurance, it turns out in this case that the high productivity types subsidize the low productivity types, which is a common characteristic of adverse selection. Overall, the program costs turn out to be negative; that is, the average premium revenue exceeds the average claim, albeit by the insubstantial amount of 0.24%.[20] We checked, as always, whether the expected utility for high productivity types is higher with the insurance plan than without it even though they pay more than the actuarial cost for the insurance. In this case it is and so high productivity types do purchase insurance even though it is offered at terms which are actuarially unfair to them. Substantial program costs can arise from adverse selection if the insurance cost for the high productivity type is sufficiently high that they drop out of the market. If that happens then only low productivity types purchase the insurance and their expected indemnities are generally much higher than the premiums which are computed on the basis of aggregate production when no insurance is available. Of course, the pattern of results can depend on many factors and parameters and so, as with all statements or

[20]Roughly speaking, this occus here because, since production is 'almost' linear, the decrease in productivity from high productivity types due to their reduced input level under insurance is approximately compensated (and can be more than compensated as in this case) by the increase in production from low productivity types due to their increased input level.

conclusions we note from our simulation exercises, these are only suggestive of what one can expect in an actual market setting.

Now consider the scenario in which both adverse selection and moral hazard are present; that is, the insurer can observe neither the input level beyond the minimal that can be required nor the productivity type of any given producer. The insurance premiums, etc., are computed in the same way as above for the adverse selection only case. However, when insurance is offered, the insurer cannot require that the producers use the average pre-insurance amount of input but rather can only enforce the minimal standard requirement, which in this case is the fraction $t = 0.25$ of the minimum input any producer uses in the pre-insurance scenario. Thus, program costs can be exacerbated by the fact that producers may substantially reduce their input levels due to the presence of insurance. This will tend to be the case especially for low productivity types since their insurance coverage is particularly attractive given that the coverage level is based on the average production of all productivity types. In comparison to the case when only moral hazard is present and the trigger value of yield was 55 bushels per acre, in this scenario it is 62 bushels per acre, meaning the set of states of the world under which insurance claims are made is broadened and so the expected marginal benefit from any increase in input is reduced. We see this is the case in this example as insurance induces low productivity types to reduce their input level to $x_l = 270$ compared to the level 279 in the scenario of moral hazard only. High productivity types, on the other hand, have an incentive to use a higher input level than under moral hazard only as their trigger value of yield was higher at 69 in the presence of moral hazard only. The result is that their optimal input choice in this scenario is $x_h = 285$ rather than 280 as it was in the presence of moral hazard only.

The result in this example is that program costs for low productivity types is 70% of premiums collected while the high productivity types subsidize the program in the amount of 9% of premiums. Overall, the average insurance claims represent 30.6% more than premiums collected. This turns out to be higher than for the case of moral hazard, which had a program cost of 26.6% of premiums collected. The program costs as a percentage of premiums collected could, of course, be much higher for the case of moral hazard and adverse selection combined if high productivity types, who subsidize the program, decided to leave the insurance pool.[21] Nonetheless, an interesting

[21] In all cases we check whether expected utility with insurance is higher than without.

aside is that this example, as well as many others, demonstrates that the implications of moral hazard and adverse selection may be super-additive in that the program costs generated by both types of asymmetric information may exceed the sum of the program costs of the two information problems taken in isolation.

We perform 'sensitivity' analysis on our base case by changing the parameter values for the distribution function $g(\omega)$ (i.e., α and β), the value of the exponent of the production function (λ), and the risk aversion coefficient (γ). The results are reported in Tables 1A, 1B, and 1C. Although the implications of all of these changes have economic interest, we focus on the implications of changing parameters of the insurance program and those parameters which are likely to change in a qualitative way the implications of insurance being available. However, a few remarks about the overall results of the sensitivity analysis are in order.

