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Essays on Externalities and Uncertainty:
On the Role of Disaster Insurance in Improving Welfare

By

Thomas Wendell Sproul

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural & Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor David Zilberman, Chair
Professor Gordon Rausser
Professor Benjamin Hermalin

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Abstract

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This dissertation evaluates risk management for disasters where the losses unfold over time, with two key applications: environmental accidents and exceptional losses in crop production. Both applications evaluate policy against goals of equity and efficiency, but the environmental policy application is a normative analysis, while the production risk application is a positive analysis.

Environmental accidents are stochastic externalities – they impose a social cost not accounted for by whichever business constitutes their source. In many cases, adequate regulation does not exist. We show that standard pollution regulations must be adjusted for accidents, because random triggers and unobservable actions lead to a moral hazard problem. We identify three policies that lead to the optimal solution when both care and cleanup are considered: strict liability, a stochastic subsidy, and a mandatory mutual insurance scheme.

The subsidy policy may be very costly to taxpayers, especially when prevention affects the probability of accident occurrence, and strict liability may be excessively draconian; polluters are also victims and liabilities must exist regardless of adherence to professional standards of care. Thus, we propose a new policy of liability risk-pooling, which demonstrates a role for insurance policy among accidentally polluting firms, even when such firms are profit-maximizers (that is, they are risk neutral). The new policy also generates, in expectation, the most equitable distribution of resources among polluting firms while preserving efficiency – in this sense it is the stochastic equivalent of a system of tradable pollution permits.

Our second application addresses production risk in US crop production and the impact of the SURE disaster support program in the 2008 Farm Act. Supplemental disaster insurance is nested insurance, an insurance policy on top of another insurance policy, which may actually increase riskiness in the distribution of outcomes. Thus, we evaluate whether, and under what circumstances, nested insurance actually provides risk management. We develop a comprehensive economic theory of nested insurance, and provide new insight into the concept of targeted subsidies, which use kinked insurance pricing to limit variation in farmers' coverage purchasing decisions.

The theoretical evaluation is supported by an in-depth simulation analysis, which simulates the joint price-yield distribution for dramatically different risk profiles of Illinois corn and South Dakota wheat. Using a time series of county- and national-level yields and expected and realized commodity prices, we construct a simulated revenue distribution over which a representative farmer can maximize expected utility. We show that disaster policies may distort acreage and insurance choices, but that these distortions are likely small. Distortions are largest for the primary beneficiaries of the SURE program, the most risk-neutral farmers, who are least in need of risk management.

Both applications take a classical, welfare economic approach to policy. In the environmental case, considerations of equity play a larger role as a result of uncertainty, whereas in the crop insurance case, nested insurance is shown to behave more like a stochastic subsidy than actual risk management. Overall, we have shown that managing the risk from disasters across varying economic agents can lead to dramatic distributional implications. When more than one efficient policy is available, then the distributional characteristics of policies will be the deciding factor. However, when equity is the objective, poorly designed disaster policies can backfire and be of little use to those who need them most.

To my parents, Daniel and Cecily.

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Thomas Sproul
May 9, 2011

Chapter 1. Introduction

A disaster is an atypical event characterized by severe loss or damage. While many definitions emphasize suddenness, as when 'disaster strikes', there are in fact a number of occurrences treated as disasters where the losses unfold over time, losses which may be influenced by policies and by the actions of parties involved. This dissertation evaluates two such examples: environmental accidents and exceptional losses in crop production. We examine environmental accidents, like the recent BP Horizon oil spill in the Gulf of Mexico, where the 'disaster' itself constitutes an extended period of environmental damage (oil leaking into the ocean), followed by an even longer period of cleanup and economic recovery. We also examine the case of corn and wheat farming, where a disaster could be instantaneous (like a tornado wiping out all crops) or it could simply be an unusually dry year where the 'disastrous' result is the realization of little or no revenue at the time of harvest. The key policy challenge in both cases is effectively managing risk.

The dissertation consists of two body chapters, each an application to different aspects of disaster insurance policy. Common to the two applications are the evaluation of policy design against goals of equity and efficiency, but each application is different. The environmental policy application is more normative – in it we propose a new type of disaster insurance policy, and demonstrate that this new policy achieves economic efficiency while improving the equitable distribution of resources, compared to other efficient policies. On the other hand, the production risk application is more of a positive analysis - it evaluates the introduction of formalized disaster insurance policy into crop insurance markets, and shows where this new policy may fail to provide risk management beyond existing, available crop insurance.

Our first application addresses environmental and environmental health risks by considering regulation of environmental accidents. Environmental accidents are stochastic externalities – they impose a social cost not accounted for by whichever business constitutes their source. In many cases, comprehensive regulations do not exist for environmental accidents or the rules of the game are imposed on an ad-hoc basis once a disaster occurs. In other cases, like off-shore oil drilling, policies like OCSLA and CERCLA are in place to help pay for the social costs of cleanup and lost revenues but the policies are unlikely to perfectly align incentives for the potential polluters with social objectives, as shown in Chapter 2.

In evaluating environmental accident regulation, we show that standard pollution regulations must be tweaked to account for the inherent randomness of environmental accidents. The involvement of random triggers and unobservable actions on the part of potential polluters leads to a moral hazard problem where incentives are more difficult to align with social objectives. As a result of these issues, environmental accidents are not adequately addressed by the deterministic environmental policy literature - that of Pigouvian taxes, abatement subsidies and cap-and-trade. Existing policy proposals to handle environmental accidents (as opposed to deterministic pollution) lack sophistication from an economic modeling standpoint; they fail to simultaneously consider the essential roles of both up-front preventive care and after-the-fact cleanup. As a result, policy recommendations of previous literature may only produce socially desirable outcomes in the sense of economic efficiency.

Not only do these policies ignore equity considerations, but they fail to recognize that the presence of uncertainty leads to larger equilibrium variations in the distribution of wealth across individuals. We identify three policies that lead to the optimal solution when both care and cleanup are considered: strict liability, a stochastic subsidy, and a mandatory mutual insurance scheme. The subsidy policy may be very costly to taxpayers, especially when prevention affects the probability of accident occurrence, and strict liability may be excessively draconian; polluters are also victims and liabilities must exist regardless of adherence to professional standards of care.

Thus, we propose a new policy of liability risk-pooling, which demonstrates a role for insurance policy among accidentally polluting firms, even when such firms are profit-maximizers (that is, they are risk neutral). The new policy also generates, in expectation, the most equitable distribution of resources among polluting firms while preserving efficiency – in this sense it is the stochastic equivalent of a system of tradable pollution permits.

Our second application addresses production risk in an application to crop production in the United States. Specifically, we evaluate the disaster support program (SURE) of the 2008 Farm Act, and compare it to the ad-hoc provision of disaster payments it is intended to replace. Supplemental disaster insurance is an interesting form of risk management because it is nested insurance, an insurance policy on top of another insurance policy, which may actually increase riskiness in the distribution of outcomes. Thus, in this application, the focus is evaluating enacted disaster insurance policies to show whether, and under what circumstances, they meet their stated goals as well as other apparent social objectives of providing insurance.

Critical to this evaluation is the adequacy of other existing insurance mechanisms and the risk management they provide. We start by developing a comprehensive economic theory of decision-makers faced with nested insurance. In doing so, we demonstrate some of the theory behind targeted subsidies, which use non-differentiable insurance pricing to limit variation in farmers' coverage purchasing decisions. The main contributions of the theoretical section of this chapter are developing an approximation for farmer indifference between various disaster support policies, and deriving predictions regarding the role of risk aversion in farmer input choices and the potential impact of disaster assistance.

The theoretical evaluation of nested insurance is supported by an in-depth simulation analysis. Because of correlations between price and yield for many agricultural cash crops, and the potentially high correlation of yields across farms (Miranda and Glauber, 1997), revenue insurance requires estimation of a joint price-yield distribution. Using a time series of county- and national-level yields and expected and realized commodity prices, we construct a simulated revenue distribution over which a representative farmer can maximize expected utility. The simulation analysis is then used to demonstrate and quantify our theoretical predictions and verify that they are robust to varying risk preference specifications and to the dramatically different risk profiles of Illinois corn and South Dakota wheat.

We show that disaster policies may distort acreage and insurance coverage choices through farmers' efforts to capture additional rents, but that these distortions may be mitigated by careful policy design and by market constraints such as inelastic acreage. It is also shown that the policy does not meet likely equity goals of helping those farmers who are most in need of risk management – the primary beneficiaries of the SURE program are the most risk-neutral farmers, those who need it *least*.

The remainder of this dissertation is structured as follows. Chapter 2 consists of a new conceptual model of stochastic externalities and the resulting proposal for a new insurance policy for an industry of accidental polluters. Chapter 3 contains a presentation and analysis of existing crop insurance policy and its interaction with supplementary disaster insurance, and Chapter 4 concludes. Bibliographic references follow Chapter 4, and are then followed by the Appendix, containing all of the tables referenced in Chapter 3.

Chapter 2. Accidents Happen:

The Effect of Uncertainty on Environmental Policy Design

2.1 Introduction: The Accidents Problem

Accidents happen to all of us. In the course of our everyday lives, or in the course of operating a business, we all bear the risk of things going wrong. An externality is created when accidents harm others, or impose costs on them, and one does not account for the social costs of risky behavior - as when preventive activities may reduce the likelihood or severity of harms. The element of randomness inherent in stochastic externalities, which include environmental accidents such as the BP spill in the Gulf of Mexico, the chemical plant explosion at Bhopal, or livestock disease outbreaks of avian or swine flu, has important implications for environmental policy design.

Classical environmental economic policy was developed around externalities created with relative certainty, like the emissions of a coal plant, which are necessary to energy production at some level. We focus on the 'holy trinity' of environmental economic policy: Pigouvian taxes, abatement subsidies, and systems of tradable pollution permits (TPPs), as described in Baumol and Oates (1988). While all of these policies can achieve optimal levels of pollution, the difference lies in the allocation of resources; taxes take money out of the polluting industry, subsidies transfer money in, and tradable permits (or 'cap-and-trade') keep all monies within the industry, but shift funds from 'dirtier' to 'cleaner' firms in equilibrium. Due to the differing resource allocations among optimal policies, political economic considerations may affect which policy is actually used, with industry preferring subsidies, then cap and trade, then taxes (Buchanan and Tullock, 1975).

In this chapter, we introduce a conceptual framework for regulating an industry of risk neutral, stochastically polluting firms. We develop a general model allowing for information asymmetry, prevention and cleanup actions (both *ex ante* and *ex post*), and for the exact prevention mechanism to affect the probability and/or severity of accidents. The information asymmetry exists because polluters have better information; it may be very costly to know the costs of prevention and cleanup technologies for every firm in a large industry, and pollution being stochastic means the regulator cannot necessarily infer the agents' activities. Thus, we focus on optimizing price-based policies of taxes and subsidies because quantity-based regulations, such as TPPs, standards or command-and-control policies, are not always possible (Zivin et al., 2005). In this setup, we demonstrate uncertainty-adjusted versions of tax and subsidy policies, but show that uncertainty may exacerbate discrepancies between resource allocations when compared to the deterministic setting.

The key results show that tax policy must take the form of strict liability, equivalent to a pricing system where the accidental polluter owes for the social cost of all pollution, even though they do not supply the random trigger. In essence, agents' actions are key components of the risk-generation process (Lichtenberg and Zilberman, 1988), a concept used to model the development and interaction of risk factors over time. The agents play a key - and exclusive - role in influencing if, and how much, damage will occur, even though they are also accident victims themselves. Strict liability can be a politically (or some argue, morally) unpalatable solution, because accidental polluters need not have violated social norms or professional standards of care when they are forced to pay.

While tax policies take money out of the polluting industry (funds which might theoretically be used to compensate the people harmed), subsidy policies establish incentives by transferring money into the industry; this relationship holds true for established, deterministic policies, as well as for their stochastic counterparts which we introduce here. We demonstrate that subsidy transfers into the industry may increase under uncertainty because subsidies must pay for reductions below a threshold *in every period*, even when no accident occurs. Given the possibility of ability-to-pay or political economic constraints for the optimal tax and subsidy policies, we introduce a novel policy of mutual insurance, which attains optimal outcomes and leads to a resource allocation similar to that of tradable permits.

This paper is, by no means, the first to examine regulation of stochastic externalities. However, we introduce a key consideration that is not present in the relevant literature: the tradeoff between care and cleanup. The basic idea here is that economic agents (also individuals, firms, or farms, herein) face choices of ex ante care (also caution, precaution, prevention) to decrease the probability of an accident and/or its severity, and *ex post* containment (also cleanup, mitigation, abatement) to lessen the harm to others once an accident occurs. Accidents releasing hazardous materials into the environment follow precisely this pattern; precautionary activities may include the imposition of safety controls and worker training, while mitigation efforts include notifying the public, or proper authorities, and actual cleanup of pollutants released.

Thus, the primary innovation in this chapter is the new, generalized conceptual framework. Prior attempts have focused on only prevention, or only cleanup, but none have combined both considerations in a meaningful way. Puelz and Snow (1998) make an effort in this direction, but focus on issues of uncertainty with respect to legal outcomes and enforcement, like much of the law and economics literature (e.g., Shavell (1993), Innes (1999b), Kolstad et al. (1990), Friehe (2010)). They show that audit costs of evaluating damages leading to discrete jumps in the 'penalty' function, and incomplete reporting for small losses. We also add generality to the prevention mechanism by considering efforts that affect both probability and severity of accidents occurring. While previous work has ultimately shown that either myopic mechanism will yield equivalent results in a comparative statics analysis,[1] none has accounted for the differing effects of these mechanisms on the menu of optimal policy choices available. We show that these considerations ultimately do matter, because the resulting moral hazard considerations limit how subsidy or compensation policies can actually pay stochastic polluters.

Other relevant literature can be grouped into three basic categories, beyond the classical externalities literature derived from deterministic

[1] Please see the later discussion of ideas advanced by Becker, Quiggin and Shogren.

frameworks. First, there is a literature of optimal second-best regulation under uncertainty, where the uncertainty arises from measurement error or information asymmetry, starting with Weitzman (1974) and including the agency literature of Holmstrom (1982) and many more. These articles do not focus on externalities *per se*, but instead deal with regulatory information problems, whereby efficiency conditions are difficult to meet. Our framework incorporates some of these informational challenges to inject realism into the analysis; we allow agents' actions and their types, or inherent characteristics, to be unobservable to the regulator - and we demonstrate conditions under which the policies we propose are robust to the resulting problems of moral hazard (actions unobservable) and adverse selection (types unobservable). We also show that policies must remain adaptive to state-dependent outcomes, where the optimal levels of pollution and containment efforts will depend on the state of nature, because price or quantity controls fixed ex ante are constrained to be second-best (Weitzman).

Beyond issues of uncertain information, there is literature on regulating stochastic externalities which is concerned with uncertainty due to randomness of outcomes. However, these papers often use simplified models, where accidents have fixed severity and where the key results are driven by risk preferences. For example, Just and Zilberman (1979) rely on risk preference to demonstrate the asymmetry of taxes and subsidies for stochastic externalities, as do Zivin et al. (2005) when evaluating Coasean bargaining under a continuum of property rights regimes. While it is clear that the Coase Theorem can hold for stochastic externalities under risk neutrality, the implications for classical environmental policy and the associated political economic considerations have not been explored. Risk neutrality is an appropriate starting point for the analysis because our framework focuses on large, infrequent environmental accidents, of which the perpetrators are generally large corporations (who act as profit maximizers). The lack of risk preference is also a staple of welfare economics; it implies that 'pure transfers' do not change aggregate welfare - which, in this context, allows for a straightforward comparison of stochastic externality policies vis-a-vis deterministic ones.[2]

Finally, there is the classic accidents literature,[3] which has evaluated legal liability standards according to economic efficiency measures, like Pareto optimality. However, the frameworks have focused only on *ex ante* care choices (Edlin (1994), Shavell (1985) and (1987), Landes and Posner (1983)),[4] or *ex post* remediation of damages (Innes (1999b)), which limits the scope of their policy prescriptions. For example, the idea of due care, where liability is limited or zero when precautions conform to industry or social norms, focuses on cases where inputs (risky behaviors) are observable.

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[2] Zivin and Small (2003) have shown that actions can be invariant under risk-aversion for both parties, though it requires strong assumptions: all agents have known, identical, constant absolute risk aversion utility functions. Outside this special case, it is clear that analytical results will be driven by assumptions about utility functions and endowments.

[3] e.g., Shavell (1980), Polinksy (1980), Cooter and Porat (2000), among many.

[4] These papers do, however, focus on the role of outside parties (victims) in the probability of an accident occurring. Here, we focus on one party's ability to control the extent of damages incurred by others.

Unfortunately, the due care approach can only be optimal when *ex post* containment efforts are nonexistent, or regulated similarly. Our paper innovates by introducing a general, and complex, risk generation function allowing for ex ante and ex post damage control activities, and for prevention that acts on probability and/or severity of accidents. We focus on liability-based regulation to address cases where outcomes are observable, but risky inputs may not be. This approach is especially useful for heterogeneous polluting firms - because varying risk profiles imply varying standards of due care, with attendant information requirements that may be costly to obtain.

We start the analysis by developing optimal stochastic externality taxes, to show that only a system with the marginal incentives of strict liability can obtain socially optimal outcomes when standards or quantity-based policies are infeasible. That is, the regulator needs no information about agents' choices, as long as the damages can be measured and traced to their source.[5] Unfortunately, strict liability can mean imposing a large fine on a party that has already suffered a substantial loss. This may be socially distasteful, politically infeasible, or practically impossible if there are bankruptcies, which is the so-called judgment-proof problem (see for example, Shavell (1986), Beard (1990), Polborn (1998), Innes (1999a)).

When a strict liability regime is infeasible, we derive a subsidy policy which can attain the social optimum even when agents must voluntarily opt-in, or when they are judgment-proof. To demonstrate this policy in a broad setting, we provide a general framework for the accident mechanism and the effects of precautionary activity, agnostically allowing for precaution to affect the yes/no probability of an accident occurring and/or the severity of an accident if it does occur. Our framework supports Quiggin's (1992, 2002) contribution that comparative statics results are unchanged whether care efforts affect severity (self-insurance) or accident probability (self-protection), as defined in Ehrlich and Becker (1972), but we show that these features do affect the optimal design of subsidy policies, and the volume of transfers into the polluting industry that they require. Specifically, we show that self-protection forces the subsidy to pay in every period, even if no accident occurs, and we show that self-insurance forces the subsidy to pay for all reductions below a decoupled threshold, rather than paying for actual pollution reductions. In the agnostic case of either prevention mechanism being active, both prescriptions hold and the optimal subsidy amounts to an ex ante bribe for agents to participate in the strict liability regime.