We see that increasing λ to 1 leads to increased input levels in all scenarios while decreasing λ leads to reduced input levels, as would be expected. The effects of changes in the parameter values α and β on the distribution function are illustrated in the figures in Appendix A. The original function $g(\omega)$ is skewed to the left while increasing β to 3 creates a substantially fatter left tail. This reduces the marginal value of increasing x while increasing the advantage to insurance. In the moral hazard only scenario, the result of increasing the probability of bad outcomes has the effect of increasing the probability of claims, enhancing the moral hazard effect (i.e., the reduction in input level resulting from insurance is greater than the base case), and leading to higher program costs. In all simulations there are insubstantial effects on program costs for the scenario of adverse selection only. The intuition for this is the same as described for the base case. The one simulation that gives substantially higher program costs in the scenario with moral hazard and adverse selection is for the case of $\beta = 3$. This follows for the same reasons as for the case of moral hazard only. In fact, this change to the base case has the greatest impact on the program costs of all the changes investigated. The other changes to the parameters of $g(\omega)$ can also be observed in the figures in Appendix A and these have effects which are also not surprising.[22]

Changing the risk aversion coefficient has implications that are also fairly

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If this isn't the case, we re-compute the implications of insurance when removing the relevant decison makers who would leave the insurance pool.

[22] That is, making the left tail thinner (i.e., reducing the probability of bad outcomes) leads to somewhat higher input levels and lower program costs.

intuitive, although one cannot trust intuition too much with so many factors present in such models. However, we see that a less risk averse producer ($\gamma = 0.05$) engages more intensively in this risky activity while a more risk averse person ($\gamma = 0.15$) opts for lower input levels. It turns out that changing the degree of risk aversion has little impact on the implications of insurance in terms of percentage reduction in inputs and program costs. We don't report effects of changing the price of the input or output. As noted earlier, prices are of course unit dependent and our stylized model is not designed to be calibrated to a particular crop or set of units. Moreover, changing price, for example, increases both the variance of the distribution of revenues for any given input level, x, as well as the mean. Hence, an increase in price increases both the mean (marginal) return to increasing x but also the riskiness. Thus, intuition isn't strong as to what one would expect to happen when changing p. We did, however, find that for the case of $\lambda = 0.8$ an increase in p or a decrease in w did lead to an increase in input levels chosen for all scenarios, although we have not reported these results. For the case of $\lambda = 0.96$ the effect was insubstantial.

We now consider changes to parameter values which we anticipate will affect in an important way the relative program costs of insurance in the various scenarios. Results of these simulations are presented in Tables 2A, 2B, and 2C. To begin, increasing the coverage level enhances the incentive to engage in moral hazard and so is expected to increase program costs in the scenario with moral hazard only or with both moral hazard and adverse selection problems persisting simultaneously. We considered the impact of increasing the coverage rate to 70% and 90%. When we increase the coverage level to 70% of average yield, both the high and low productivity types reduce their inputs relative to the no insurance scenario even more than with 50% coverage, as expected. The reduction in input was approximately 10% in the case with 50% coverage, for both types, and 22% in the case of 70% coverage. When the insurance coverage rate is increased to 90%, both types reduce their inputs as much as possible (i.e., the minimal required input level constraint, which is set at 50% of the input level used in the absence of insurance, becomes binding). This is not surprising since 90% coverage of average output is guaranteed and substantial cost savings are obtained by reducing the input level as much as is possible. In the case of moral hazard and adverse selection, the input level is constrained to be the average for the population in the no insurance scenario and so, for the same reasons as were indicated earlier, the program cost created by the lack of information is insubstantial. In fact, this turns out to be the case for all but the last of the simulations (see Table 2B), and so we address this possibility only for this case.

In the case with moral hazard and adverse selection, the terms for insurance cover are based on the mixed distribution of yields in the no insurance scenario and so are relatively more favourable for low productivity types than for high productivity types. The result is that, with 70% coverage, the low productivity types choose the lowest possible input level (i.e., that minimally required that can be enforced) and create very high program costs. The high productivity types choose even a higher input level (261 vs. 245) than in the situation of moral hazard only because the insurance terms are less favourable in this case.[23] The program costs are almost triple what they would be in the scenario of moral hazard only (i.e., 185% of premiums collected vs. 67%).

When we increase insurance coverage to 90%, we find that both low and high productivity types choose the lowest possible input level that they can and so program costs are very large at 236% of premiums collected. With moral hazard and adverse selection, it is also the case that both productivity types choose the lowest possible input level and program costs are approximately the same as for the moral hazard case only. Thus, if the minimal input requirement becomes binding for both productivity types, we find that adding the information problem of adverse selection to moral hazard does not increase program costs. In fact, using 80% coverage level we find, but do not report in Table 2, that in the case of both moral hazard and adverse selection, the insurance terms are sufficiently unfavourable to the high productivity types, in comparison to the case of moral hazard only, that high productivity types do not choose the minimally required input level.[24] The result is that program costs actually fall quite substantially, from 264% of premiums collected to 174%, when one adds the problem of adverse selection (hidden type) to moral hazard (hidden action). Thus, program costs may also be sub-additive, as well as super-additive (as demonstrated in an earlier case), in the information problems faced by the insurer.

The way we have parameterized the difference between high and low pro-

[23]Note that in the scenario with both moral hazard and adverse selection, the second term on the right side of equation (7), which represents the producer's expected payoff when no insurance is collected, becomes more important to high productivity types than in the scenario with moral hazard only.

[24]In the case of moral hazard only $x_h = 156.5$ while in the case with moral hazard and adverse selection, $x_h = 239$.

ductivity types, using parameters ϕ_h and ϕ_l, leads to the outcome that, given the same input level, the low productivity types output is the fraction ϕ_l/ϕ_h of the high productivity types. For all the scenarios discussed above, the low productivity type parameter was 80% of that of the high productivity type. If we increase the degree of heterogeneity between the two types by reducing ϕ_l, one might expect that the problems caused by adverse selection, whether on its own or in conjunction with moral hazard, would be exacerbated. This is seen to occur when we set $\phi_l = 0.6$, with program costs being 50% of premiums collected in the case of moral hazard and adverse selection problems combined, compared to 27.5% in the case of moral hazard only. The reason this happens is that, with low productivity types facing a substantially worse technology than high productivity types, the low productivity types are that much more likely to collect insurance when the insurance coverage is based on average output across types. Note in Table 2 for this case that, when going from the scenario of moral hazard only to that of moral hazard and adverse selection, the low productivity type's probability of collecting insurance increases from 14% to 34% when cover is based on average production while the high productivity types probability of collecting insurance only falls from 14% to 8%. When we increase the difference between types to $\phi_l = 0.4$ (i.e., assuming low productivity types are only 40% as productive as high productivity types), this phenomenon is exacerbated substantially. The low productivity types choose the minimally required input level when both information problems are present, but not in the case of moral hazard only. The result is that program costs rise from 27.5% in the case of moral hazard only to 214% when both information problems are present.

All of the above simulation cases have involved a population of producers made up of an equal number of high and low productivity types. Since adverse selection problems may be sensitive to the precise make-up of the population, we consider what happens to the base case when increasing the proportion of high productivity types to 80%, and then reducing it to 20%. We find the results of these cases to be fairly similar to the base case. With a population composed of 80% high productivity types, low productivity types reduce their input level (from 279 to 264) when both information problems are present compared to the case when only moral hazard is an issue. The reason is that insurance cover for low productivity types is higher when both information problems are present. This increases program costs. However, the majority of producers in this case are high productivity types and they find insurance terms less favourable when both information problems are present and so choose a higher input level than for the case of moral hazard only (i.e., 282 versus 280). The overall result is that program costs are almost identical to the base case for all information scenarios (i.e., the two contrary effects balance out). We also have reported the results of increasing the fraction of low productivity types to 80% (see second last row in Table 2). In this scenario we actually have slightly lower program costs for the moral hazard and adverse selection scenario than in the base case. This may seem peculiar at first glance since increasing the fraction of low productivity types might be expected to lead to an increase in program costs when types cannot be identified. However, when the population is composed of 80% low productivity types, the insurance terms with both information problems present are not so favourable to low productivity types (i.e., compared to the base case with only 50% low productivity types). This leads to the result that, in the scenario with both adverse selection and moral hazard, low productivity types choose a somewhat higher input level (276 vs. 270) than in the base case. Of course, the insurance terms are also worse for high productivity types in this case and they also choose a higher input level than in the base case (288 vs. 285). Thus, the information costs imposed on the insurer due to adverse selection and moral hazard combined can actually be smaller when the fraction of low productivity types is higher.