In cases where high costs make subsidies infeasible, we propose a system of mandatory insurance which can still reach an optimal solution. This policy induces optimal choices of care and cleanup, but it keeps all monies within the polluting industry in expectation, so it is budget-neutral. The insurance policy thus has parallels to existing policies, like a carbon tax, whereby optimal behavior is induced but no payment is made to the parties suffering from global warming. In addition, we show that the within-industry distribution of resources

[5] For a thorough review of optimal regulation when damages cannot be traced, see Segerson (1988), Swierzbinski (2002), and Millock et al (2002) for theory on collective punishment, Ribaudo and Caswell (1999) for documentation of actual policy using the threat thereof, and Hamilton and Zilberman (2006) for an evaluation of voluntary traceability to capture consumer willingness-to-pay.

under this policy is similar to that of tradable pollution permits; 'dirtier' firms end up subsidizing 'cleaner' firms according to the disparities between their optimal levels of pollution.

The next section introduces a general framework of decision-making under uncertainty (a principal-agent game), with the innovation that agents' actions before *and* after the accident can affect economic outcomes. Then, we develop optimal tax and subsidy policies, demonstrate the key results, and introduce a mutual insurance policy which is revenue-neutral for the regulator in expectation. We conclude with a discussion of policy implications and areas for future research.

2.2 Optimal Regulation of a Stochastically Polluting Industry

We frame the accidents problem in terms of a principal-agent game between one regulator and a continuum of accident-prone agents, representing an industry. The regulator sets the rules of the game, recognizing the social cost of potential and realized accident damages, with the objective of maximizing total welfare, and the agents maximize expected profits. Each agent faces a known distribution of accident outcomes, F, an a priori choice of care to prevent accidents from occurring and/or decrease their severity, and a choice of cleanup efforts if an accident does happen. The agents are differentiated by type, which is a characteristic representing the inherent riskiness of their operations. For an oil company type might constitute onshore vs. offshore drilling, and for industry it may reflect production using more hazardous chemicals. As discussed above, the regulator cannot observe agents' actions (or type) or an accident's innate severity if it occurs, but both parties are aware of any damages, which are measurable and traceable to their source.

Our framework closely follows the notation of Hanley, Shogren and White (2007, p.401), herein "HSW". We start by considering the decisions of an individual agent, with riskiness type θ. Let w denote the benefits of economic activity, and let L denote a personal loss to the agent, which is increasing in accident severity, if an accident occurs. The ex ante choice of prevention expenditure is denoted z, which can be self-protection (lower probability of accident occurring), self-insurance (decreased severity if an accident does occur) or both. Prevention efforts might include avian flu vaccination by a poultry producer, the use of water sprayers and overflow/blow-off tanks at chemical plants, or measures to reduce the likelihood and severity of an oil spill.

If an accident does happen, the accident severity is parameterized by the continuous, non-negative random variable, $\gamma \in \Gamma = [0, \bar{\gamma}]$, which could be infection rate or viral count, or explosion or spill severity, depending on the application. The severity parameter could also indicate an accident happening in a sensitive location, as with a fire in dense apartment units, an oil spill in the habitat of an endangered species, an industrial accident in a city center, or a disease outbreak in a vulnerable population. We consider this parameter to be an increasing hazard, which is to say that a higher γ means a more harmful accident, and a realization of $\gamma = 0$ means no accident occurs. The accident severity follows a probability distribution, $\gamma \sim F(\gamma; \theta, z) : \Gamma \to [0,1]$, which is dependent both on an agent's type, and on his prevention efforts.

If an accident does occur, there is social damage $D(\gamma,a)$, from the spread of fire, disease or the release of hazardous substances, which is denominated in dollars. An agent can reduce the damage by an abatement expenditure, *a*, where $D_a < 0$, but with decreasing marginal returns, so $D_{aa} > 0$. Abatement measures can include assistance with fire control and cleanup of hazardous materials, slaughter of sick animals and sterilization of facilities and equipment, and notifying proper authorities to prevent the spread of harm. Clearly, the issue here is that cleanup efforts are costly to the accident victim, but they only benefit society. Accounting for social costs, as the agent will do when behaving optimally, yields the objective function:

$$E[\pi] = w - z - \int_0^{\bar{\gamma}} \Big(L(\gamma) + D\big(\gamma, a(\gamma)\big) + a(\gamma) \Big) dF(\gamma;\theta,z)$$

where *E* denotes the expectation operator and the integral is the Stieltjes integral. We assume that *z* and θ interact with *F* in the sense of first-order stochastic dominance, so that z makes the distribution unambiguously better and θ makes it unambiguously worse. Formally,

$$F(\gamma;\theta,z) \underset{FSD}{\succ} F(\gamma;\theta,z') : z < z' \text{ and}$$

$$F(\gamma;\theta,z) \underset{FSD}{\prec} F(\gamma;\theta',z) : \theta < \theta'$$

where dominance in this case implies a 'worse' distribution because our focus is the distribution of the social cost of accidents. Equivalently, we can say $F_z \geq 0 \ \forall \gamma$ and strictly greater for some γ. Similarly, $F_\theta \leq 0 \ \forall \gamma$ and strictly less for some γ. We also assume that prevention experiences decreasing marginal returns, so $F_{zz} \leq 0$, because damage-control spending uses up the lowest cost measures first.

While restrictive for ranking lotteries, the first-order stochastic dominance assumption is actually quite general when evaluating accident prevention mechanisms. Recall the two common specifications of self-protection and self-insurance. Self-protection, where care affects only the probability of an accident, often models expected damages as $p(z) \cdot \int_\Gamma D \, dF(\gamma;\theta)$. Similarly, self-insurance, where care only affects severity when the accident does occur, might show damages modeled as $\int D(\gamma,z,a) dF(\gamma;\theta)$. Our agnostic model of generic first order stochastic dominance allows either or both of these specifications to hold.

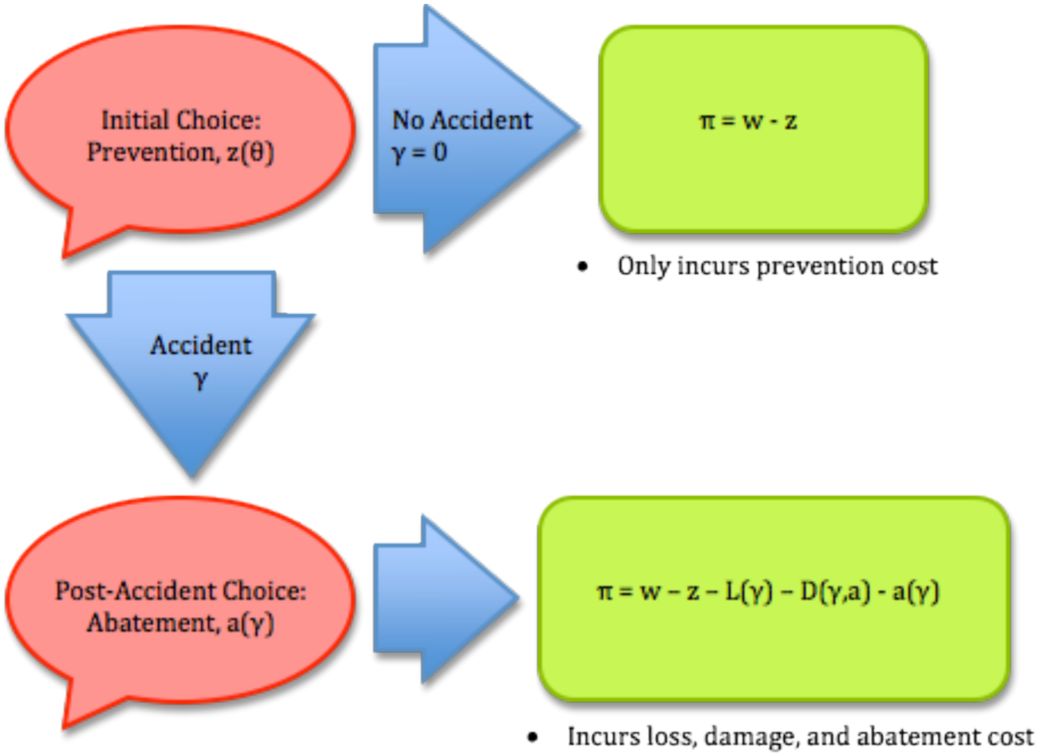

Figure 1-1: The Risk Generation Process

Figure 1-1 presents the risk-generation process captured by our framework. We solve for optimal behavior through a backwards inductive approach; first, we develop an optimal abatement response for every outcome if an accident does occur, and then we use this information to solve for the ex ante care choice. Since no accident occurs when $\gamma = 0$, the agent faces two basic scenarios:

$$u = w - z \qquad \text{with probability } F(0);$$

$$u = w - z - L(\gamma) - D(\gamma,a) - a \qquad \text{otherwise,}$$

where the accident scenario is dependent on the realized severity, γ. Thus, if an accident occurs, the agent solves:

$$\max_a \pi = w - z - L(\gamma) - D(\gamma,a) - a$$

where the optimal abatement expenditure is given by setting the marginal cost equal to the marginal benefits of damage reduction in the first order condition below:

$$-D_a = 1.$$

The second order condition, $-D_{aa} < 0$, ensures that the optimal choice exists and is unique, as long as the initial benefits are greater than the marginal cost - which we assume is the case, so abatement activities are worthwhile at some level. Taking comparative statics results in the traditional fashion, we find that $a^*(\gamma)$ responds to changes in γ according to the sign of $-D_{\gamma a}$, about which we have made no assumption. For example, a more severe industrial fire might burn hotter, causing water sprayed on it to evaporate rapidly - an example of decreasing returns to the water expenditure. In essence, the cross-partial effect boils down to an empirical question - specific to the problem at hand - as to whether abatement experiences increasing or decreasing marginal returns when disasters are more severe.

Since the optimal containment response is deterministic, given the state of nature, we are equipped to evaluate the up front choice of care - with this information in mind. The ex ante choice is characterized by the following problem:

$$\max_z E[\pi] = w - z - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF(\gamma;\theta,z)$$

where $D^* \equiv D\left(\gamma, a^*(\gamma)\right)$, and the other arguments are suppressed for clarity. The optimal care investment is given implicitly by the first order condition:

$$\frac{\partial E[u]}{\partial z} = -1 - \frac{\partial}{\partial z}\left[\int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF(\gamma;\theta,z)\right] = 0$$

To verify an interior solution is possible, let $\tau(\gamma) \equiv L(\gamma) + D\left(\gamma, a^*(\gamma)\right) + a^*(\gamma)$ denote the social cost of an accident, which we know to be monotone increasing in γ by the envelope theorem. Then,

$$\begin{aligned}
\frac{\partial}{\partial z}\int_0^{\bar{\gamma}} \tau(\gamma)\, dF(\gamma;\theta,z) \quad &= \frac{\partial}{\partial z}\left[\tau(\gamma)\cdot F(\gamma;\theta,z)\Big|_0^{\bar{\gamma}} - \int_0^{\bar{\gamma}} F(\gamma;\theta,z)\, d\tau(\gamma)\right] \\
&= \frac{\partial}{\partial z}\left[\tau(\bar{\gamma}) - \int_0^{\bar{\gamma}} F(\gamma;\theta,z)\,\tau_\gamma(\gamma)\, d\gamma\right] \\
&= -\int_0^{\bar{\gamma}} F_z(\gamma;\theta,z)\,\tau_\gamma(\gamma)\, d\gamma < 0
\end{aligned}$$

where the first equality follows from integration by parts. The second equality follows from observing that $F(\bar{\gamma}) = 1\ \forall z$ and converting the Stieltjes integral to a Riemann integral. Therefore, the first order condition amounts to setting:

$$\int_0^{\bar{\gamma}} F_z(\gamma;\theta,z)\,\tau_\gamma(\gamma)\, d\gamma = 1,$$

and accordingly, the second order condition for the care choice is:

$$\int_0^{\bar{\gamma}} F_{zz}(\gamma;\theta,z)\,\tau_\gamma(\gamma)\, d\gamma < 0.$$

As with the abatement choice, we assume that the marginal benefits of prevention are initially greater than the marginal costs, so care activities are worthwhile. Thus, the optimal prevention choice, *z*, which might be investment in avian flu vaccine, or emergency training for workers, is selected such that the marginal benefits of preventing harm to the producer and limiting externality exposure for others are set equal to the marginal cost of these efforts. The second order condition is everywhere negative, ensuring concavity, so the optimal choice z^* exists for each agent, and is unique.

Finally, there is a continuum of agents, of unit measure, who are differentiated by a type parameter, $\theta \in \Theta$, which is a continuous variable with probability distribution $G:\Theta \to [0,1]$. The type parameter can be considered as riskiness, or a propensity for more frequent and/or severe accidents. That is, a higher θ means a more risky agent. Riskiness might be a geographical element, like location within a city – as pertains to disease or fire risk, though we assume this parameter to be unobservable by the regulator, in general. Type could also index outdated equipment or the use of hazardous chemicals, or high interaction rates with other farms for the livestock producer.

For the care choice, we derive comparative statics results for the effect of increasing an agent's type, obtaining:

$$\frac{\partial z^*}{\partial \theta} = -\frac{\partial^2 E[u]}{\partial z \partial \theta} \Big/ \frac{\partial^2 E[u]}{\partial z^2} = \frac{\int_0^{\bar{\gamma}} F_{z\theta}(\gamma;\theta,z)\tau_\gamma(\gamma)\,d\gamma}{-\int_0^{\bar{\gamma}} F_{zz}(\gamma;\theta,z)\tau_\gamma(\gamma)\,d\gamma}.$$

So, optimal prevention will adjust to an agent's type according to the sign of $F_{z\theta}$. A traditional assumption is more riskiness will *increase* the marginal returns to care efforts, $F_{z\theta} > 0$, which is consistent with a Cobb-Douglas specification, with multiplicatively separable risk-generating functions from the environmental health literature, as in Starr (1985), and with exponential dose-response functions used in epidemiology (Wilson and Crouch, 1987; Bogen, 1995; Lichtenberg, 2010). However, this assumption can be controversial, as noted in HSW (2007, p.403), and is likely a problem-specific empirical question - as was the case in our discussion about damage containment efforts and accident severity, above. We leave for future research the examination of cases where type means more frequency but lower severity (i.e., not an FSD shift), as might occur when a meter-maid has a high probability of car accidents in congested spaces, but collisions very often occur at low speed.

Given the above setup, we are able to characterize the social optimum as the maximum, expected aggregate welfare - with optimal choices by all agents, ex ante, and optimal response strategies ex post. Since π denotes individual profits, let Π denote the aggregate, so the maximal, expected total welfare is defined as:

$$E[\Pi]^* = \int_\Theta \left[w - z - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF\left(\gamma;\theta,z^*(\theta)\right) \right] dG(\theta)$$

where the loss, damage and abatement terms are zero when no accident occurs, but are optimized if it does. This specification also allows for each agent to experience his own realization of γ, whose correlation across agents we have not yet addressed. Under our risk neutrality assumption, correlation would not affect the expectation operator, but future research may be needed to examine its effects when risk preferences are considered.

We now turn to developing policies which attain the social optimum; in essence, a new triumvirate of environmental policies under uncertainty. Before doing so, we turn briefly to the unregulated case for comparison.

2.3 The Unregulated Case

Without a liability standard, or other form of regulation, agents will choose sub-optimally ex ante, and there will be no ex post response to contain accidental harm to others.[6] This might occur if a livestock producer is not responsible for spreading swine flu, or if an oil refinery is not responsible for releasing air pollution. In the context of our framework, the unregulated case is suboptimal because the second stage disappears.[7]

Thus, the unregulated agents only solve the problem of making first-period prevention investments according to their own best interest:

$$\max_z E\left[\pi^{UR}\right] = w - z - \int_{\Gamma} L(\gamma)\, dF(\gamma;\theta,z)$$

$$\pi_z^{UR} = -1 + \int_0^{\bar{\gamma}} \left(F_z(\gamma;\theta,z) L_\gamma\right) d\gamma = 0 \quad .$$

As in the optimal case, the unique solution is defined implicitly by the first order condition. The agent does incur some personal loss as a result of the accident, so the prevention efforts still exist at a positive level in the absence of regulation, but no regulation means agents will under-prevent, relative to the social optimum.

Proposition U1: $z_{UR}^* < z^*$

Proof: Follows directly by inspection. First, fix the agent's type, θ. Then, by substitution of the first order conditions, we obtain:

$$\begin{aligned}
\int_0^{\bar{\gamma}} \left(F_z\left(z_{UR}^*\right) \cdot L_\gamma\right) d\gamma \qquad &= \int_0^{\bar{\gamma}} \left(F_z\left(z^*\right) \cdot \tau_\gamma\right) d\gamma \\
&= \int_0^{\bar{\gamma}} \left(F_z\left(z^*\right) \cdot \left(L_\gamma + D_\gamma^* + a_\gamma^*\right)\right) d\gamma \\
&> \int_0^{\bar{\gamma}} \left(F_z\left(z^*\right) \cdot L_\gamma\right) d\gamma
\end{aligned}$$

[6] Neglecting, of course, any utility payoff from 'doing the right thing.'

[7] Consider the application of our framework to the poison-gas disaster at the Union Carbide pesticide plant in Bhopal, India in 1984, as documented by Eckerman (2005). The chemical manufacturer was operating essentially as if unregulated, as evidenced by the choices made. Care: safety measures were turned off, others left on were inadequate, and the operating crew was both under-trained and undermanned – all in order to save on the costs of these measures. Methyl isocyanate was also used instead of less hazardous, but more expensive alternatives. Containment: Once the accident occurred (a pressure spike, causing poison-gas to be released into the surrounding community), no efforts were made to notify authorities of the gas leak (it was denied at the moment of the disaster), and no assistance was provided to medical responders about the nature of the chemical exposure suffered by accident victims.

Since, $F_{zz} \leq 0 \ \forall \gamma$ and strictly less than zero for some γ, it follows that $z^* > z^*_{UR}$.

□

The preceding proposition verifies our earlier claim that some prevention will still exist - the polluting firm has its own losses to protect, after all - but that it will be lower than the optimal level because of a disregard for social accident costs. Unregulated behavior and the associated expected profits will also inform the participation decision when agents must be induced to accept the subsidy program.

2.4 Optimal Policy – Strict Liability/Penalty System

As with the point-source externality problems already assessed in deterministic frameworks, tax policy under uncertainty can maximize social welfare similarly by forcing polluters to "internalize the externality" – that is, they will account for the social cost of their actions as part of their decision-making process. In fact, we explicitly demonstrated this point in the derivation of the social optimum, above. The key element of stochastic pollution taxes is that the tax amount, or even the unit pollution tax, cannot be fixed in advance (as in Weitzman, 1974) because the optimal containment response is state-dependent - which would lead to second-best outcomes. Thus, we propose that a policy regime of strict liability will lead to socially optimal behavior by making agents liable to pay *D* after an accident, perfectly aligning their personal incentives with the social objective.