In all cases discussed thus far, the high productivity types have never been "forced" out of the market when adverse selection persists, whether on its own or in conjunction with the moral hazard problem. One reason this is so is that in our model of a public insurance plan, insurance terms are determined by the yield distribution of producers in the absence of insurance and no change is made once experience on claims is acquired. In a private market setting, of course, this would not be the case and so 'excess claims' due to information problems would lead to rising prices. This may induce high productivity types to leave the insurance pool and drive prices even higher, leading to an adverse selection death spiral.[25] Nonetheless, it is certainly possible in our model of public insurance to create cases in which high productivity types find insurance terms too unfavourable to participate in the program. Our last simulation case demonstrates this possibility. By simultaneously adopting the changes to the base case as indicated by the parameter change

[25]This may be especially so if there is heterogeneity in preferences among high productivity types, with the less risk averse being less willing to pay an excess premium and so being 'first' to leave the market, with more risk averse high productivity types to follow their lead once price starts to rise.

noted *set #1* in Table 2 (last row), we generate an example in which high productivity types do not participate in the market both in the scenario of adverse selection only and in the case of moral hazard and adverse selection problems arising simultaneously. In this case we have low productivity types having very poor technology ($\phi_l = 0.08$), a large fraction of low productivity types ($q_l = 0.8$), along with a fairly high coverage level of 70% of average yield. Thus, program costs are not insignificant for the scenario of adverse selection only, and this is the only instance in which we have such an outcome for this scenario. For this example a cautionary note in interpreting the results in the table is necessary. Since for this simulation low productivity types pay such a small premium in the moral hazard only case, the percentage program costs are misleading in that the absolute program costs are not very high. In fact, the absolute program costs are much higher in the adverse selection only scenario (4.0 vs. 1.0 per acre per contract), and higher yet for the scenario with both moral hazard and adverse selection (10.2 per acre per contract). For all other simulation results reported, the percentage cost figures are not misleading in this way.

5 Conclusions

The model and simulations in this paper show that the implications of the information problems associated with moral hazard and adverse selection can combine in quite complex ways to affect the program costs of a publicly provided crop insurance plan. By comparing the program costs under the information scenarios of (i) moral hazard conditions only, (ii) adverse selection conditions only, and (iii) both conditions persisting simultaneously, we have shown that the costs of these two information problems can be either sub-additive or super-additive. By adopting a wide variety of examples which use different sets of parameters and assumptions, we have given some guidance regarding how one can attribute program costs to these various information problems. It is important to note that such advice is very provisional due to consideration of all the factors that can affect our results. However, one novel and useful finding of our work has been to show that since program costs may be superadditive, then solving one or the other information problem may be more effective than one might have expected. Thus, suppose it is not very costly to solve one of these information problems but very costly to solve the other. If it is the joint influence of these problems that is creating large costs then it may not matter which of the two information asymmetries is corrected and so the cheaper problem to solve becomes the obvious candidate for attention.

Regarding the lessons we have learned from this work, perhaps most important is the recognition that in order to understand or anticipate program costs of a public insurance program one must pay careful consideration to many aspects and parameters of the activity being insured. These include those aspects regarding production technologies (or the activity being insured), population proportions of different types of producers, design features of the insurance plan, and the risk preferences of the clients. One must also pay close attention to the design features of the insurance plan and how all of these factors interact in creating an insurance environment and set of outcomes. Of particular interest, we believe, are our results associated with combining the information problems of moral hazard and adverse selection. In our simulations, we found program costs of adverse selection on its own to be minimal. Although this is due in part to the fact that we adopted certain symmetries in the production relations of the two types of producers in our model, these results were nonetheless quite robust to variations in our parameter choices. Only in the case when higher productivity types are driven from the market did we see substantial program costs resulting from adverse selection problems occurring in isolation. If only the problem of adverse selection persists in an insurance setting, then this problem could eventually be corrected if the insurance provider were to base its claim frequency on the data of those insured, rather than using data based on a population of non-insured producers. However, when both adverse selection and moral hazard problems persist in an insurance setting, then the program costs that can be assigned to the information problem giving rise to adverse selection may be quite large even when high productivity types are not driven out of the insurance market.

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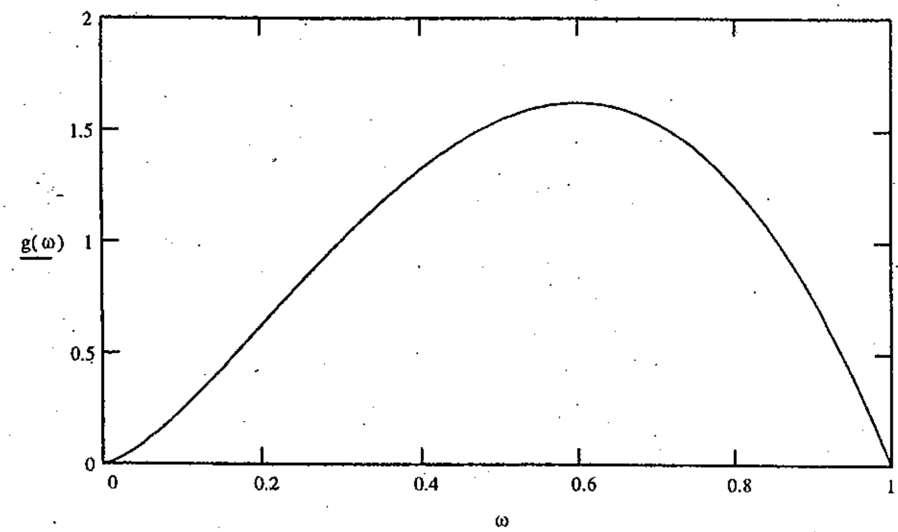
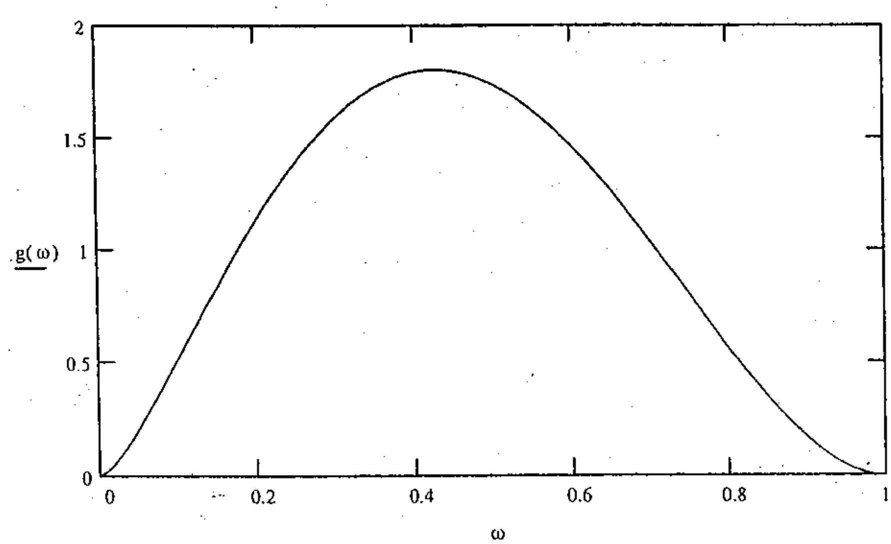
Appendix

Following are graphs of the various cases of the beta distribution used in the simulations.