Some considerations are worth mentioning here. The liability system proposed here relies on perfect detection and traceability of the social damages, either by regulators or by the individuals affected, and no transaction costs of enforcement. However, it has been shown by Polinksy and Shavell (1992) that costs of detection and enforcement are really just a part of the externality, so these costs can be included in the damage function, *D*, without loss of generality. Even with the detection and traceability problem solved, other constraints might still exist; as van't Veld (1997) suggests, imposing high penalties may not be practical because of limited ability to pay - bankruptcies create an effective upper bound on financial penalties, preventing proper alignment of incentives for low probabilities of detection. This is the judgment-proof problem, which Innes (1999a) addresses in a liability setting by applying a stochastic penalty to balances the distribution of outcomes by mandating over-payment of fines above a certain threshold. This approach, of course, breaks down when optimal responses need to be maintained post-accident.

Thus, the problem of inability to pay can play a critical role in policy formation. While it might be argued that strict liability is the "purest" form of optimal regulation, since collected fines could theoretically be distributed to those harmed, many environmental taxes exist only to properly align incentives - there is often no mechanism for the actual payment of damages to those harmed. For example, carbon taxes in OEDC countries are not readily distributed to a farmer in Afghanistan who loses his farm due to global warming. Thus, for those unable to pay the accidental damages, alternative policies may be sought to induce optimal producer behavior.

Subsidy programs may appear when there is a historical right to pollute, when there is limited ability to pay, or when there is political power that interferes with enforcement of strict liability (Bulte et al, 2008). The term, payment for environmental services, reflects exactly this situation where individuals must be induced to voluntarily comply with environmental policy. We show in the next section that a compensation policy can still attain socially optimal outcomes, both ex ante and ex post, but that its design must fundamentally differ from its deterministic counterpart.

2.5 Compensation Policy – Abatement Subsidies

Consider a classical abatement subsidy in a deterministic setting. Depending on the amount of information available to the environmental regulator, agents can be compensated for actual abatement of damages or for curtailing production to limit emissions. In a stochastic environment, the optimal behavior is state dependent, so the ex ante care investment is important, but it is not sufficient for an optimal outcome. We demonstrate two special issues that arise: first, if care affects the probability of an accident then the subsidy must pay each agent in every period - even if no accident occurs. This requirement alone may test a regulator's budget constraint if accidents are rare.

Second, if care affects severity then the subsidy cannot pay compensation for actual abatement of damages - the payment must instead be based on abatement below a fixed (decoupled) threshold, e.g., $S = D_0 - D$. The decoupling requirement exists because compensation tied to actual abatement perverts incentives; it encourages risky behavior by rewarding agents when $D(\gamma, a = 0)$ is higher. There may also be practical measurement issues, since actual abatement is calculated based on un-contained damages, which may be unobservable, or may never come into existence.

Combining these two considerations, where care affects both probability and severity, or where the exact mechanisms are not known by the regulator, necessitates that agents be compensated for abatement below a fixed threshold, D_0, in every state of nature. Equivalently, agents may be paid an ex ante bribe to submit themselves to participation in a strict liability regime, preserving optimal incentives at the margin.

Note that there is nothing about this specification that requires the subsidy payment to be positive in all states of nature; for example, $D_0 = 0$ reduces to the optimal tax policy of the previous section. Therefore, the material distinction between the subsidy and tax policies is that a subsidy must induce voluntary participation from the accident-prone agents.

The first step in developing an optimal subsidy policy is recognizing that all agents must participate, because non-participation by any non-zero measure of agents means they make (suboptimal) unregulated choices. For the moment, we will assume universal participation to demonstrate the key results, and then evaluate the participation constraint explicitly in the context of the political-economic and budgetary implications of the subsidy policy under uncertainty.

For the following propositions, an agent's expected profits when participating in the subsidy program are given by:

$$E\left[\pi^S\right] = w - z + \int_0^{\bar{\gamma}} \left(S - L - a^*\right) dF(\gamma;\theta,z)$$
$$= w - z + \int_0^{\bar{\gamma}} \left(D_0 - L - D^* - a^*\right) dF(\gamma;\theta,z)$$

Proposition S1: Suppose D_0 is large enough to satisfy the participation constraint for all agents (universal participation), and suppose $S = D_0 - D : D \neq 0$, so that the subsidy <u>only</u> pays in states of nature where an accident occurs. If $dF(0)/dz > 0$, then the resulting choices will not be socially optimal for any agent.
Proof: This is a policy that pays for all abatement below a threshold, except when there is no accident. The expected profits for a subsidized agent are thus:

$$E\left[\pi^{S1}\right] = w - z + \int_{\gamma\neq 0} \left(D_0 - L - D^* - a^*\right) dF(\gamma;\theta,z)$$
$$= w - z + D_0 \cdot \left(1 - F(0;\theta,z)\right) - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF(\gamma;\theta,z)$$

where the variable arguments in the integrals are the same because losses, damages and abatement are zero when no accident happens ($\gamma = 0$). Maximizing expected profits of this form yields the first order condition:

$$\int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z_{S1}^*\right)\tau_\gamma(\gamma)\,d\gamma = 1 + D_0 \cdot F_z\left(0;\theta,z_{S1}^*\right)$$

where the right-hand side is less than one. Substituting in the first order condition for the social optimum, we see that this subsidy produces a suboptimal (lower) level of ex ante care because $F_{zz} < 0$:

$$\int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z^*\right)\tau_\gamma(\gamma)\,d\gamma = 1 < 1 + D_0 \cdot F_z\left(0;\theta,z_{S1}^*\right) = \int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z_{S1}^*\right)\tau_\gamma(\gamma)\,d\gamma$$

□

Proposition S2: Suppose D_0 is large enough to satisfy the participation constraint for all agents (universal participation), and suppose $S = D_0 - D$ in all states of nature if $dF(0)/dz > 0$. If $dF(\gamma)/dz > dF(0)/dz$ for some γ , then $D_0 = D(\gamma, a = 0)$ will not achieve the social optimum. That is, the subsidy threshold cannot pay for actual damage reductions due to abatement post-accident.
Proof: Expected utility is given by:

$$E\left[\pi^{S2}\right] = w - z + \int_0^{\bar{\gamma}} \left(D(\gamma,0) - L - D\left(\gamma, a^*(\gamma)\right) - a^*(\gamma)\right) dF(\gamma;\theta,z)$$

Taking a first order condition yields:

$$\int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z_{S2}^*\right)\left(\tau_\gamma(\gamma)-D_\gamma(\gamma,0)\right)d\gamma=1$$

$$\Rightarrow \int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z_{S2}^*\right)\tau_\gamma(\gamma)d\gamma=1+\int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z_{S2}^*\right)D_\gamma(\gamma,0)d\gamma>1=\int_0^{\bar{\gamma}} F_z\left(\gamma;\theta,z^*\right)\tau_\gamma(\gamma)d\gamma$$

which implies prevention will be smaller than optimal, exactly as in Proposition S1.

□

Combining the insights of Propositions S1 and S2 shows that when prevention activities affect both the probability and severity of accidents, or when the regulator does not know the exact, effective mechanism of prevention efforts, a subsidy payment will achieve socially optimal behavior if it pays in every period, based on abatement below a decoupled threshold. As discussed above, one equivalent method of decoupling payments in this fashion, and making sure they pay in every state of nature, is simply paying D_0 to each agent *ex ante* as compensation for participating in a system of strict liability for accidental environmental damages.

Now it remains to derive the conditions for fulfillment of the participation constraint, to ensure that all agents voluntarily participate in the subsidy program. Using the decoupled ex ante payment as a guide, Condition 1 says that the expected profits with no regulation must not exceed the expected profits generated by participation in the subsidy program, for all agents:

Condition 1: $E\left[\pi^S\right]\geq E\left[\pi^{UR}\right] \quad \forall\theta.$

By comparing the objective functions, Condition 1 reduces to:

$$D_0-\int D^*+a^*dF\left(\gamma;\theta,z^*\right)\geq z^*-z_{UR}^*+\int L\,dF\left(\gamma;\theta,z^*\right)-\int L\,dF\left(\gamma;\theta,z_{UR}^*\right)$$

$$\equiv \Delta z+\Delta E\left[L\right]>0$$

where $\Delta z=z^*-z_{UR}^*>0$, and the sign of the sum is known because z_{UR}^* minimizes the sum of $z+E\left[L\mid z\right]$, while $z^*>z_{UR}^*$ does not.

Thus, in expectation, the subsidy threshold must exceed the abatement expenditure and the social cost of accidents, a^*+D^*, which together we will dub the total externality cost ($TEC=D^*+a^*$). Put another way, Condition 1 shows that (in expectation) the subsidy payment, net of the expected abatement expenditure, must exceed the profits lost by an unregulated agent who voluntarily switches from the unregulated choice, z_{UR}^*, to the socially optimal z^*. In addition, we demonstrate a critical relationship of D_0 with the TEC in the following proposition. Namely, that the threshold will be bounded below by the expected, optimal-response TEC of the first-best care choice, z^*, and it will be bounded above by the hypothetical TEC corresponding to the unregulated prevention choice.

Proposition S3: If the threshold D_0 is paid ex ante and the participation constraint (Condition 1) is satisfied with equality, then $E\left[TEC^*\mid z^*\right]<D_0<E\left[TEC^*\mid z_{UR}^*\right]$.

Proof: Let Condition 1 be satisfied with equality. Payment of D_0 ex ante means it does not vary with the state of nature, so:

$$D_0 - \int D^* + a^* dF\left(\gamma;\theta,z^*\right) = \Delta z + \Delta E\left[L\right]$$

$$\Rightarrow \quad D_0 = \Delta z + \Delta E\left[L\right] + E\left[TEC^* \mid z^*\right] > E\left[TEC^* \mid z^*\right]$$

$$or \ = \Delta z + \Delta E\left[L\right] + \Delta E\left[TEC^*\right] + E\left[TEC^* \mid z^*_{UR}\right] < E\left[TEC^* \mid z^*_{UR}\right]$$

where the Δ-notation follows that of Condition 1, and TEC^* denotes optimal-response with respect to abatement. The signs are known because the care choices minimize their respective loss-plus-cost functions.

□

Thus far we have established conditions for optimality of the subsidy, depending on universal adoption thereof, but it is important to note that this program has higher information requirements than strict liability. Specifically, the subsidy must pay from a threshold high enough such that the participation constraint is satisfied for all agents, so the regulator needs some information about how profits might change when switching from an unregulated to a regulated environment. However, any subsidy at the necessary level or higher will be sufficient to attain optimality - it will just do so at increased budgetary cost with a higher level of transfers into the polluting industry. Similarly, the subsidy program can thus solve the judgment-proof problem (when bankruptcies prevent the proper alignment of incentives) by raising D_0 to a level where polluting firms are always able to pay their liabilities.

To guarantee universal participation, it is clear that the regulator needs to know TEC information for the highest cost type, which may or may not be the riskiest (highest) type. Consider a threshold, $D_0(\theta)$, that satisfies the participation constraint with equality, by type. Applying the envelope theorem, we obtain:

$$\frac{\partial D_0(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta}\left[\int_0^{\bar{\gamma}} F\left(\gamma;\theta,z^*_{UR}\right)\cdot L_\gamma \, d\gamma - \int_0^{\bar{\gamma}} F\left(\gamma;\theta,z^*\right)\cdot \tau_\gamma \, d\gamma\right]$$

$$= \int_0^{\bar{\gamma}}\left[-L_\gamma \cdot \int_{z^*_{UR}}^{z^*} F_{z\theta}\left(\gamma;\theta,z\right)dz - \left(D^*_\gamma + a^*_\gamma\right)\cdot F_\theta\left(\gamma;\theta,z^*\right)\right]d\gamma$$

where the first term has the opposite sign of $F_{z\theta}$ and the second term is positive because type leads to an objectively worse distribution of accident outcomes.

There are two effects, an externality effect and a switching effect, which arises from the impact of changing type and care on the expected personal loss. In general, $F_{z\theta} \leq 0$ is sufficient for the signs to agree and for the threshold to be increasing in type. However, we noted that the sign of this cross partial is an empirical question, and the traditional assumption (based on Cobb-Douglas specifications, etc.) is the opposite: $F_{z\theta} > 0$. Our intuition is that the externality effect dominates in many cases we care about, and though we do not demonstrate them rigorously, this intuition is supported by ideas like 'the externality and abatement cost are large relative to the personal loss,' and/or 'the marginal effect of type on the returns to care is small, relative to the effect of type on the externality distribution.'

So, if the participation threshold is everywhere increasing in type, then the regulator need only calculate the threshold for the highest one. If not, then he must know the 'worst' type, in terms of highest total externality cost and lost profits from regulation. Unfortunately, paying decoupled subsidies in every period when subsidies must hold for all agents - and accordingly, for the most costly type - means outliers or skewness in the distribution of agents may make the optimal threshold very high relative to the participation constraint of most agents.

For example, chemical plants using highly toxic inputs may face higher externality costs in expectation, but the decoupled subsidy requires plants with less-toxic inputs to receive the same transfer, if the regulator cannot observe type. Thus, the information problems of the regulator may inflate the volume of subsidy payments to the polluting industry, or - to put it another way, the value of information about polluters is the direct reduction of information rents paid based on type. However, the participation constraint only binds on the expected optimum of total externality cost; the optimal total cost may be substantially lower than uncontrolled damages, as when prevention or abatement are inexpensive.

Thus far, we have considered two scenarios where the accidental externality problem is optimally regulated; either by a penalty system (or one of strict liability) that potentially places a heavy burden on accident victims, which might also comprise an industry with strong political influence, or by a compensation system where money flows into the polluting industry, and the volume of transfers increases for infrequent accidents (payment in every period), worse information, or more variation across producers' risk profiles.

In essence, a strict liability system is characterized by agents paying for what is known, but under a subsidy the regulator pays for what is *not* known, because the threshold has to cover the threshold for the worst type in order to obtain the optimal outcome. As a result, while the penalty policy may face ability to pay constraints from the polluters, the subsidy policy may face an ability to pay constraint for the government. Thus, we conclude our analysis by discussing the possibility of a mutual insurance policy, one that would be budget neutral for the regulator by keeping all funds within the polluting industry, in expectation.

2.6 Revenue Neutral Optimal Policy: Mutual Insurance

The third major tool of environmental policy is a system of cap and trade, or tradable pollution permits. While the state-dependent nature of stochastic externalities (when cleanup is possible), and realistic restrictions on government information about damage control technologies, prevent quantity-based environmental policy per se, we introduce a third policy to accomplish similar goals while attaining optimal behavior under uncertainty. The new policy involves mutual insurance for the polluters, while functioning like a system of bonded liability, and it retains the flavor of a system of tradable permits: revenue neutrality for the regulator (in expectation) because no funds move into, or out of, the polluting industry, and subsidization of 'safer' firms by riskier ones.

The insurance policy we propose functions similarly to the subsidy policy outlined in the previous section, but it is funded by the firms themselves and relies on the regulator imposing compulsory participation because there is no incentive from outside funds. Because participation cannot be made voluntary (which would require outside funding, as with the subsidy), the volume of transfers may be lower under the insurance program because abatement costs and forgone unregulated profits need not be compensated to achieve optimality.

As with the subsidy, the insurance program is structured to pay compensation below a specified threshold, D^I, in every period. However, since participation is mandatory, the threshold need not be tied to the highest type. Instead, our goal is assigning a threshold that leads to a balanced budget in expectation, where D^I and the premium, *P*, are the same for all agents. An agent's expected profits under the insurance program are thus given by:

$$E\left[\pi^I\right] = w - z - P + D^I - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF \; .$$

The balanced budget constraint can be expressed as:

$$\int D^I - \int D^* \, dF\left(\gamma;\theta,z^*(\theta)\right) dG(\theta) = P$$

$$\Rightarrow D^I - P = \int\int D^* dF^* dG$$

which necessarily contains a degree of freedom between the threshold faced by the firms and the premiums collected - so either D^I or *P* can be established, and then the other calculated accordingly.

The key result of this program is that imposing a balanced budget means that all firms' net expected profits from participation (which may be negative) are based on their variation from the average expected level of environmental damage. To clarify this point, consider the insurance program where $P = 0$, so that:

$$D^I = \int\int D^* dF^* dG \; .$$

In this scenario, the expected profit function for each agent looks remarkably similar to that of the subsidy program outlined in the previous section. Each agent pays no premium up front and receives a decoupled subsidy payment of D^I in the ex ante decision-making stage. However, the level of the subsidy is set according to the average optimal environmental damage, so that some agents will exceed the threshold amount of damages and receive a negative subsidy (net loss), in expectation, while others will beat the threshold and experience a net gain. To complete the cycle, once accidents are realized ex post, all liability payments are paid into a common pool, leading to expected budget neutrality because some firms are net payers and others are net receivers of funds from the pool.

While there are distributional disparities among members of the industry, these differences are similar across all of our optimal stochastic externality policies, only subject to different baseline levels of wealth: the 'cleaner' or safer types are always better off, in expectation, than the riskier ones, when we define relative riskiness not by the type parameter necessarily, but by the optimal, expected TEC discussed in the subsidy section (which may be monotone in type, anyway). This process of subsidization from high-cost to low-cost agents mimics the results of deterministic cap and trade policies, where agents with higher costs of pollution control subsidize those who can carry out abatement more efficiently. However, unlike the outcome of tradable permits schemes this redistribution of resources is not an essential feature of the insurance policy design - instead, it is simply the by-product of the information problems we have assumed throughout.

If types are observable to the regulator, then each agent could be insured individually, leading to revenue neutrality for all, in expectation. Observability of types is the only such condition, though, because otherwise agents either collect or pay information rents when they participate in a compensation policy. To see this, consider the expected profits of an agent, θ, operating under the mutual insurance program, in the special case where $P=0$ and $D^I = D^I(P=0)$:

$$E\left[\pi^{I*(\theta)}\right] = w - z^*(\theta) + D^I - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF\left(\gamma;\theta,z^*(\theta)\right)$$

$$= w - z^*(\theta) + \int\left[\int_0^{\bar{\gamma}} D^*\, dF\left(\gamma;\theta,z^*(\theta)\right)\right] dG(\theta) - \int_0^{\bar{\gamma}} \left(L + D^* + a^*\right) dF\left(\gamma;\theta,z^*(\theta)\right)$$

Thus, outside the private costs experienced by each agent, the net cost (or profit) from participation in the subsidy program is given by the information rents - the departure of expected damages, $E\left[D^*\right]$, from the industry average. Each agent's net expected disbursement from the insurance pool is given by his information rent, resulting from the regulator's inability to observe his type, which is given by:

$$R(\theta_0) = \int\left[\int_0^{\bar{\gamma}} D^*\, dF\left(\gamma;\theta,z^*(\theta)\right)\right] dG(\theta) - \int_0^{\bar{\gamma}} \left(D^*\right) dF\left(\gamma;\theta_0,z^*(\theta_0)\right)$$

$$= \int\left[\int_0^{\bar{\gamma}} D^*\, dF\left(\gamma;\theta,z^*(\theta)\right) - \int_0^{\bar{\gamma}} \left(D^*\right) dF\left(\gamma;\theta_0,z^*(\theta_0)\right)\right] dG(\theta)$$

$$= \int\left[\int_{\theta}^{\theta_0}\left(\int_0^{\bar{\gamma}} D^*_{\gamma} \cdot F_{\theta}\left(\gamma;t,z^*(t)\right) d\gamma\right) dt\right] dG(\theta)$$

where the final equality results from integration by parts and simplifying, as above. Next, we implicity define the "average" agent in the sense of expected optimal environmental damages, so $\hat{\theta} = \theta : R\left(\hat{\theta}\right) = 0$. Thus, "above-average" agents are riskier and will be net payers into the pool, in expectation, while safer firms of below average riskiness will experience a net expected profit:

$$\theta \geq (<) \hat{\theta} \Leftrightarrow R(\theta) \geq (<) 0,$$

because $F_{\theta} < 0$ and the integral runs in the negative direction for $\theta > \hat{\theta}$. The resulting resource allocation is analogous to that of cap-and-trade policies for deterministic externalities - dirtier firms subsidize cleaner ones, defined relative to the industry average, because they do more environmental damage - even when their behavior optimally accounts for the social costs of production.

2.7 Discussion

The value of information about polluters is apparent - hidden types translate directly to information rents when policy is constrained to a compensation mechanism like subsidies or insurance. As a result, the budgetary cost, or the necessary volume of total transfers, of compensation-based policies can be lowered when polluters' inherent riskiness is known. Another benefit of exposing types is allowing for adequate handling of entry into the polluting industry, which we have not addressed.

In fact, similar to the deterministic abatement subsidy, our proposed subsidy and insurance programs rely on the industry excluding firms when their optimal behavior is non-operation. When types are unobservable and/or when we consider the long run, where entry is possible, then these policies fall short just like their deterministic counterpart because firms will enter who operate at a net social loss. Thus, while robust to moral hazard issues, these policies are not robust to adverse selection, because these firms should not be producing at all - but they join the industry because the insurance or subsidy program allows for positive expected profits. Unfortunately, without being able to identify types, or impose barriers to entry, only the harshest policy of strict liability will ensure the proper composition of a stochastically polluting industry.

We foresee other areas where expanding the analysis may be helpful. While Just and Zilberman demonstrate the asymmetry of taxes and subsidies due to risk aversion, deriving the optimal insurance policy may be of interest in this setting, or when considering polluting firms who are loss averse. Risk preferences will also play a role in evaluating the accident mechanism itself. Correlation across agents - such as might happen over space, when accidents are weather-related - doesn't affect the expectation under risk neutrality, but it might affect the agents' welfare if they are utility maximizers, especially if their accidents harm one another. We leave this exploration as an area for future research.

Under risk neutrality, we have outlined three efficient policy regimes to deal with uncertainty, which fulfill the roles of their deterministic counterparts - especially in the broader sense of resource transfer into, out of, or within the polluting industry. Only the strict liability regime can produce funds to compensate outside accident victims, because it takes money from the industry as fines collected by the regulator - or even in the form of direct claims by those harmed. However, in many cases, no such mechanism readily exists, and this policy may be constrained by equity considerations or ability-to-pay constraints because the polluter is a victim who also adheres to the optimal standard of care.

The compensation policy can circumvent agents' ability-to-pay constraints, but may induce a constraint on the regulator's ability to pay, due to the volume of payments when accidents are infrequent, or when there are known high-risk outliers who cannot be identified (because they increase the decoupled threshold, which forms the basis of payment to all firms). While strict liability forces agents to pay for what is known (the damages), the stochastic abatement subsidy makes government pay for what is not known - types, actions, control technologies, etc. - resulting in large transfers into the polluting industry, and no mechanism for compensation of outside victims.

Like the other policies, the mutual insurance policy we propose preserves the marginal incentives of strict liability, but it recycles the fines into a pool so that all funds remain in the industry. While this mechanism denies compensation to the victims of environmental accidents outside the polluting firms, it is budget-neutral in expectation, and it facilitates a transfer from riskier to safer firms, as can occur under cap-and-trade in the deterministic setting.

Major environmental accidents do not always occur in a well-regulated environment, but we have shown that classical, deterministic environmental economic policies can be adapted to uncertainty in recognizable forms. Their stochastic counterparts have similar distributional implications with respect to the polluting industry, though uncertainty exacerbates the disparities between resource allocations generated by the various policies. Our proposed risk-pooling scheme thus reflects a new policy ideal; namely, goals of efficiency and minimal redistribution of resources can be achieved simultaneously, even in the context of asymmetric or limited information and stochastic mishap.

Chapter 3. The Economics of Nested Insurance:

The Case of SURE

Farming is a risky business. One of the realities of modern life is that farmers need to deal with multiple tools to address risk. Recently, it has been advanced that many of the various risks can be addressed in aggregate by revenue insurance, but since the magnitude of the risk can vary drastically, the same random variable (farm revenues) may be targeted by two programs. Historically, farmers could rely on a standardized crop insurance program to deal with moderate to extreme risk, with some *ad hoc* disaster assistance as well. The 2008 Farm Act introduced the Supplemental Revenue Assistance Payments (SURE) program, which is a standing disaster assistance program that explicitly and structurally linked to traditional multi-peril crop insurance. While there is an established literature on the economics of regular crop insurance,[8] a conceptual understanding of both adoption and impact of nested insurance is lacking, and this paper provides a framework to address this issue.

Two key questions that are addressed by this framework are: what are the effects of nested disaster insurance programs, like SURE, on acreage and insurance purchasing, and under what conditions will farmers be indifferent between the new SURE program and historically available ad-hoc disaster assistance? To answer these questions, we develop a conceptual framework to examine the farmer's choice problem with respect to acreage and the level of insurance purchased for a given crop. In doing so, we demonstrate the theory behind targeted insurance subsidies, and derive an indifference condition for the various forms of disaster assistance.

The theoretical findings are supported by an extensive numerical simulation, which verifies the initial findings, calculates otherwise-intractable comparative statics results, and identifies future challenges for policymakers in the area of disaster assistance. Our key results show that the level of risk bearing by farmers is endogenous to their choice of an insurance product, so that they may face substantially less risk than predicted by previous research. Even so, we show that varying risk aversion across farmers induces a wide range of preferences for adequate disaster assistance, as compared to the relative homogeneity of their insurance purchasing decisions.

3.1 Background

The USDA operates programs that provide financial support to farmers in the form of payments or low interest loans to compensate them for crop losses due to weather events or other natural disasters. In addition, despite significant growth in insured acreage under the Federal crop insurance program, Congress has continued to pass legislation providing ad-hoc disaster assistance payments to producers in response to drought and other adverse events.[9] Ad-hoc support

[8] See Glauber (2004) for a comprehensive review.

[9] The Administration can also provide ad hoc disaster assistance without congressional legislation via the Section 32 permanent appropriation.

varies substantially from year to year depending on the weather and whether/how much ad-hoc disaster assistance is actually passed into law. For instance, crop disaster outlays including noninsured assistance (NAP) were $75 million in 2008 but $2.5 billion in 2005. These figures are above and beyond the $2.5 billion annual average cost of crop insurance subsidies (GAO, 2007).

With the 2008 Farm Act, Federal agricultural legislation includes for the first time a formal disaster assistance program, known as the Supplemental Revenue Assistance Payments (SURE) program, which provides producers benefits for 2008 through 2011 crop year farm revenue losses due to natural disasters. SURE is a whole farm program that provides supplemental payments to farmers with Federal crop insurance and NAP in a "disaster county" (a county declared by the Secretary of Agriculture to have suffered weather-related production losses of 50 percent or more, and contiguous counties), subject to other conditions. Essentially, SURE payments mimic ad-hoc disaster support and, though the payment amounts are generally smaller, they have added value to risk-averse farmers because they are not subject to the uncertainty of the political process inherent in ad-hoc disaster assistance.

Arguably, a key political motivation for SURE is that it has become increasingly difficult over time to pass ad hoc payments into law, or at least, that farmers may not receive disaster support when they need it most (Cooper, 2009a). In principle, one may assume that the SURE program would eliminate the ad-hoc payments, but this assumption appears to be unrealistic. Indeed, in late 2009 and early 2010, the head of the Senate Agricultural committee pressed for ad-hoc assistance for farm losses in some regions in 2009 due to bad weather, even when the SURE program had already been passed into law. Thus, we undertake an examination of the conditions where SURE could actually serve to make farmers indifferent to the availability of ad-hoc legislation. Clearly, the farmers themselves should not be counted on to turn down free money, but we hope that our analysis can provide policymakers with the insight to know when ad-hoc assistance is no longer needed.

Being a free supplement to crop insurance, SURE is likely to impact land use and crop insurance decisions, and to a different extent than would an *ad hoc* disaster regime, particularly in regions where high yield variability could result in frequent disaster declarations. In a deterministic analysis, Smith and Watts (2010) find that SURE has the potential for creating moral hazard conditions on top of those already associated with Federal crop insurance. Our simulation analysis sheds some light on these findings, and shows that while disaster assistance will increase acreage (where available), the impact is minimal compared to that of small variations in risk preference and the impact on insurance purchasing is minimal as well. Nonetheless, it is critical to examine these considerations under appropriate risk modeling because of the literature on decoupling. Economic theory shows that decoupling usually involves a reduction in the efficiency losses associated with coupled policies (Chambers, 1995), but subsequent literature showed that wealth effects and risk preferences rendered perfect decoupling impossible for crop insurance programs (Serra et al., 2006).

The remainder of this paper is laid out as follows. Section 3.2 introduces a conceptual model of crop revenue insurance, and the expected utility-maximizing choices of risk averse farmers with respect to acreage and insurance participation. We go on to identify comparative statics results to be estimated, including the impacts of disaster assistance policies. Section 3.3 develops a comprehensive simulation exercise to assess this decision making process using an empirically estimated revenue distribution. The simulation covers representative farmers with differing risk profiles (Illinois corn and South Dakota spring wheat), as well as evaluating their decisions under a wide range of potential risk preferences. Section 3.4 covers the main discussion points, identifies areas for future research and concludes.

3.2 A Conceptual Model of Crop Revenue Insurance

We model a risk-averse farmer facing choices about adoption of crop insurance and aggregate land use (e.g., when acreage is variable, the conversion of marginal lands to crops). If the farmer does not adopt crop insurance, he accepts the natural revenue variability associated with his farm size, but for large losses he *may* receive (ad hoc) government assistance with some positive probability. If he does adopt crop insurance, disaster assistance is nested in the sense that it provides supplemental coverage. Evaluating these farmer decisions will help to shed some light on the potential effects of the SURE program, which provides supplemental disaster insurance for free – but only to those farmers who purchase crop insurance.[10]

Consider a farmer with a von Neumann-Morgenstern utility function, u, which is everywhere increasing and concave in wealth. The farmer has a number of acres, A, with identical revenues per acre, $R = yp$ (revenue equals yield times price), so that total revenue is given by AR.[11] R is a non-negative random variable with continuous, cumulative distribution function, F. The cost of production is a function of acreage, $c(A)$, which is increasing and at least weakly convex in A. In the US, this model of farm size choice is most applicable in regions where marginal lands are available for inclusion in farming operations at some cost. Inclusion of additional lands can include a range of diverse activities, including rental or acquisition from adjacent property owners, conversion of marginal lands, and/or removal or withdrawal of lands from the Conservation Reserve Program (CRP).

[10] To be eligible for ad hoc payments, the farmer generally needs to have at least some minimal level of insurance coverage but the payment levels are not a function of the insurance coverage levels. SURE payments on the other hand are a direct function of insurance coverage levels – though the SURE guarantee is fixed for all coverage levels above 75%.

[11] The AR formulation is useful in our analysis because it provides a sort of 'maximum variance' approach to farm revenues where $Var = A^2 \cdot Var(R)$. Specifically, this specification induces perfect correlation between the revenues of farmed acres, though there may be cases where the revenues are identically distributed and only partially correlated. Consider that a 'minimum variance' approach models each acre as IID, resulting in a revenue variance of $Var = A \cdot Var(R)$. Thus, our formulation provides an upper bound on the variance induced by acreage decisions, which in turn means that risk management behavioral results herein are upper bounds. This is useful because we estimate the distortionary effects of disaster policy to be small. In addition, we avoid making assumptions about the correlation structure between acres on a single farm.

In addition to acreage, the farmer must also select the level of insurance coverage, a threshold level of revenue, which we denote, *T*. Crop revenue insurance is unique among insurance markets, in that losses are defined simply as realizations of the revenue distribution below a specified threshold. Property-casualty insurance, on the other hand, generally treats losses as unforeseen costs, or liabilities, arising from a single event, for which the insurer reimburses the insured according to a share of the loss. Two standard types of coverage are employed, alone or in tandem: coinsurance and deductible insurance. Coinsurance requires the insurer to pay a fixed percentage of the loss, agreed upon when the policy is purchased, whereas deductible insurance requires the insurer to pay the full amount of losses above the deductible. There are certainly more detailed considerations, but these are the key points for our analysis.

We characterize crop insurance for our analysis according to the contract mechanisms generally found in crop revenue-insurance programs offered in the United States, as administered by USDA. That is, the farmer faces a choice of crop insurance that parallels deductible insurance; a stop-loss is specified, below which the farmer faces no losses. This stop loss is the threshold, T, so the insurance transforms the per-acre revenue, such that:

$$R_c = \begin{cases} T & if \quad R \le T \\ R & if \quad R > T \end{cases}$$

where the insurance is activated for $R < T$, which occurs with probability *F(T).* The choice of *T* is associated with a per-acre premium the farmer must pay, *P(T),* and it may be subject to constraints or distortions – to which we will return momentarily.

The farmer's objective function, maximizing expected utility over the choices of acreage, A, and the insurance threshold, T, is given by:

$$\max_{A,\,T} E[u] = \int_T^{\bar{R}} u\big(AR - AP(T) - c(A)\big)dF + t \cdot u\big(AT - AP(T) - c(A)\big)$$

where $t = F(T)$, the probability of an insurance payout, and the arguments of the utility functions show that premium must be paid in every period. Assuming $P(0) = 0$, we can see that choosing $T = 0 = t$ is equivalent to non-adoption of crop insurance, and that $T = \bar{R}$ means the farmer receives $R_c = \bar{R} - P(\bar{R})$ with certainty. The first order condition for maximizing the farmer's objective with respect to acreage is thus given by:

$$\begin{aligned} \frac{\partial E[u]}{\partial A} &= \int_T^{\bar{R}} u'\big(AR - AP(T) - c(A)\big) \cdot \big(R - P(T) - c'\big)dF \\ &\quad + t \cdot u'\big(AT - AP(T) - c(A)\big) \cdot \big(T - P(T) - c'\big) \\ &\equiv \int_T^{\bar{R}} u' \cdot (R - P - c')dF + t \cdot \big(T - P(T) - c'\big) \cdot u'\big|_{R=T} \end{aligned}$$

Acreage is only constrained to be non-negative, so since we assume some positive level of production to be worthwhile, verifying concavity means the optimal solution *A** is unique for all insurance threshold choices, *T*. The second-order condition is given by:

$$\frac{\partial^2 E[u]}{\partial A^2} = \int_T^{\bar{R}} u''\left(AR - AP(T) - c(A)\right) \cdot \left(R - P(T) - c'\right)^2 dF$$
$$+ t \cdot u''\left(AT - AP(T) - c(A)\right) \cdot \left(T - P(T) - c'\right)^2 < 0.$$

Since the cost of acreage, *c(A)*, is increasing and convex, there exists some level of acreage where marginal expected utility is decreasing, so a unique interior solution exists.

Evaluating the choice of crop insurance threshold is more complex. Namely, the choice is affected by policy constraints on which thresholds can actually be selected and by the structure of the premium function, *P(T)*. To begin the analysis, we consider the unconstrained threshold case, where $T \in \left[0, \bar{R}\right]$ without loss of generality, because wider bounds on the threshold have no effect on loss activity. This setup also conveniently allows for $T = 0$ to be conceptualized as electing non-participation in crop insurance, so that *that* choice is endogenized to the threshold choice. We assume that the premium *P(T)* is a smooth function, but it is not necessarily actuarially fair; premiums may be unfair (higher than expected payments), fair, or over-fair (subsidized) according to policy, and the 'fairness' may even vary across different thresholds.

After some algebra, the first order condition for the insurance threshold is:

$$\frac{\partial E[u]}{\partial T} = -AP' \cdot \int_T^{\bar{R}} u'\, dF + t \cdot (A - AP') \cdot u'\big|_{R=T} = 0$$

However, the second order condition is not signable without further assumptions, indicating that expected utility is not necessarily concave in the insurance threshold, and that the first order condition of $dE[u]/dT = 0$ may not exist. To examine this more closely, we start by evaluating the choices under the constraint of actuarially fair insurance premiums.

3.2.1 Actuarially Fair Insurance

When insurance is constrained to be actuarially fair,

$$P = E[T - R \mid R \le T] = \int_0^T (T - R) f(R) dR = T \cdot F(T) - \int_0^T R \cdot f(R) dR.$$

Integrating by parts obtains:

$$P = T \cdot F(T) - R \cdot F(R)\Big|_0^T + \int_0^T F(R) dR = \int_0^T F(R) dR, \text{ so } dP/dT = F(T) = t.$$

Thus, under conditions of actuarially fair premiums for all insurance threshold levels, and with the choice of level unconstrained, we substitute the above into the first order condition for the threshold choice to obtain:

$$\frac{\partial E[u]}{\partial T} = -At \cdot \int_T^{\bar{R}} u' \cdot f(R) dR + (A - At)t \cdot u'\big|_{R=T} = At \cdot \left[(1-t)u'\big|_{R=T} - \int_T^{\bar{R}} u' \cdot f(R) dR\right]$$

Integrating by parts yields:

$$= At \cdot \left[(1-t)u'\big|_{R=T} - u' \cdot F(R)\big|_{R=T}^{\bar{R}} + A \cdot \int_T^{\bar{R}} u'' \cdot F(R) dR \right]$$

$$= At \cdot \left[u'\big|_{R=T} - u'\big|_{R=\bar{R}} + A \cdot \int_T^{\bar{R}} u'' \cdot F(R) dR \right]$$

$$= At \cdot \left[-A \cdot \int_T^{\bar{R}} u'' dR + A \cdot \int_T^{\bar{R}} u'' \cdot F(R) dR \right]$$

where the last step follows by reverse application of the chain rule, since $du'/dR = Au''$. Thus, we obtain:

$$\frac{\partial E[u]}{\partial T} = A^2 t \cdot \int_T^{\bar{R}} u'' \cdot (F(R) - 1) dR \ > 0 \ \ \forall T : T \in (0, \bar{R})$$

where $T = 0$ (no insurance coverage) is a minimum with respect to expected utility, and $T = \bar{R}$ is a maximum. Thus, when the threshold choice is unconstrained, agents offered actuarially fair insurance will always choose maximal insurance – in line with standard predictions of expected utility models. Specifically, after accounting for the premium cost, maximal coverage results in agents receiving *E[R]* with certainty. This result follows the standard intuition for risk aversion and insurance adoption, and returning to the acreage choice, we see that it degenerates to the deterministic case, so the agent just sets $A^* : E[R] = c'(A)$.