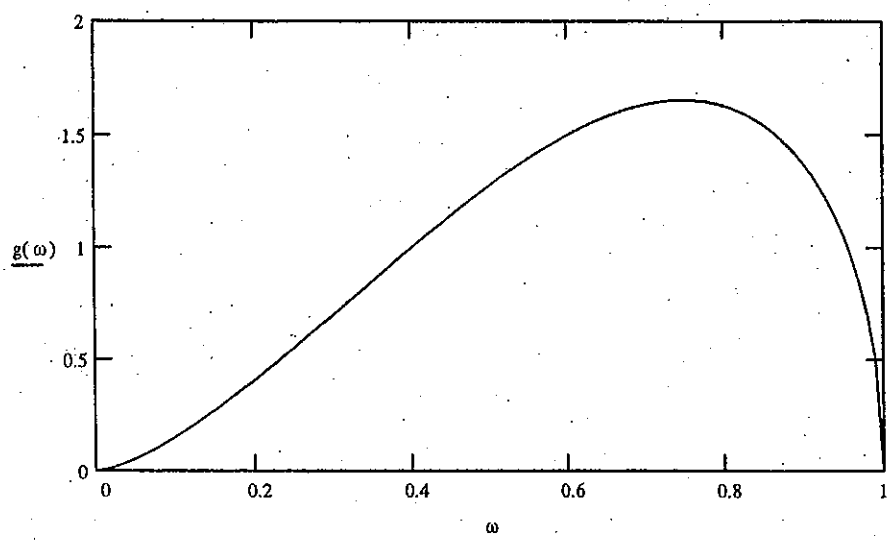
$\alpha = 2.5 \qquad \beta = 2$



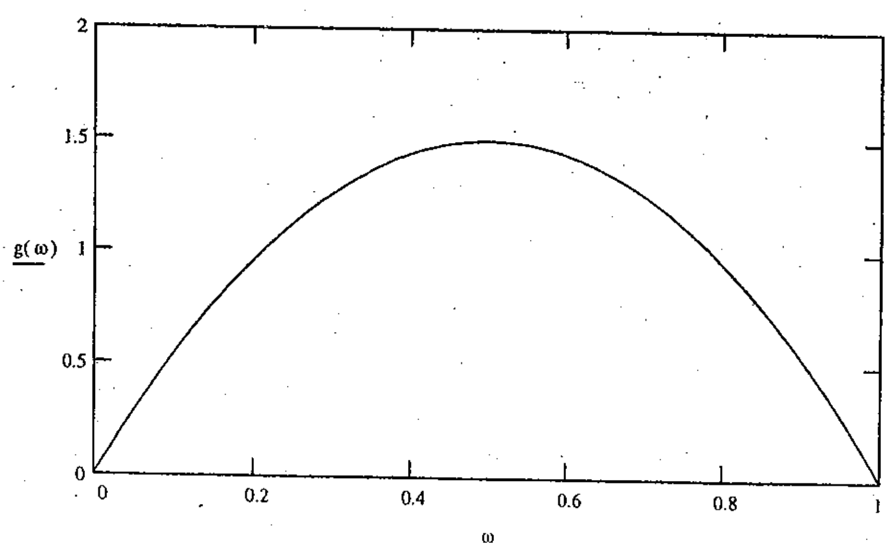
$\alpha = 2.5 \qquad \beta = 3$



$\alpha = 2.5 \qquad \beta = 1.5$



$\alpha = 2 \qquad \beta = 2$



$\alpha = 3 \qquad \beta = 2$

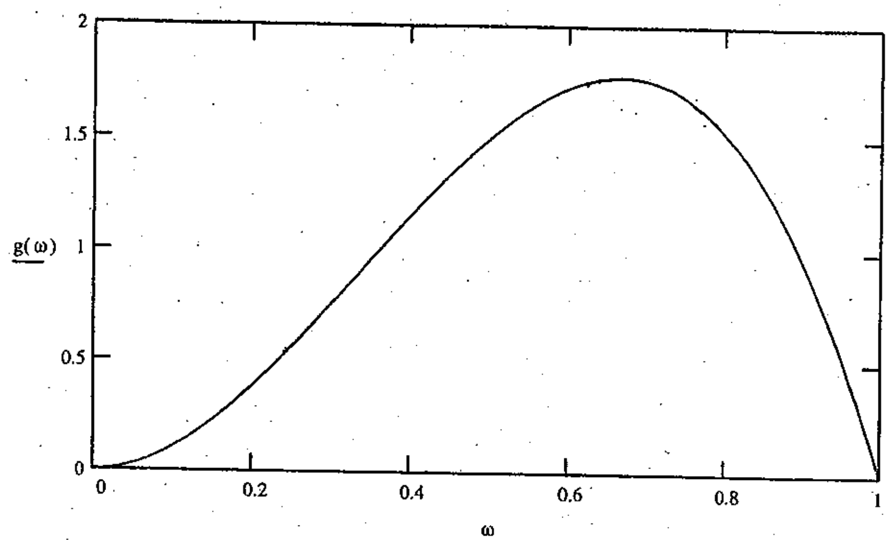


Table 1A
Base Case and Sensitivity Analysis
Moral Hazard Only

Parameters for Base Case

Distribution of random variable ω: $g(\omega) \sim \text{Beta}(\alpha, \beta)$, $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$;
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance				Moral Hazard Only							
	Input		Expected Output		Input		Expected Output		Prob. of claims		Program Costs (%)	
	x_l	x_h	Ey_l	Ey_h	x_l	x_h	Ey_l	Ey_h	k_l	k_h	c_l	c_h
Base	310	313	110	138	279	280	99	124	0.14	0.14	27	28
$\lambda = 1$	326	327	145	182	291	292	129	162	0.15	0.15	30	30
$\lambda = 0.8$	244	250	36	46	220	226	33	42	0.14	0.14	21	21
$\beta = 3$	304	307	88	111	250	252	73	92	.20	.20	51	51
$\beta = 1.5$	314	313	125	156	297	298	118	148	.11	.11	14	12
$\alpha = 2$	248	250	80	100	221	223	71	90	.19	.19	22	22
$\alpha = 3$	374	373	142	177	337	338	128	161	.11	.11	32	30
$\gamma = 0.05$	621	626	213	269	558	559	192	241	.14	.14	27	28
$\gamma = 0.15$	207	209	74	94	186	187	67	84	.14	.14	26	28

Table 1B
Base Case and Sensitivity Analysis
Adverse Selection Only

Parameters for Base Case

Distribution of random variable ω: $g(\omega) \sim \text{Beta}(\alpha, \beta)$, $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$,
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance			Adverse Selection Only				