Figures 3-1 and 3-2 below show the expected utility surface over the choices of acreage and insurance coverage for the representative corn and wheat farmers, respectively, when they face actuarially fair insurance rates. The revenue distributions and costs functions are drawn from the simulation section that follows. While the surface is perhaps more 'dramatic' for wheat, both Figures show that expected utility is concave in acreage, but is monotone increasing in insurance coverage, so both farmers will choose the maximal level of insurance coverage available. This is plotted as 90% coverage in the Figures, corresponding to actual policy.

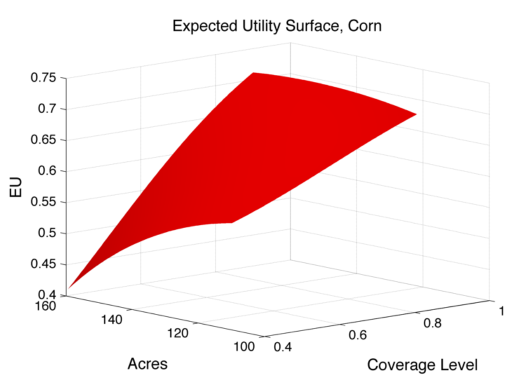

Figure 3-1

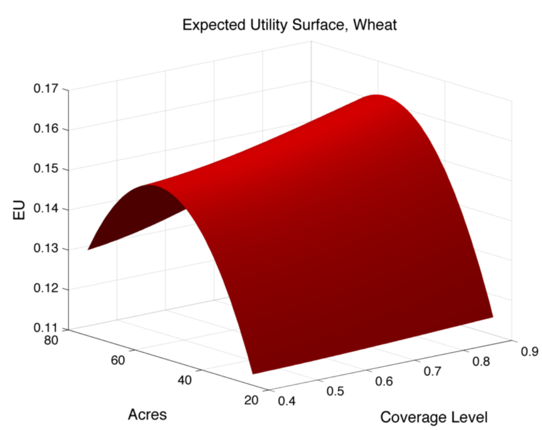

Figure 3-2

In practice, moral hazard problems or budget constraints may result in less-than-full insurance coverage being offered (in which case agents will adopt the maximum coverage available), even in scenarios where premiums are subsidized (e.g., Shavell, 1979, among others). Actuarial fairness itself is a simplification because it ignores transaction costs associated with administering the insurance, which can be large.[12] Nonetheless, government may choose to subsidize the transaction costs if limiting risk to the agricultural sector is in the greater public interest – a concern that seems to drive policy historically in the United States (Dismukes and Glauber, 2005). Even so, when the maximal coverage threshold is constrained below $\overline{R}$, there will be lower acreage than under full coverage.[13]

3.2.2 Non-Fair Insurance

Clearly, many scenarios exist where insurance rates are not actuarially fair, either for specific levels of coverage or for all levels. Actuarial fairness may also vary according to the marginal rate increase, since insurance transaction costs and/or policy-induced levels of subsidization may vary over different levels of coverage.[14] It is also possible to further generalize, by considering possible upper and lower bounds on the thresholds available ($T_0 \geq 0$, $\overline{T} \leq \overline{R}$, respectively) and consider that non-adoption, $T = 0$, may be a separate, discrete choice from the choice of coverage level. However, in this subsection we focus on interior solutions; we show that if an interior solution exists then it depends on the rate at which the marginal premium increases with the coverage level, beyond the role of the absolute premium level on the yes-no choice of insurance participation.

Consider the insurance premium defined as $P(T) = P_0(T) + D(T)$, where $P_0(T)$ is the actuarially fair premium derived in the previous section, and $D(T)$ is a disturbance which may be positive or negative, and may vary with T. Accordingly, the non-fair first order condition for the threshold choice is now given by:

$$\frac{\partial E[u]}{\partial T} = -A(t + D')\int_T^{\overline{R}} u'\, dF + At \cdot (1 - t - D') \cdot u'\big|_{R=T} = 0$$

Proposition: If there exists a unique interior solution for the insurance choice, characterized by a threshold level, T, such that $\partial E[u]/\partial T = 0$, then $D'(T) > 0$. That is, the insurance premium must be increasing faster than the actuarially fair premium.

Proof: See the first order condition characterizing T^* above. After some algebra, we obtain:

[12] Administrative costs are as high as 35% of premiums in property-casualty insurance, plus an average 5% profit margin. Administrative costs are only about 20% for crop insurance, but the underwriting profits for participating insurers have historically been nearly as large (GAO, 2007).

[13] This can be easily shown following Sandmo (1971).

[14] As documented on the website of USDA's Risk Management Agency (RMA).

$$D' = t \cdot \frac{u'|_{R=T} - t \cdot u'|_{R=T} - \int_T^{\bar{R}} u'\, dF}{\int_T^{\bar{R}} u'\, dF + t \cdot u'|_{R=T}} = t \cdot \left(\frac{u'|_{R=T}}{\int_T^{\bar{R}} u'\, dF + t \cdot u'|_{R=T}} - 1 \right)$$

Applying integration by parts to the denominator yields:

$$\begin{aligned}
\int_T^{\bar{R}} u'\, dF + t \cdot u'|_{R=T} \quad &= u'|_{R=\bar{R}} - A\int_T^{\bar{R}} u''\cdot F(R)\, dR \\
&< u'|_{R=\bar{R}} - A\int_T^{\bar{R}} u''\, dR \qquad \textit{because } F(R) \le 1 \\
&= u'|_{R=T} \qquad\qquad\qquad\quad \textit{by reverse chain rule}
\end{aligned}$$

$$\Rightarrow u'|_{R=T} \Big/ \left(\int_T^{\bar{R}} u'\, dF + t \cdot u'|_{R=T} \right) > u'|_{R=T} / u'|_{R=T} = 1 \qquad \Rightarrow D' > 0$$

□

Thus, it is necessary for an interior solution that $D' > 0$, which implies $P' > t$, so the marginal premium increase must be greater than the marginal increase of the actuarially fair premium for an interior solution to occur. As a result, any constant subsidy or surcharge on the premium will not lead to an interior solution, but only to a yes-no decision between maximal coverage and non-participation in crop insurance.

Therefore, our conceptual framework rounds out the economic theory for an empirical phenomenon observed by Babcock and Hart (2005). They find that fixed (equivalently, decoupled) subsidies do not affect the decision on the level of insurance threshold, and that subsidies only increase insured coverage levels by increasing the total amount of the subsidy as purchased coverage increases. Our work is complementary to theirs in that they address raising optimal coverage purchases through subsidies, while we address limiting those purchases from reaching their upper bound. That is, once the increasing total subsidy has raised the purchased coverage above the minimum level, then we have shown that the marginal decrease in subsidy must be sufficiently great to avoid a corner solution of maximal coverage. We leave as an area for future research the exact policy constraints or social objectives which call for an insurance design that always leads to an interior coverage choice.

However, such an objective may well be at work in the design of the existing crop insurance program. Construction of a subsidy with these properties could be extrapolated from the menu of subsidy rates from the RMA website, using a linear spline, as shown below in Figure 3-4. Please note that Figure 3-4 is "zoomed in" to coverage levels actually allowed by policy – that is, 0.0-1.0 on the x-axis refers to a percentage of mean revenue.

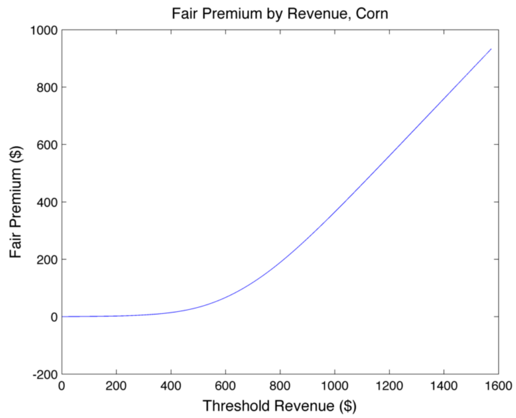

Figure 3-3

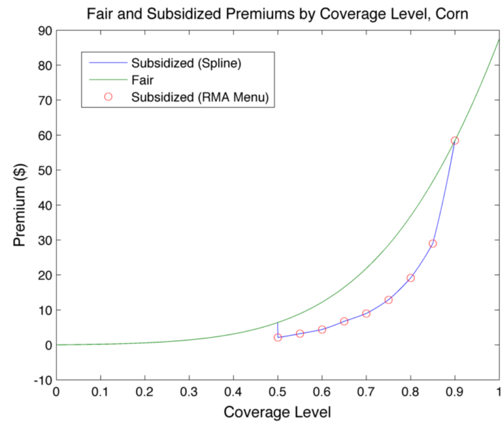

Figure 3-4

Figure 3-3 shows the actuarially fair premium for revenue insurance, for each guarantee level in the revenue distribution for a representative corn farmer in DeKalb County, Illinois, as estimated in the empirical section. The premiums are calculated by integrating over the empirical cumulative distribution function, as demonstrated above. Figure 3-4 highlights the limited menu of subsidized premium choices available under the Farm Bill, along with a. linear-spline function interpolated from the subsidy menu to provide a continuous threshold choice, both of which are overlaid on the actuarially fair premium schedule. In Figure 3-4, the section where the subsidized premium increases most rapidly, relative to the actuarially fair premium, is that which induces the interior choice of insurance coverage even though more insurance is available at a better-than actuarially fair price.

3.2.3 Comparative Statics Under Crop Insurance Alone

In the simulation section below, we will evaluate the sensitivity of acreage and insurance choices to parameter changes when farmers do not receive disaster support – that is, for choices under stand-alone crop insurance. Specifically, we are interested in the effect of risk aversion on the optimal acreage and insurance threshold. The conceptual model takes the utility function agnostically, so there is no ready parameter for comparative statics analysis. Furthermore, the crop insurance premium, and hence the insurance coverage choice, may not be differentiable at the optimal threshold level.

Later, in the simulation analysis, we assume a CARA-exponential utility function and derive the premium non-parametrically. For a theoretical approximation of the actual comparative statics, assume that the premium function is everywhere differentiable and the utility function is defined as $u(w) = 1 - \exp(-\lambda \cdot w)$, where w is wealth and λ is the coefficient of constant absolute risk aversion. Then,

$$\begin{bmatrix} \dfrac{\partial A^*}{\partial \lambda} \\ \dfrac{\partial T^*}{\partial \lambda} \end{bmatrix} = \begin{bmatrix} \dfrac{\partial^2 E[u]}{\partial A^2} & \dfrac{\partial^2 E[u]}{\partial A \partial T} \\ \dfrac{\partial^2 E[u]}{\partial A \partial T} & \dfrac{\partial^2 E[u]}{\partial T^2} \end{bmatrix}^{-1} \begin{bmatrix} \dfrac{\partial^2 E[u]}{\partial A \partial \lambda} \\ \dfrac{\partial^2 E[u]}{\partial T \partial \lambda} \end{bmatrix}$$

but we still cannot sign the results without further assumptions on the Hessian. However, we can leverage the CARA-utility assumption to show that $\partial^2 E[u]/\partial A\partial\lambda > 0$ and $\partial^2 E[u]/\partial T\partial\lambda < 0$, which implies that more risk-averse agents will choose less acreage and more insurance, if the off-diagonal terms of the Hessian ($\partial^2 E[u]/\partial A\partial T$) are sufficiently small.

For example:

$$
\begin{aligned}
\frac{\partial^2 E[u]}{\partial A\partial\lambda} &= \int_T^{\bar{R}} \left(-u''\cdot(R-P-c')\left(AR-AP-c(A)\right)\right)dF - t\cdot(T-P-c')\left(AT-AP-c(A)\right)\cdot u''\big|_{R=T} \\
&= \lambda\cdot\left[\int_T^{\bar{R}} \left(u'\cdot(R-P-c')\left(AR-AP-c(A)\right)\right)dF - t\cdot(T-P-c')\left(AT-AP-c(A)\right)\cdot u'\big|_{R=T}\right] \\
&> \lambda\cdot\left[\int_T^{\bar{R}} \left(u'\cdot(R-P-c')\left(AT-AP-c(A)\right)\right)dF - t\cdot(T-P-c')\left(AT-AP-c(A)\right)\cdot u'\big|_{R=T}\right] \\
&= 0
\end{aligned}
$$

where the first, simplifying step follows from CARA-utility, and the last line is zero by the first order condition for A^*. The result for $\partial^2 E[u]/\partial T\partial\lambda < 0$ follows similarly. We verify these results for the actual crop-revenue insurance policy in the simulation section, for both corn and wheat farmers. For the simulated revenue distribution under actual policy, we observe that the comparative statics are monotone for all but the lowest levels of risk aversion, as demonstrated in Tables 2 and 3.

3.2.4 Ad-Hoc Assistance and SURE

In practical applications, crop insurance does not exist in a vacuum. There are questions of localized actuarial unfairness to some farmers (as in Just, Calvin and Quiggin, 1999, and Makki and Somwaru, 2001), which may cause them not to participate in crop insurance at all. There are no doubt other causes to be examined as well, but they are beyond the scope of this paper. However, ad-hoc disaster assistance has historically been made available to a wide spectrum of farmers, even extending to include those not participating in government crop insurance programs, but legislation has made participation mandatory to receive disaster assistance as early as 1988 (Glauber, 2004).

In this section, we examine the claim that the SURE (supplemental revenue assistance) program is an attempt to codify ad hoc disaster assistance into law, or that it can serve as a suitable substitute for the repeated passage of ad hoc disaster support legislation. Specifically, we check for existence of a SURE program which leaves insured farmers indifferent to the presence of ad-hoc assistance as an available alternative. Both disaster assistance policies are triggered by occurrence of a disaster, which is defined as realized revenues below a pre-set level. This level may be tied to a percentage of mean revenues in practice, though we will express it equivalently as a known percentile of the per-acre revenue distribution in keeping with our prior notation.

Disasters for the purpose of ad-hoc assistance are generally determined on the basis of yield losses due to natural causes. For simplicity, the theoretical model assumes that the disasters declarations are triggered by revenue losses, consistent with the crop revenue insurance that the farmer may purchase. In this manner, we address the interaction of price-risk and yield-risk as a composite source of randomness, in order to facilitate comparison between ad-hoc assistance and the SURE program.

The two policies operate in similar ways. Both disregard the presence of crop insurance, in the sense that the payments are not affected by crop insurance indemnities received, and both operate on the concept of reimbursement according to losses below a threshold level. However, the critical distinction between the two policies is that SURE only pays a percentage reimbursement of the difference between realized 'disaster' revenues and the threshold (as opposed to 100% of the difference as paid by ad-hoc support programs), so there is an element of coinsurance in the way SURE is administered.

In addition, the policies are different in that SURE is only made available conditional on adoption of crop insurance whereas ad hoc assistance is available to both insured and uninsured farmers. However, risk-averse farmers refusing insurance at a better-than-actuarially-fair price is an area of research beyond the scope of this paper so we only evaluate the preferences of farmers who already buy crop insurance. Thus, SURE amounts to a stochastic subsidy that is triggered by especially low revenues; it pays through a combination deductible-coinsurance scheme (guarantee threshold with percentage reimbursement) even though the farmer never really experiences a disaster because the losses are covered by crop insurance, and the minimum available crop insurance covers the loss threshold which defines a disaster.

On the other hand, ad-hoc assistance generally makes larger payments because it pays the full difference between a compensation threshold and the realized revenue (no coinsurance scheme), and the compensation threshold is generally higher than the SURE threshold (mean revenue vs. a typical SURE guarantee of 90% of mean revenue), though the ad-hoc support is subject to legislative uncertainty and may not occur at all.

To extend our basic model of crop insurance we add a disaster threshold, shared by both policies, where Δ is the threshold and $\delta = F(\Delta)$, which is the probability of a disaster occurring. The ad hoc assistance restores farmers to a level of revenue $H > T > \Delta$, so it pays $H - R$ when a disaster occurs, and it pays regardless of participation in crop insurance or the indemnities paid thereby. In practice, ad-hoc payments often set $H = E[R]$ in an effort to restore farmers to their expected revenues, which is the standard we use in the simulation section that follows. The SURE policy is structured similarly to ad-hoc assistance, but with its own guarantee of S and with a percentage reimbursement similar to coinsurance, so it pays $\alpha \cdot (S - R)$, where $\alpha \in (0,1)$. Other than the level and manner of reimbursement, both policies are similar in that they are provided free by the government.

Again, we compare SURE and ad-hoc only for farmers participating in crop insurance. We do not address non-adoption of crop insurance directly, instead focusing on cases where the coverage level is a corner solution, possibly constrained, or an interior solution as developed in the discussion above on targeted subsidies. For brevity, the arguments inside the utility function are omitted where possible. Note that $u = u(AR - AP - c(A))$ and the premium is the actuarially fair premium P_0 plus a distortion function D, both of which can vary with the choice of insurance threshold, T. Thus, the expected utilities under SURE $E[u_S]$ and under ad-hoc $E[u_H]$ are given by:

$$E[u_S] = \int_T^{\bar{R}} udF + t \cdot u|_{R=T} + \int_0^{\Delta} \left(u|_{R=T+\alpha\cdot(S-z)} - u|_{R=T} \right) dF(z)$$

$$E[u_H] = \int_T^{\bar{R}} udF + t \cdot u|_{R=T} + \varphi \int_0^{\Delta} \left(u|_{R=T+H-z} - u|_{R=T} \right) dF(z)$$

where φ represents the probability that ad-hoc assistance can be passed into law if a disaster occurs, since its passage is not certain. The critical component of both expected utilities is the integral over low levels of realized revenues, which is where the disaster assistance actually occurs. The first two terms are non-insured revenue realizations and insured (but not disastrous) revenue realizations, respectively.

Given arguments that the SURE program is meant to replace ad-hoc disaster assistance, it is natural to compare expected utilities under the two policies. The indifference condition is given by setting $E[u_S] = E[u_H]$:

$$\int_T^{\bar{R}} udF + t \cdot u|_{R=T} + \varphi \int_0^{\Delta} \left(u|_{R=T+H-z} - u|_{R=T} \right) dF(z) = \int_T^{\bar{R}} udF + t \cdot u|_{R=T} + \int_0^{\Delta} \left(u|_{R=T+\alpha\cdot(S-z)} - u|_{R=T} \right) dF(z).$$

Despite the simplified notation, it is important to remember that the non-disaster terms do not cancel because they are based on the optimal acreage and insurance choices for each policy. With a little algebra we obtain:

$$\varphi = \frac{\int_0^{\Delta} \left(u|_{R=T+\alpha\cdot(S-z)} - u|_{R=T} \right) dF(z) - D_{A^*,T^*} \left(\int_T^{\bar{R}} udF + t \cdot u|_{R=T} \right)}{\int_0^{\Delta} \left(u|_{R=T+H-z} - u|_{R=T} \right) dF(z)}$$

where the D_{A^*,T^*} term represents the total differential resulting from adjustment of optimal inputs for the different policies, and it is generally small. In the simulation section, we demonstrate that estimating φ without the differential term leads to errors on the order of 0.1% or less when comparing the resulting expected utilities and input choices. Thus, this approximation (without the differential term) will be useful in future policy analyses to verify farmer indifference between various forms of disaster support.