	Input		Expected Output	Input	Expected Output	Prob. of claims		Program Costs (%)
	x_l	x_h	Average	$x_l = x_h$	Average	k_l	k_h	Overall
Base	310	313	123.9	312	123.8	.15	.09	-0.23
$\lambda = 1$	326	327	163.4	326.7	163.4	.15	.09	-0.04
$\lambda = 0.8$	244	250	41	247	41	.15	.09	-0.58
$\beta = 3$	304	307	99.5	305.5	99.4	.17	.11	-0.24
$\beta = 1.5$	314	313	140.3	313.7	140.3	.13	.07	-0.05
$\alpha = 2$	248	250	89.9	248.9	89.8	.19	.13	-0.13
$\alpha = 3$	374	373	159.1	373.5	159.1	.11	.06	.10
$\gamma = 0.05$	621	626	241.0	623.4	241.0	.15	.09	-0.25
$\gamma = 0.15$	207	209	84.0	208.0	84.0	.15	.09	-0.27

Table 1C
Base Case and Sensitivity Analysis
Moral Hazard and Adverse Selection

Parameters for Base Case

Distribution of random variable ω: $g(\omega) \sim \text{Beta}(\alpha, \beta)$, $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$;
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance				Moral Hazard and Adverse Selection						
	Input		Expected Output		Input		Expected Output		Prob. of claims		Program Costs (%)
	x_l	x_h	Ey_l	Ey_h	x_l	x_h	Ey_l	Ey_h	k_l	k_h	Overall
Base	310	313	110	138	270	285	96	126	.20	.11	31
$\lambda = 1$	326	327	145	182	283	297	126	165	.20	.11	33
$\lambda = 0.8$	244	250	36	46	212	230	32	43	.19	.10	25
$\beta = 3$	304	307	88	111	232	262	68	95	.30	.15	61
$\beta = 1.5$	314	313	125	156	293	301	117	150	.15	.08	14
$\alpha = 2$	248	250	80	100	215	227	69	91	.25	.15	14
$\alpha = 3$	374	373	142	177	327	344	124	164	.16	.07	36
$\gamma = 0.05$	621	626	213	269	541	571	187	246	.20	.11	31
$\gamma = 0.15$	207	209	74	94	181	191	65	86	.20	.11	30

Table 2A
Simulation Results II
Moral Hazard Only

Parameters for Base Case

Distribution of random variable ω: $g(\omega) \sim Beta(\alpha, \beta)$, $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$;
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance				Moral Hazard Only							
	Input		Expected Output		Input		Expected Output		Prob. of claims		Program Costs (%)	
	x_l	x_h	Ey_l	Ey_h	x_l	x_h	Ey_l	Ey_h	k_l	k_h	c_l	c_h
Base	310	313	110	138	279	280	99	124	0.14	0.14	27	28
r = 0.7	310	313	110	138	243	245	87	109	0.38	0.38	67	67
r = 0.9	310	313	110	138	155*	157*	56	71	0.99	0.99	236	236
$\varphi_l = 0.6$	308	313	82	138	277	280	74	124	0.14	0.14	27	28
$\varphi_l = 0.4$	303	313	54	138	272	280	48	124	0.14	0.14	27	28
$q_h = 0.8$	310	313	110	138	279	280	99	124	0.14	0.14	27	28
$q_h = 0.2$	310	313	110	138	279	280	99	124	0.14	0.14	27	28
set #1	52	313	2	138	26*	245	1	109	0.8	0.38	290	67

NOTES: * Input level is the minimally required input level.
set #1: r = 0.7, $\varphi_l = 0.08$, $q_h = 0.2$.

Table 2B
Simulation Results II
Adverse Selection Only

Parameters for Base Case

Distribution of random variable ω: g(ω) ~ Beta(α, β), $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$,
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance			Adverse Selection Only				
	Input		Expected Output	Input	Expected Output	Prob. of claims		Program Costs (%)
	x_l	x_h	Average	$x_l = x_h$	Average	k_l	k_h	Overall
Base	310	313	123.9	312	123.8	.15	.09	-0.23
r = 0.7	310	313	123.9	312	123.8	0.30	0.19	-0.21
r = 0.9	310	313	123.9	312	123.8	0.50	0.32	-0.18
$\varphi_l = 0.6$	308	313	110	310.5	110	0.22	0.07	-0.89
$\varphi_l = 0.4$	303	313	96	308	95	0.38	0.05	-2.6
$q_h = 0.8$	310	313	132	312	132	0.17	0.10	-0.17
$q_h = 0.2$	310	313	115	311	115	0.13	0.08	-0.13
set #1	52	313	29	$x_l = 104$	$Ey_l = 4$	1	N.A.	12

set #1: r = 0.7, $\varphi_l = 0.08$, $q_h = 0.2$. This set of parameter values leads to high productivity types dropping out of the market.

Table 2C
Simulation Results II
Moral Hazard and Adverse Selection

Parameters for Base Case

Distribution of random variable ω: g(ω) ~ Beta(α, β), $\alpha = 2.5$, $\beta = 2$;
Prices of input and output: $p = 2.2$, $w = 0.75$;
Production function parameters and risk aversion coefficient: $\lambda = 0.96$, $\varphi_h = 1$, $\varphi_l = 0.8$, $q_h = 0.5$, $q_l = 0.5$, $\gamma = 0.1$;
Insurance parameters (minimal input requirement - t, and coverage level - r): $t = 0.25$ (0.5 for all other cases), $r = 0.5$ (i.e., 50%).

Change to Base Case	No Insurance				Moral Hazard and Adverse Selection						
	Input		Expected Output		Input		Expected Output		Prob. of claims		Program Costs (%)
	x_l	x_h	Ey_l	Ey_h	x_l	x_h	Ey_l	Ey_h	k_l	k_h	Overall
Base	310	313	110	138	270	285	96	126	.20	.11	31
r = 0.7	310	313	110	138	155	261	56	116	0.92	0.27	185
r = 0.9	310	313	110	138	155	155	56	70	1	0.94	226
$\varphi_l = 0.6$	308	313	82	138	247	290	66	128	0.34	0.08	50
$\varphi_l = 0.4$	303	313	54	138	151*	295	28	130	1	0.06	214
$q_h = 0.8$	310	313	110	138	264	282	94	125	0.24	0.13	31
$q_h = 0.2$	310	313	110	138	276	288	98	128	0.16	0.09	28
set #1	52	313	2	138	26	N.A.	1	N.A.	1	N.A.	31

NOTES: * Input level is the minimally required input level.
set #1: $r = 0.7$, $\varphi_l = 0.08$, $q_h = 0.2$. This set of parameter values leads to high productivity types dropping out of the market.