In obtaining this result, we have made a simplifying assumption with respect to the SURE guarantee, namely, that it is fixed instead of dependent on the level of insurance coverage purchased. However, this is accurate for all coverage levels over 0.70, which would not be a binding constraint for any level of risk preference according to our simulation model. Furthermore, we tie the disaster event to a threshold in the farm-level revenue distribution. In fact, the event is tied to a combination of available triggers, including county level losses and losses in adjacent counties, but these triggers are the same for both SURE and ad-hoc, so we simplify the analysis by dropping an extra probabilistic parameter that would indicate these triggers (a coefficient on the integrals from 0 to Δ in the above equation). The larger is the rounded-off differential term, the more significant a role the joint probabilistic trigger would play in the calculation of indifferent policies.

3.2.5 Comparative Statics for Nested Disaster Insurance Policies

In order to identify the marginal effects of changing disaster policies, we derive the familiar comparative statics results via the implicit function theorem. For the SURE policy, we are interested in the marginal effects of changing the SURE guarantee, *S*, as well as the reimbursement rate, α. For ad-hoc disaster support, we are interested in the effects of the guarantee level, *H*, as well as the effects of changing the probability, φ, that ad-hoc legislation is actually passed into law when a disaster occurs. The comparative statics for the parameters of interest in the SURE policy are given by:

$$\begin{bmatrix} \frac{\partial A^*}{\partial S} & \frac{\partial A^*}{\partial \alpha} \\ \frac{\partial T^*}{\partial S} & \frac{\partial T^*}{\partial \alpha} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 E[u_S]}{\partial A^2} & \frac{\partial^2 E[u_S]}{\partial A \partial T} \\ \frac{\partial^2 E[u_S]}{\partial A \partial T} & \frac{\partial^2 E[u_S]}{\partial T^2} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial^2 E[u_S]}{\partial A \partial S} & \frac{\partial^2 E[u_S]}{\partial A \partial \alpha} \\ \frac{\partial^2 E[u_S]}{\partial T \partial S} & \frac{\partial^2 E[u_S]}{\partial T \partial \alpha} \end{bmatrix}$$

whereas the comparative statics for the ad-hoc parameters are given by:

$$\begin{bmatrix} \frac{\partial A^*}{\partial H} & \frac{\partial A^*}{\partial \varphi} \\ \frac{\partial T^*}{\partial H} & \frac{\partial T^*}{\partial \varphi} \end{bmatrix} = \begin{bmatrix} \frac{\partial^2 E[u_H]}{\partial A^2} & \frac{\partial^2 E[u_H]}{\partial A \partial T} \\ \frac{\partial^2 E[u_H]}{\partial A \partial T} & \frac{\partial^2 E[u_H]}{\partial T^2} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial^2 E[u_H]}{\partial A \partial H} & \frac{\partial^2 E[u_H]}{\partial A \partial \varphi} \\ \frac{\partial^2 E[u_H]}{\partial T \partial H} & \frac{\partial^2 E[u_H]}{\partial T \partial \varphi} \end{bmatrix}.$$

Without further assumptions, none of these terms can be signed ex ante, in part because of the unspecified probability distribution for revenues and its interaction with changing marginal utility over wealth. As we will examine further in the simulation that follows, the farmer's choice problem may not be globally concave, or even everywhere differentiable.

3.3 Simulating the Farm-Level Choice Problem

While our conceptual analysis could identify some of the directional effects of policy choices on adoption and land-use, a simulation, accounting for the fine points of the policy, is required to get a more detailed understanding of the impacts of a program like SURE. The empirical simulations evaluate representative farmers, each planting one crop and each with a range of possible risk preferences. The farmers plant corn in DeKalb County, IL and spring wheat in Hyde County, SD, respectively. We chose these two crops because they represent dramatically different risk profiles: the corn farmer faces a revenue distribution that is relatively stable with a high value per acre, whereas the wheat farmer plants in a region with a high coefficient of variation of yields (and of revenues) relative to the Corn Belt.

The farms are representatives of the counties in that their mean yields are the same as those at the county level, but their farm level yield variances are inflated above the county level using the approach discussed below. Each representative farmer maximizes the expected utility of wealth using acreage and the crop insurance coverage levels as choice variables. While a variety of simplifying assumptions are necessary to make the theoretical model tractable, our empirical implementation has a richer, "real life" model. Furthermore, the simulation uses bootstrap procedures to solve problems that do not have closed form solutions to integrals, so we are able to calculate empirical comparative statics results that proved intractable in the theory section. Finally, we verify the theoretical conditions for farmer ambivalence between SURE and ad-hoc disaster assistance.

Our simulation analysis uses an econometrically estimated revenue distribution coupled with estimated costs of fertilizer and acreage, evaluated under realistic options of insurance coverage and insurance subsidization. In this simple framework, we explore the nature of targeted insurance subsidies and the possibilities made available by policy options of subsidy menus, splines, and smooth subsidy functions. While contrasting the two risk profiles across a range of preferences, it becomes clear in both cases that the net subsidy being collected (in expectation) is a key driver of insurance adoption, as opposed to risk preferences per se. Coincident to this analysis we revisit some known results with respect to the risk premium.

3.3.1 Data

The simulation exercise draws data from a number of sources. County-level and national-level yield data are drawn from the National Agricultural Statistical Service (NASS) for the period 1975-2008. For each crop in our simulation (recall that we construct representative mono-crop farmers for each of Illinois corn and South Dakota spring wheat), we follow Risk Management Agency (RMA) definitions of the expected and realized prices. For the realized price of corn, we use the average of the daily October prices of the December Chicago Board of Trade corn future in period *t*. For the expected price we use the average of the daily February prices of the December CBOT corn future. For hard red spring wheat, the expected and realized prices are obtained by averaging the closing prices March and August, respectively, for the Minneapolis Grain Exchange (MGE) September contract. We leverage expected and realized prices together to econometrically estimate the price-yield relationship, in order to construct a revenue distribution which preserves price-yield correlations. Crop insurance premiums and the revenue insurance subsidy schedule are drawn from the RMA website to calibrate the model.

3.3.2 Modeling the Distribution of Yields and Prices

While the theoretical model assumed an abstract distribution of revenue per acre, the empirical analysis must build revenue per acre from the joint distribution of yield and price, taking account of correlations between the two, since actuarial fairness must be described non-parametrically. The remainder of this subsection is dedicated to estimating the joint distribution of per-acre yield and price faced by farmers. We model the joint distribution of yields and prices using a method based on generating correlated within-season price and yield deviates, as in Cooper (2010, 2009b), and then forecast an empirical distribution for 2009, just following the final year of the dataset.

Under this approach, national average yields are expressed as within-season yield deviations: $\Delta y_t^N = \left(y_t^N - E\left[y_t^N\right]\right) / E\left[y_t^N\right]$, where $E\left[y_t^N\right]$, expected national average yields per acre, are estimated by regressing average yields on a linear trend using data for t = 1975-2008, to allow for growth of average yields over time. Then, in order to set expectations to the current time, the linear trend is used to adjust deviates "as if" our empirical revenue distribution takes place in 2009. County yields are de-trended and transformed to deviation form (denoted as Δy_t^c) using the same methods.

Realized harvest prices, p_t, are also transformed into deviation form, where $\Delta p_t = \left(p_t - E\left[p_t\right]\right) / E\left[p_t\right]$ and where $E\left[p_t\right]$ is the pre-season expected price, which is taken from the futures markets as discussed above. Next, the relationship between Δp_t and Δy_t is econometrically estimated. We assume that Δp_t can only be partially explained by Δy_t, and that the uncertainty in this relationship can be incorporated into the empirical distribution as

$$\Delta p_t = g\left(\Delta y_t, z_t\right) + \varepsilon_t$$

where z_t is a vector of other relevant variables that may contribute to the price deviation, including energy demand and crop diversion into biofuels.[15] This equation represents a linear regression in which g is an affine function and ε_t is the error term. Naturally, we expect the OLS coefficient on Δy_t^N to be negative, because demand curves slope down. That is, the harvest-time price is more likely to exceed the expected price if national average yields do not meet expectations.
We jointly estimate the distributions of price and yield deviations by repeated estimation of the equation above using a bootstrap procedure. Specifically, we use a joint[16] re-sampling methodology (a pairs bootstrap) that involves drawing *i.i.d.* observations with replacement from the original data set (as in Yatchew, 1998). This bootstrap procedure is used to generate coefficient vectors representing uncertainty in the yield-price relationship. Variation in estimates results from the fact that the regression equation is estimated for an independently-drawn bootstrapped sample at each iteration. That is, for each draw of a yield deviation, this process induces a distribution of estimated price deviations, with M = 1,000 draws. The average yield-deviate coefficient on the price-deviate was -0.938 for corn, and -0.955 for wheat, with yields sampled at the national level.

After estimating the distribution of price deviates, simulated county yield deviate vectors, $\left(\Delta y_t^c\right)$, were generated for each crop using a version of the block-bootstrap approach in which the pair-wise relationship between county- and national-level yield values is maintained across each crop and yield aggregation (Lahiri, 1999). We draw N = 1,000 times, with replacement, from the actual yield

[15] As explained below, the regression estimation is repeated 1,000 times for each bootstrapped draw of price and yield deviates. It is verified that the demand coefficient is negative and significant at a level ≥95% in each regression. Please see Cooper (2010) for further model description.

[16] That is, if the original data consist of column vectors of prices and yields, 'joint' re-sampling refers to row-by-row sampling from the vectors, with replacement.

data to generate the simulated yield data. The simulated yield data maintains the underlying historical Pearson and rank correlation – as well as any other relationship in the relevant explanatory variables – between county- and national-level yields. Finally, for each simulated yield deviate, Δy_{tn}, we generate M simulated price deviations, $\Delta\hat{p}_{tnm}$, based on the M coefficient vectors from the regression bootstrap above. This process results in $N \cdot M = 1{,}000{,}000$ simulated values of $\Delta\hat{p}_{tnm}$ with pair-wise relationships maintained between the simulated prices and the yield draws.

The estimated price distributions, not conditioned on yields, are shown below for corn and wheat. The overall price-yield correlations (for the values, not the deviates) were -0.884 for corn and -0.464 for wheat, so the wheat farmer faces a considerably larger share of price uncertainty that is not explained/hedged by yield uncertainty, relative to the corn farmer.

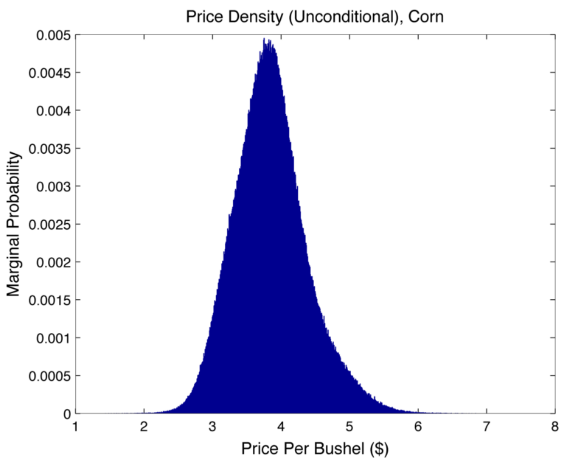

Figure 3-5

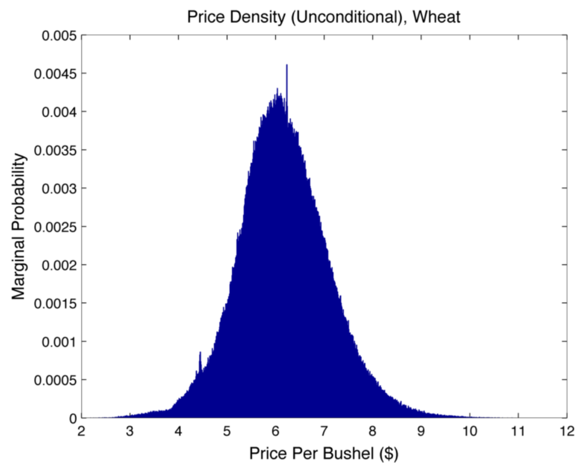

Figure 3-6

To represent farm-level conditions, we inflate the standard deviation of county-level yields. Based on the results of Carriazo, Claassen, and Cooper (CCC) (2009), using a variation on an approach by Coble and Dismukes (2008), we "blow-up" the county level yield distribution until it matches actuarially fair premiums as calculated by RMA.[17] In essence, CCC show that reasonable farm-level yield distributions can be generated by adding scaled Gaussian white noise to county-level yields, where the correct scale factor, α, is identified through an iterative process which ends when the RMA actuarially fair premium (at a baseline coverage level of $\theta = 0.70$) corresponds to the augmented distribution.

We found a scale factor of 2.85 for DeKalb corn, as compared to 1.03 for Hyde Wheat, indicating more within-county variation among corn farmers. Just as the wheat farmer faces more outside price risk, he also faces more yield risk. For example, the correlation of farm-level yield and price for wheat was -0.164, while it was -0.223 for corn.[18] The resulting empirical, per-acre, gross revenue

[17] The RMA premium calculator is available at: http://www3.rma.usda.gov/apps/premcalc/index.cfm

[18] However, these factors combine in interesting ways. The correlation of county level yields per-acre with national yields per-acre was *0.357* for Hyde County wheat, vs. *0.773* for DeKalb corn. Corn farm-to-county yield correlation was *0.322* and farm-to-national

distributions for our representative corn and wheat farms are shown below. The spike at zero represents a total loss of the farmer's crop. It is apparent from the Figures that wheat production in South Dakota is relatively risky compared to the Corn Belt, and as such, the former is a region where disaster assistance is likely to be particularly relevant.

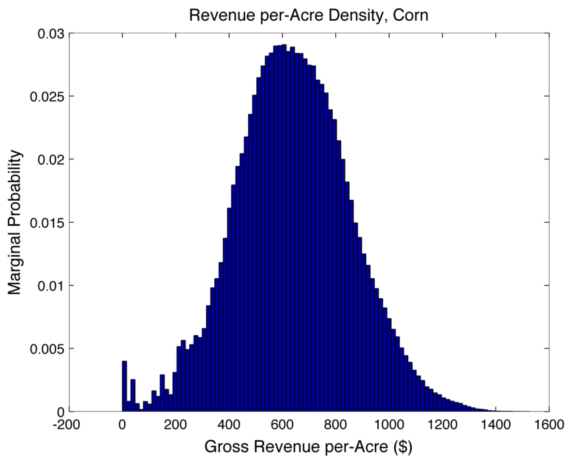

Figure 3-7

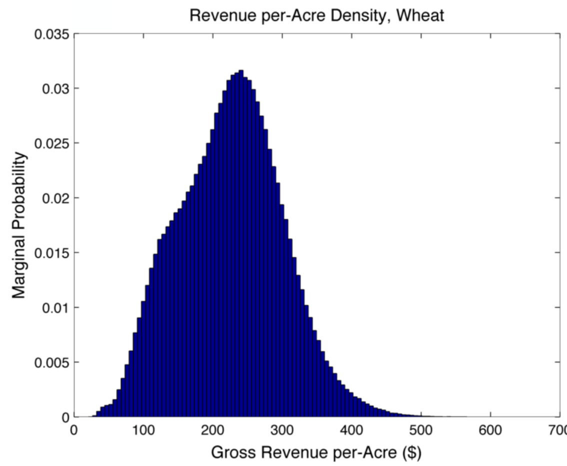

Figure 3-8

3.3.3 Policy Details: Federal Crop Insurance

The U.S. Dept. of Agriculture's (USDA) Risk Management Agency (RMA) implements and oversees the Federal crop insurance program, which is administered via partnership with private insurers. By law, USDA must try to devise actuarially fair premium rates, independently of the rates actually paid by farmers.[19] Premium subsidies (in expectation, according to claims paid) resulted in net transfers of $1.63 Billion to farmers in 2006, so a key source of producers' return to crop insurance purchase is the premium subsidy. For example, at 70 percent coverage, 59 percent of the full premium is paid by the Federal government, so if premiums are actuarially fair the net return to producers would equal 59 percent of expected indemnities.[20] While a variety of Federal crop insurance products are available, we focus on Revenue Assurance (RA) applied on a single-crop basis; though "whole farm" coverages are available, current trends indicate that single crop revenue insurance is adopted at a much higher level (Saak et al., 2003).

Revenue assurance acts much like a deductible in traditional property and casualty insurance, as mentioned in the theory section above. Specifically, revenue assurance guarantees a certain threshold level of revenue, below which the farmer incurs no losses. This threshold is specified according to the revenue distribution and, in practice, guarantees a percentage of mean revenues according to the farmer's historical performance. In technical terms, an RA

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correlation was 0.252. For wheat, farm-to-county yield correlation was 0.968 and farm-to-national was 0.353. An interesting example of the non-transitivity of correlation between random variables, as documented in Langford et al. (2001).

[19] At best, as the insurance products are not calculated using individual-specific yield risk measure, they can only be actuarially fair on average.

[20] Please see Table 20 for the complete RMA premium subsidy table.

indemnity is paid when realized revenue falls below the guarantee, which equals the RA base price multiplied by the producer's APH (average production history) yield and the coverage level. The per-acre indemnity is:

$$I_t = \max\left(0,\, \theta \cdot p_t^b \bar{y}_{-t} - p_t y_t\right)$$

where $\theta \in [0,1]$ is the coverage level, t indexes the planting year, p_t^b is the RA base price or "expected price" (defined by futures markets), p_t is the RA realized price (according to spot markets after harvest), $\bar{y}_{-t}$ is the expected yield (based on previous years' production) and y_t is the actual, realized yield. In essence, the insurance pays for the difference between realized revenue and the guarantee, a threshold determined as a percentage of expected revenue. To clarify notation and unite the concepts of our theoretical model with the actual policy parameters, note that we use *R* in the theoretical model to denote revenue, which is equal to $p_t y_t$ in the above specification, and *T* to denote the insurance threshold, which amounts to selecting θ.

Figures 3-9 and 3-10 below show the simulated, optimized profit density functions (at the farm level) for our representative farmers when their coefficient of absolute risk aversion is 5E-05. This level of risk aversion is chosen in part because both farmers choose an optimal coverage level of 0.85. The optimal acres are 60.18 for wheat and 142.50 for corn. The Figures omit an atomistic point (induced by the nature of revenue insurance) because of scaling – the wheat farmer experiences profits of \$722.83 with a 32.95% probability, and the corn farmer obtains profits of \$11,936.14 with a 33.04% probability.

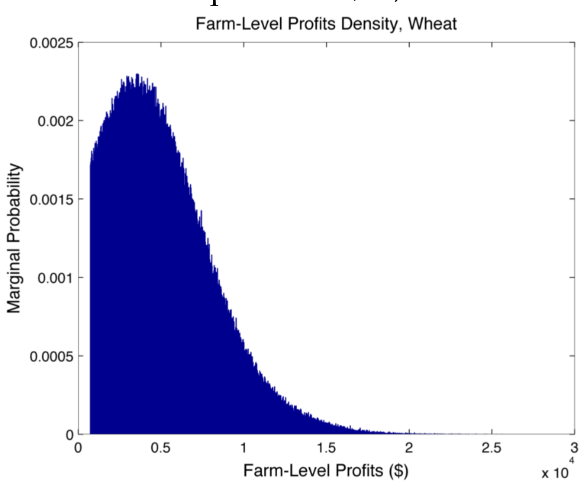

Figure 3-9

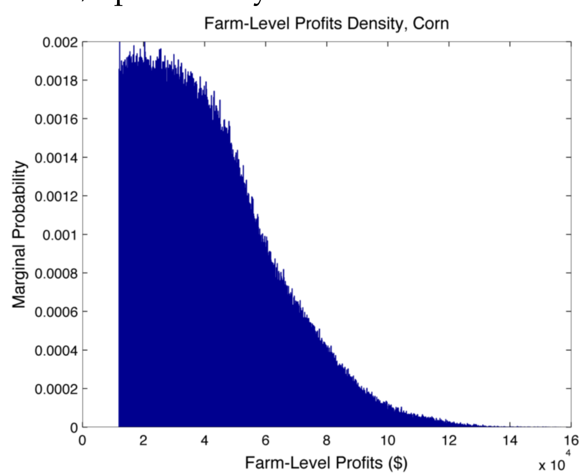

Figure 3-10

3.3.4 Simulating the Farmer Choice: CARA Expected Utility

We start with a simulation exercise that examines only the effects of the targeted insurance subsidy on the choices of coverage level and acreage. This basic setup allows for empirical generation of comparative statics results for risk preferences, as well as a discrete comparison across risk profiles by contrasting the decisions of our representative corn (safer) and wheat (riskier) farmers with one another. Each representative farmer is assumed to be expected utility-maximizing, with constant absolute risk aversion (CARA) exponential utility. Thus, they solve:

$$\underset{A,\,\theta}{Max}\ EU(w) = E[1-\exp(-\lambda \cdot w)] = \frac{1}{N \cdot M}\sum_{j=1}^{N \cdot M}\left[1-e^{-\lambda w_j}\right]$$

where λ is the coefficient of absolute risk aversion and w_j is the wealth outcome for each draw from the revenue-per-acre distribution. The wealth outcome for each draw is defined as:

$$w_j = A \cdot \left(p_{tj} \cdot y_{tj} + I_{tj}(\theta, py) - P_{sub}(\theta)\right) - c(A)$$

where A is acreage, θ is the choice of insurance coverage, $p_{tj} \cdot y_{tj}$ is the revenue realization for draw *j*, I_{tj} is the realization of the insurance indemnity, $P_{sub}(\theta)$ is the post-subsidy insurance premium, and $c(A)$ is the cost of acreage.

To simplify the results, we ignore baseline farmer wealth (i.e., $w_0 = 0$), as well as ignoring credit and budget constraints since the functional forms provide interior solutions with respect to acreage. With respect to insurance coverage, the available levels of coverage depend on the exact specification of the policy regime, which we will detail below. We do not, however, abstract away from the production cost of crops or from including an explicit, increasing cost of expanding acreage. Production costs per-acre of fertilizer, etc. are given in Table 1, and are then adjusted according to the guaranteed Direct Payments for each representative farmer's county, while acreage costs follow a simple quadratic as in Howitt (1995): $C(A) = v_0 A + v_1 A^2$.

We also evaluate the choice scenarios with acreage fixed to represent cases where farmland is inelastic, as might be more likely to occur in the middle of the Illinois Corn Belt than for our representative wheat farmer in Hyde County, South Dakota. This consideration is most important to the evaluation of disaster support programs, and we cover it in Section 3.4 below. It turns out that constraining acreage has a minimal effect on the results – it just leads to a smaller effect on the insurance choice when disaster support is introduced.

Table 1 presents summary statistics for inputs to the simulation analysis. The first few rows present the mean and standard deviation of the yield density function that was simulated for each representative farmer, which are followed by the 2009 crop year planting time output prices, around which the estimated price density functions are centered. The final rows indicate net costs of acreage and the cost function used. The farm-level yield data was generated by scaling up the variance of estimated county level yield densities based on analysis of NASS/USDA and RMA/USDA data for Hyde County, South Dakota and DeKalb County, Illinois, as detailed previously. Operating costs per acre are for the regions including South Dakota and Illinois, respectively (USDA, 2008).

3.3.5 Simulation Results: Crop Insurance Only

We start with a basic simulation of the crop insurance and acreage choice, before expanding it to explore the impact of providing disaster assistance. Expected utility is maximized over a vector of one million sample revenue draws, using Matlab's non-linear, unconstrained optimization function, `fminsearch`, which uses a simplex method (see Miranda and Fackler, 2002) to identify a global optimum in $\mathbf{R}^2$-space (acreage, coverage). The simulation was repeated for both representative farmers over many orders of magnitude of the CARA risk aversion coefficient, λ. A condensed version of the results is shown in Tables 2 and 3. The results were found to be robust to a high level of mis-specification of the starting guess for the simplex, though we did find that the optimal insurance choices were highly clustered around the 0.85 value, for risk-neutral producers all the way to highly risk-averse ones.

Table 2 shows the basic simulation results for the spring wheat farmer in Hyde County, SD. In Table 2, *Acres** and *Covg** denote the optimized values for these variables. Because of the linear-spline subsidy function (based on the actual RMA schedule in Figure 3-4), acreage choices are clustered for all levels of risk aversion in a very small range. It appears that the motivation for this is more one of profit-maximization than risk management, as acreage fluctuates much more dramatically across risk preferences. Nonetheless, we have unambiguous comparative statics results that acreage decreases with risk aversion, and insurance increases, subject to the non-differentiability of the insurance premium function around 0.85. The table also shows how expected profits, the standard deviation of profits, and the coefficient of variation all change with risk preferences. [21]

Table 3 shows the initial simulation results for our representative corn farmer in DeKalb County, IL. The immediately apparent difference between corn and wheat is the corn profits are almost ten times larger in expectation. In addition, while the same comparative statics results for acres and coverage held true, the coefficient of variation decreased much more rapidly (at lower levels of risk aversion) and then leveled out. The corn farmer also entered, and departed, the 85% coverage 'sticking point' at levels of risk aversion ten times lower than the wheat farmer.

Figures 3-11 and 3-12 below summarize the acreage and insurance coverage elections found in Tables 2 and 3. The flat area in both optimal coverage graphs identifies the sticking point resulting from the kink in the insurance premium schedule at the 85% coverage level. The Figures provide a summary of the complex interactions between acreage, insurance, and risk aversion for the two crops, demonstrating the substantial differences in the risk profiles of the various representative farmers. These Figures also identify conditions under which the approximated comparative statics results in the theory section hold. Specifically, wherever the objective function (profits, and hence, expected utility) is differentiable, acreage is decreasing in risk aversion and insurance is increasing, with one exception. The simulated distribution for wheat is such that some low levels of risk aversion experience non-monotonicity of the optimal acreage choice.

[21] Resulting expected utilities are omitted from Tables 2 and 3 because of a quirk of the CARA utility function, which is somewhat misleading when included in a table – for a fixed level of wealth, utility is increasing in risk aversion ($du / d\lambda = w \cdot e^{-\lambda w} > 0$), and this effect dominates the utility-decreasing effect of increased curvature.

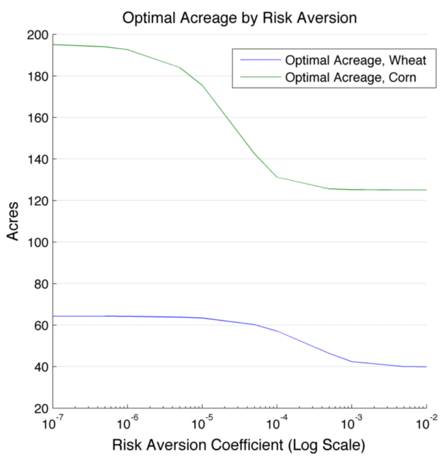

Figure 3-11

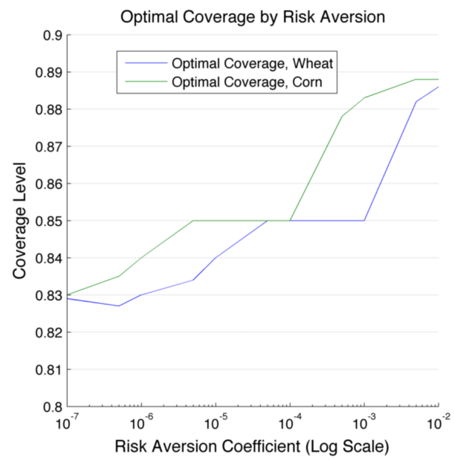

Figure 3-12

3.3.6 Measuring Risk Premiums

Our initial approach to parameterizing the risk aversion included a moderate risk aversion premium of 20 percent (e.g., Hurley, Mitchell, and Rice, 2004; Mitchell, Gray, Steffey, 2004). The risk premium is calculated according to the approach in Babcock, Choi, and Feinerman (1993):

$$RP = \frac{\ln\left[0.5\cdot\left(e^{-\lambda h}+e^{\lambda h}\right)\right]}{\lambda h}$$

where *RP* is the risk premium and denotes a percentage of the expected profits from a gamble that are forfeited to reduce the risk faced, and *h* denotes the size of the gamble, which they claim can be approximated as the standard deviation over the set of outcomes, when gambles depart from the coin-flip variety. However, in evaluating the farmer choices over different levels of risk aversion, it became apparent that the Babcock et al. (BCF) formula was an increasingly poor approximation of the share of expected profits forfeited relative to the risk-neutral producer, as the level of constant absolute risk aversion increased. Table 4 summarizes the BCF risk premium and actual risk premium for the levels of risk aversion included in Tables 2 and 3.

There are two factors contributing to the divergence of the BCF risk premium approximation from actual. First is the revenue distribution for each crop, which departs substantially from a coin-flip gamble, and second is the optimization of the gamble itself, where the farmers' ability to manage risk through both insurance coverage and farm size can minimize the lost profits associated with risk aversion. The sharply-sloped acreage cost function we imposed, $C(A)=v_0\cdot A+A^2$, also plays a role. As can be clearly seen in Table 4, the standard of 20% risk premium from Hurley et al. (2004) may need to be revisited in the context of the measurement method used. While our evaluation over many orders of magnitude of the risk aversion coefficient covered the full range of reasonable BCF-risk premiums (as discussed in their paper), the actual risk premium did not quite reach 20% for even the most risk-averse farmers we considered. This finding will prove critical to future research on risk – it will be necessary to identify the appropriate setting for 'standardized' risk premiums, and when approximations such as BCF remain appropriate to evaluating the gambles in question.

3.3.7 Incorporating Disaster Assistance into the Simulation

This section presents the details of calculating SURE payments that are essential to a realistic computation of the tradeoffs faced by farmers, and interpretation of the policy parameters. Supplemental Revenue Assistance (SURE) is a whole farm program that provides supplemental payments to farmers who purchase crop insurance either through the Federal crop insurance program or through the Noninsured Crop Disaster Assistance Program (NAP). As most crop acreage in the regions we examine is insurable through the former, we focus on SURE as it applies to crops eligible for Federal crop insurance. SURE is analytically described in CCC (2009) and Smith and Watts (2010), but the description here is updated to account for the SURE regulations released in December 2009.

SURE payments can be made only to producers who are located in counties where a disaster has been declared: this occurs when the Secretary of Agriculture determines that there has been a weather-related production loss of 30 percent or more in at least one crop, in counties contiguous to disaster counties, or when any producer has experienced production 50 percent or more below normal levels. In addition, producers must suffer a 10 percent production loss to at least one crop of economic significance on their farm in order to be eligible for SURE. The level of the SURE payment is:

$$SURE_t = 1_t \cdot \max\left(0,\, 0.60 \cdot \left(S_{-t} - p_t y_t\right)\right),$$

where S_{-t} is the SURE guarantee, $p_t y_t$ is total farm revenue, and where 1_t is an indicator variable for the disaster trigger; it is equal to 1 if either a disaster is declared in the farmer's county or in a contiguous county, or if actual production on the farm is 50 percent or less than expected production (recall from above: $p_t^b \bar{y}_{-t}$), as measured by overall revenue, and 0 otherwise. Our representative farmers plant only one crop so that the question of economic significance is ruled out, and we consider only the 50% revenue-loss component of the trigger for the SURE vs. ad-hoc indifference calculations because the two disaster support programs share the same triggers, in general.

The SURE guarantee depends on the level of crop insurance coverage selected by the producer, expected prices, and the producer's APH yield, but is limited to no more than 90 percent of typical or expected revenue: [22]

$$S_{-t} = \min\left(1.2 \cdot \theta \cdot p_t^b \bar{y}_{-t},\ 0.90 \cdot p_t^b \bar{y}_{-t}\right).$$

We also abstract away from other sources of total farm revenue (outside of crop sales), which include marketing loan benefits, direct payments, and counter-cyclical payments or ACRE (the Average Crop Revenue Election program) which are mutually exclusive,[23] and simplify the modeling approach by assuming away "farm-gate" prices that are different than the national average market price, p_t.

[22] This specification abstracts away from planted acreage shares between crops and from counter-cyclical payments, as included in the actual SURE program, in part because of our assumption of a mono-crop farmer.

[23] If the eligible farmer chooses to be in enrolled in the Average Crop Revenue Election program (ACRE) rather than in the traditional commodity program, then the CCP payment in *t* is replaced by an ACRE revenue payment, DP's are reduced by 20% and

The ad-hoc payment is modeled similarly to the SURE payment where, contingent on the disaster trigger, payments are made according to the difference between realized revenues and a given threshold. As is common in practice, we assume the threshold $H_t = E[p_t y_t] = p_t^b \bar{y}_{-t}$. However, while an ad-hoc payment which does occur is larger than the corresponding SURE payment (all else equal), the ad-hoc support is subject to political uncertainty, which we denote with another indicator variable, 1_φ. Thus, the level of the ad-hoc payment is given by:

$$AdHoc_{t,\varphi} = 1_t \cdot 1_\varphi \cdot \max\left(0,\ p_t^b \bar{y}_{-t} - p_t y_t\right).$$

The political uncertainty associated with ad-hoc is incorporated into the simulation by a vector of uniform random variables $X \sim U[0,1]$, such that for every revenue realization below 50% of the mean (the disaster trigger), $X < \varphi$ implies that ad-hoc was successfully passed into law.

While we do not explicitly consider the simultaneous presence of ad-hoc support and the SURE program, we use the simulation/optimization procedure to estimate the probability of ad-hoc support which would make farmers indifferent to SURE. In the next sub-section we show that the indifferent ad-hoc probability is increasing in the risk aversion coefficient, and that the representative wheat farmer is indifferent to lower probabilities than the corn farmer across most levels of risk aversion. We also show that implementing a disaster support program like SURE, in its entirety, leads to increased acreage across nearly all levels of risk aversion, but only small changes in insurance coverage. As shown in Section 3.4, and in Tables 18 and 19, the distortions are even smaller when acreage is bounded above, as may more likely be the case for our DeKalb County, IL representative corn farmer.

3.3.8 Simulation Results: The Impact of Disaster Assistance

Tables 5 and 6 present the optimal input choices, along with expected profits and descriptive statistics as in Tables 2 and 3, for the wheat and corn farmers over a range of risk aversion coefficients, λ. For the wheat farmer, expected SURE payments are \$66.33 per acre given that they occur. However, since they only occur with the frequency of revenues below 50% of expected (7.31% for wheat), they have a small impact on farmer decision-making at \$4.85 an acre in expectation. Indeed, by comparing expected profits in Table 5 with Table 2, it can be shown that the insurance and acreage decisions are nudged slightly in order to capture the SURE transfers, so that some of the expected transfer amount is used up due to the sub-optimality of these choices. Overall, the SURE program results in small adjustments to the level of insurance coverage selected by both corn and wheat farmers, on the order of less than 0.5%, and to acreage increases of several percentage points for the more risk-neutral among them.[24]

Table 6 shows similar results for the representative corn farmer. For corn the expected SURE payment is \$211.91 per-acre when it occurs, but the corn farmer experiences fewer disasters than the wheat farmer (only 6.72%), so the

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the loan rate in the MLB by 30%. We do not incorporate these details into the simulation analysis.

[24] Tables 16 and 17 in the Appendix explicitly show the impacts of disaster assistance on input choices. They compare Table 2 vs. 5 and Table 3 vs. 6 explicitly.

program only nets him an expected $14.24 per acre overall. As with wheat, the corn farmer experiences negligible changes in the amount of optimal insurance coverage purchased, but increases acreage for most levels of risk aversion (when compared to no disaster assistance), with stronger effects for more risk-neutral farmers. While Tables 5 and 6 show that the program serves to lower the coefficient of variation faced by the farmers, this effect does not constitute much risk management *per se*, since the standard deviation of profits remains virtually unchanged after optimization (as compared to Tables 2 and 3) so it comes almost entirely from the increase in expected profits.[25]

Table 7 confirms the earlier results in Table 4, showing that the BCF risk premium approximation may not be appropriate for this setting. In fact, the BCF risk premium is nearly unchanged, since it is an approximation based on the standard deviation of total profits and behavior is largely unaffected by introduction of the SURE program. The actual risk premium has only changed slightly, representing the increase in profits across the board.

Overall, several lessons are clear from the simulation introducing SURE into the optimization problem. First, SURE does not change the relative risk profiles of the farmers, but induces small changes in their input selections intended to capture extra rents. Indeed, there is very little effect on expected utilities for the more risk-averse farmers. In addition, the lessons regarding the riskiness of each crop remain from the initial simulation. The wheat crop has a riskier revenue profile, a slightly higher probability of disaster and more frequent insurance activation at many coverage levels. Yet, once the farmers optimize over acreage and insurance, the coefficient of variation faced by the farmers are about equal and the wheat farmers pay consistently less risk premium, except at the highest levels of risk aversion. The addition of the SURE program does not affect this comparison between the two crops.

3.3.9 Simulation Results: Ad-Hoc Indifference

So as not to overwhelm the reader, the equivalents of Tables 5-7 can be found in the Appendix as Tables 10-15, for both ad-hoc disaster support passed into law with a 70% probability ($\varphi = 0.70$) and certain ad-hoc support ($\varphi = 1.0$). Given these results, we use the approximation derived in the theoretical section to identify the indifferent ad-hoc probability (that is, indifferent to the SURE program as written) for each level of risk aversion. In doing so, we show that the indifferent probability is increasing in the risk aversion and that, for the range of RA coefficients examined, there may be a wide range of probabilities that are acceptable to some subsets of farm producers.

Tables 8 and 9 show the ad-hoc support probability leading to indifference between ad-hoc disaster assistance and SURE, for both Hyde spring wheat and DeKalb corn. As discussed previously, the wheat farmer who faces a riskier revenue distribution ends up taking on 'less risk-averse' behavior than the equivalently risk-averse corn farmer, once we have accounted for optimizing behavior. This means that, given an ad-hoc probability, wheat farmers are more likely to accept the SURE program in its stead, as long as risk aversion is

[25] Recall that the formula for the coefficient of variation is given by: $CV = \sigma / |\mu|$.

similarly distributed among corn- and wheat-farming populations. This is demonstrated in Column 2 of each Table.

In Table 8, the last column shows the precision of our approximation, where all changes in expected utility from the 'indifferent' switch are less than 0.15%. Thus, it is clear that disregarding the total differential term from the approximation (as outlined in the theoretical section) does not have much of an effect on the accuracy of these results. The changes in purchased insurance coverage and in acreage are also small, though clearly the insurance 'sticking point' of 85% coverage leads to some larger fluctuations in acreage for certain levels of risk aversion by the representative farmer. Table 9 shows a similar presentation of the relevant results for our DeKalb County, IL, representative corn farmer, where the approximation appears to be slightly less precise (as measured by the percentage change in expected utility after switching, which should ideally equal zero).

Table 9 shows that the corn farmer will be indifferent only for much higher levels of ad-hoc support probability, given the level of risk aversion. It also shows that the precision of our indifference approximation is about the same, and that the coverage election is much less elastic for the representative corn farmer than for the wheat farmer.

Overall, the wheat farmer requiring higher levels of risk aversion to approximate the corn farmer's indifference means that wheat farmers across the board will be happier with lower levels of ad-hoc support probability than their corn-farming cousins, ceteris paribus. In other words, the corn farmers have a more favorable disposition to SURE based on their specific distribution of optimally risky production, whereas wheat farmers will almost always prefer the larger, but less certain, payments of ad-hoc disaster support. As identified in the crop insurance section of our simulation exercise, this fact likely results from the wheat farmers' riskier per-acre distribution being completely dominated (in terms of riskiness) by the larger scale of operations and the post-optimization behavior of the simulated corn farmers.

3.4 Discussion.

We have shown here that assumptions about farmer risk aversion, or empirical findings on the distribution thereof, may be critical drivers of policy. If acreage is variable, even if at substantial marginal cost when farmers optimize, then introduction of disaster support policies means farm acreage will necessarily expand as farmers pursue additional expected profits. The highest level of acreage expansion in our simulation was over 7%, observed for many wheat farmers and some of the more risk-neutral corn farmers, when receiving ad-hoc support with 100% probability. However, the most risk-averse farmers experienced essentially no changes in their input choices under all of the various disaster assistance policies considered. The indifference of the highly risk-averse farmers to any form of disaster support is no doubt a result of the fact that all the disaster policies increase the mean revenue per acre, but do so in a way that adds considerable variability to the revenue distribution, for which they have a strong distaste (as in Saha, 1997). Thus, Tables 16 and 17 show the percentage changes in acreage and insurance coverage induced by each disaster policy, as compared to a baseline of crop insurance participation only.

The current schedule of insurance subsidies, with the sharp kink at 85% coverage, forces farmers' insurance purchase decisions to be held relatively constant in our simulation so a majority of risk management is handled by varying the planted/insured acreage in any given season. Thus, policymakers must not only focus on the role of acreage in affecting environmental policy goals, but also focus on tradeoffs with respect to the social costs of expanding acreage, vis-à-vis the distortionary burden of government financing of aggregate insurance subsidies.

Aggregate costs, in turn, will be determined by the percentage of total adoptions, which we do not address directly as non-adoption of actuarially over-fair insurance is not consistent with an expected utility framework. Further research remains to identify local unfairness of RMA insurance premiums within the farm sector, or to evaluate alternate expected utility models under prospect theory to accurately account for this behavior. This research will be critical since, even under the current regime of heavily subsidized insurance supplemented with disaster assistance, there remain farmers who do not participate in the Federal crop insurance program. As of 2004, 75-80 percent of corn, soybean, wheat, and cotton acres were insured, primarily through larger, commercial farms (Dismukes and Glauber, 2005), so explanations revolving around transaction costs of purchasing insurance or alternate expected utility models seem more likely than those focused on localized actuarial unfairness. This point is bolstered by the fact that it would take a very strong deviation in the revenue distribution to make the premiums actuarially unfair to the point of non-adoption, both due to the high level of subsidies and considering the high level of risk premium involved in property-casualty insurance products outside the farm sector.

Nonetheless, the analysis sheds some light on these issues when given a starting point of the level of insurance adoption (yes/no participation) in a particular crop industry. While exact calculations and theory are an area for future research, one could imagine a social optimization problem in which tradeoffs were faced between potential environmental damages from acreage expansion and social welfare costs of (necessarily) inefficient taxation. In this context, there would exist a tradeoff for the social planner in increasing acreage (through disaster assistance) while attempting to advance a social goal of farm-sector risk management, causing social costs at both the intensive and extensive margin. These social costs would be counterbalanced by the decreased level of insurance purchased by already-participating farmers at the intensive margin, though our simulation shows this effect to be quite small, and the relative size of these two effects will ultimately depend on the starting level of Federal crop insurance participation. Using a standard S-curve adoption model, we expect that pre-existing high levels of crop insurance participation would lower the negative welfare effects of expanding disaster support programs.

3.4.1 Acreage Considerations

The present analysis adds richness by incorporating both the insurance coverage and acreage choice simultaneously into the farmers' decision problems, but it might be argued that this generalization does not always coincide with reality. Specifically, while it might be expected that our representative spring wheat farmer in Hyde County, SD, has relative flexibility with respect to acreage planted, the representative corn farmer in the middle of the Corn Belt in Illinois is likely to face considerable constraints in expanding acreage because of the high level of existing agricultural production (and productivity) in the region. While the preceding tables showed variation in the optimal acreage choice across risk preferences, this was not a thought experiment about changing a given farmer's preferences and observing the resulting change in acreage. Rather, the tables presented variation across different individual farmers according to their inherent risk preferences, so this variation is emblematic of varying farm sizes within the industry. As a result, one might consider that farmers optimize according to their risk preferences when the farm is purchased and therefore, the acreage constraints are not relevant here.

Nonetheless, when disaster support is introduced we are clearly observing a change in acreage as a result of policy. To explore this point, we conducted a duplicative, full simulation analysis with acreage bounded above at the optimal level without disaster support. The results coincide perfectly with the earlier analysis, but are somewhat surprising in that bounded acreage effectively limits farmers' ability to seek extra rents by altering their input choices. Specifically, just as the introduction of disaster programs led to little change in the level of insurance coverage purchased, so too does the introduction of the same programs when acreage is constrained not to exceed the crop-insurance-only acreage choice.

The results of the constrained optimization are shown in Tables 18 and 19.[26] Note that we only constrain acreage from above, since it is relatively costless for farmers to reduce planted acreage, and since the disaster policies only act to increase acreage – ignoring changes smaller than 0.1%, since the most risk-averse farmers are essentially indifferent to the disaster support programs. When acreage is bounded above, the constrained optimization results show that changes in the insurance choice are still small across all levels of risk aversion, though wheat farmers closest to the sticking point of 0.85 experienced increases as large as 2%.

3.4.2 Conclusions

We have implemented and tested a theory of nested insurance to evaluate the impact of disaster support and risk preference acreage decisions and crop insurance purchases. The results suggest that parameters of a government program like SURE may enhance the value of crop insurance to the farm sector, but counter-intuitively, disaster support programs are most valuable to the least risk-averse farmers. This result follows from the fact that disaster programs currently available are simply stochastic subsidies that add expected value to planted acreage, but do so in a manner that also increases variability of revenue outcomes. In addition, we show that disaster support, whether through ad-hoc legislation or via the new SURE program, essentially leads to a moral hazard problem, whereby insurance purchases are discouraged at the intensive margin (albeit marginally) and planted/insured acreage is encouraged to increase. However, acreage being constrained not to exceed pre-disaster policy levels will eliminate the acreage component of the moral hazard problem and will also

[26] Though they each omit a single value of risk aversion where disaster assistance actually caused optimal acreage to decrease, and so the acreage constraint did not bind.

mitigate the insurance component. Thus, for farmers in the Illinois Corn Belt, existing constraints on acreage will mitigate the adverse effects of disaster support policies, in contrast to our representative wheat farmer in Hyde County, SD.

Overall, we have shown that existing crop insurance policies provide a substantial risk management tool to farmers. In contrast, disaster support policies provide little risk management but do encourage more risky behavior in favor of additional expected profits. However, the impacts of disaster support policies on insurance purchases are relatively small. Across a wide range of risk preferences, and for two substantially different risk profiles (those of DeKalb Corn and Hyde Wheat), the transition from no disaster support to full disaster support engenders less than a 2% change in insurance coverage elected, and far less than that in the majority of cases considered. On the other hand, the same policies may lead the more risk-neutral farmers to pursue acreage increases of 3-7%, and these same farmers will be less likely to accept SURE as a substitute for existing ad-hoc assistance, because of the impact on their rent-seeking behavior.

Nonetheless, acreage distortions can be controlled by limiting acreage to pre-disaster support levels, and the resulting insurance distortions remain smaller and less costly than the acreage distortions they replace. Thus, while existing disaster support policies may fail to provide effective risk management, at least the distortions caused by these policies can be kept small.

Chapter 4. Conclusion

This dissertation has included two distinct analyses of risk management for disasters: a normative analysis proposing a new type of insurance policy for stochastic externalities, and a positive analysis evaluating supplemental disaster insurance legislation in the United States crop insurance market. Both applications take a classical, welfare economic approach to policy. In the environmental case, we showed that welfare considerations of equity play a larger role as a result of uncertainty, and suggested a new policy addressing this issue by mirroring the equilibrium allocation of a system of tradable pollution permits. In the crop insurance case, we showed that the nested insurance acts more like a stochastic subsidy than like risk management *per se*, and that as a result the primary beneficiaries were the most risk-neutral farmers.

In evaluating environmental accident regulation, we showed that standard pollution regulations must be updated to properly address environmental accidents, and that one of the key challenges is the exacerbation of distributional disparities resulting from uncertainty. The new policy proposed demonstrates a role for insurance in achieving social objectives, even when all parties are risk-neutral. It does so by leveraging the re-distributional aspect of insurance, which ultimately allows for a stochastic policy to replicate the cap-and-trade outcome of dirtier (riskier) firms subsidizing cleaner (safer) ones.

In the second half of the dissertation, we developed a comprehensive economic theory of nested insurance. In doing so, we were able to demonstrate some of the quirks and challenges of existing US farm policy. We showed that disaster support programs, like SURE, may distort input choices, but these distortions are limited by non-differentiability of the insurance price-coverage menu and by existing constraints on the availability of acreage. The results suggest that parameters of a government program like SURE may enhance the value of crop insurance to the farm sector, but counter-intuitively, disaster support programs are of almost no value to highly risk-averse farmers because the added expected value of disaster payments is offset by the increased variability of farm revenues.

Overall, we have shown that managing the risk from disasters across varying economic agents can lead to dramatic distributional implications. When more than one efficient policy is available, then the distributional characteristics of policies will be the deciding factor. This observation drives the proposal of mutual insurance for stochastic externalities - minimal redistribution of resources can still be achieved under asymmetric information. On the other hand, when equitable distribution is ostensibly the goal of government-provided risk management, poorly designed policies can backfire and lead to cases where insurance only helps those who don't need it. Fortunately, other frictions in agricultural markets limit how much advantage they can gain, controlling the deadweight loss associated with these policies and the distributional disparities they may cause.

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Appendix.

Table 1. Summary Statistics for Simulation Inputs

	Hyde County, SD Spring Wheat	DeKalb County, IL Corn
Yield Data (bushels/acre)		
Mean	37.65	169.03
Standard Deviation	20.00	39.85
Price Data ($/bushel)		
Expected price, 2009	$6.20	$4.04
Cost Data ($/acre)		
Fertilizer	$44.21	$146.62
All other	$65.54	$147.12
Direct Payments[27]	($6.86)	($20.97)
Total	$102.89	$272.77
Resulting Cost Function:	$C(A) = Total \cdot A + A^2$	

[27] Wealth w_j under each scenario includes direct payments for corn, soybeans, and wheat, with the share of payments for each crop based on the number of base acres in each crop in the county, valued at the base yield rates for that county, with the total value of these payments being DP = $6.86 and $20.97 per acre for Hyde and de Kalb, respectively. Note that these are annual fixed payments not requiring production of the crops, and hence, we include the soybean direct payments regardless of whether or not the representative farmer grows soybeans.

Table 2. Optimization Results, Wheat, Crop Insurance Only[28]					
Aversion, λ	Acres*	Covg*	E[Profit]	Std[Profit]	CV
0.00	64.36	82.78%	$4,138.07	$3,623.97	0.88
1.00E-07	64.29	82.87%	$4,138.07	$3,616.54	0.87
5.00E-07	64.31	82.75%	$4,138.07	$3,622.78	0.88
1.00E-06	64.25	82.97%	$4,138.05	$3,609.76	0.87
5.00E-06	63.84	83.41%	$4,137.60	$3,568.32	0.86
1.00E-05	63.38	84.04%	$4,136.24	$3,516.23	0.85
5.00E-05	60.18	85.00%	$4,118.06	$3,300.41	0.80
1.00E-04	57.11	85.00%	$4,083.25	$3,131.69	0.77
5.00E-04	46.27	85.00%	$3,809.72	$2,537.21	0.67
1.00E-03	42.36	85.00%	$3,653.58	$2,323.08	0.64
5.00E-03	40.00	88.16%	$3,402.11	$2,106.84	0.62
1.00E-02	39.92	88.65%	$3,372.72	$2,089.09	0.62

[28] The optimization for aversion = 0 was conducted as profit maximizing, rather than utility maximizing.

Table 3. Optimization Results, Corn, Crop Insurance Only					
Aversion, λ	**Acres***	**Covg***	**E[Profit]**	**Std[Profit]**	**CV**
0.00	195.33	82.86%	$38,169.19	$32,775.34	0.86
1.00E-07	195.13	83.05%	$38,169.10	$32,672.94	0.86
5.00E-07	194.03	83.50%	$38,165.52	$32,328.63	0.85
1.00E-06	192.69	84.02%	$38,155.57	$31,919.95	0.84
5.00E-06	184.05	85.00%	$38,019.17	$30,151.40	0.79
1.00E-05	175.54	85.00%	$37,754.93	$28,755.62	0.76
5.00E-05	142.50	85.00%	$36,023.01	$23,343.23	0.65
1.00E-04	131.25	85.00%	$34,655.65	$21,500.34	0.62
5.00E-04	125.63	87.79%	$32,176.84	$19,904.07	0.62
1.00E-03	125.19	88.33%	$31,870.85	$19,702.87	0.62
5.00E-03	125.08	88.77%	$31,639.01	$19,575.00	0.62
1.00E-02	125.08	88.83%	$31,609.43	$19,559.97	0.62

Table 4. Post-Optimization Risk Premiums, Wheat and Corn[29]						
	Spring Wheat Farmer			***Corn Farmer***		
Aversion	**E-Profit**	**RP-BCF**	**RP-Actual**	**E-Profit**	**RP-BCF**	**RP-Actual**
0.00	$4,138.07	0.000	0.000	$38,169.19	0.000	0.000
1.00E-07	$4,138.07	0.000	0.000	$38,169.10	0.002	0.000
5.00E-07	$4,138.07	0.001	0.000	$38,165.52	0.008	0.000
1.00E-06	$4,138.05	0.002	0.000	$38,155.57	0.016	0.000
5.00E-06	$4,137.60	0.009	0.000	$38,019.17	0.075	0.004
1.00E-05	$4,136.24	0.018	0.000	$37,754.93	0.142	0.011
5.00E-05	$4,118.06	0.082	0.005	$36,023.01	0.485	0.056
1.00E-04	$4,083.25	0.154	0.013	$34,655.65	0.684	0.092
5.00E-04	$3,809.72	0.514	0.079	$32,176.84	0.930	0.157
1.00E-03	$3,653.58	0.706	0.117	$31,870.85	0.965	0.165
5.00E-03	$3,402.11	0.934	0.178	$31,639.01	0.993	0.171
1.00E-02	$3,372.72	0.967	0.185	$31,609.43	0.996	0.172

Table 5. Optimization Results, Wheat, Crop Insurance Plus SURE

Aversion	Acres*	Covg*	E[Profit]	Std[Profit]	CV
0.00	66.74	82.84%	$4,455.90	$3,626.80	0.81
1.00E-07	66.74	82.84%	$4,455.90	$3,626.80	0.81
5.00E-07	66.74	82.84%	$4,455.90	$3,626.66	0.81
1.00E-06	66.64	82.88%	$4,455.89	$3,619.99	0.81
5.00E-06	66.28	83.32%	$4,455.51	$3,584.63	0.80
1.00E-05	65.82	83.77%	$4,454.44	$3,543.55	0.80
5.00E-05	62.67	85.00%	$4,436.27	$3,331.59	0.75
1.00E-04	59.56	85.00%	$4,401.38	$3,166.32	0.72
5.00E-04	47.90	85.00%	$4,098.07	$2,546.18	0.62
1.00E-03	43.20	85.00%	$3,899.20	$2,296.62	0.59
5.00E-03	40.02	87.98%	$3,606.66	$2,059.91	0.57
1.00E-02	39.91	88.50%	$3,573.53	$2,042.05	0.57

Table 6. Optimization Results, Corn, Crop Insurance Only Plus SURE					
Aversion	**Acres***	**Covg***	**E[Profit]**	**Std[Profit]**	**CV**
0.00	202.49	82.88%	$41,000.60	$33,125.94	0.81
1.00E-07	202.23	82.97%	$41,000.52	$33,054.88	0.81
5.00E-07	201.11	83.34%	$40,997.69	$32,760.40	0.80
1.00E-06	199.82	83.83%	$40,988.93	$32,402.43	0.79
5.00E-06	191.13	85.00%	$40,848.82	$30,652.39	0.75
1.00E-05	182.42	85.00%	$40,576.04	$29,254.74	0.72
5.00E-05	149.26	85.00%	$38,149.32	$23,936.45	0.63
1.00E-04	135.00	85.00%	$37,061.08	$21,650.10	0.58
5.00E-04	125.59	87.53%	$34,079.62	$19,639.22	0.58
1.00E-03	125.21	88.20%	$33,715.15	$19,443.03	0.58
5.00E-03	125.08	88.76%	$33,423.80	$19,307.96	0.58
1.00E-02	125.11	88.82%	$33,399.22	$19,300.89	0.58

Table 7. Post-Optimization Risk Premiums, Wheat and Corn, under SURE						
	Spring Wheat Farmer			***Corn Farmer***		
Aversion	**E-Profit**	**RP-BCF**	**RP-Actual**	**E-Profit**	**RP-BCF**	**RP-Actual**
0.00	$4,455.90	0.000	0.000	$41,000.60	0.000	0.000
1.00E-07	$4,455.90	0.000	0.000	$41,000.52	0.002	0.000
5.00E-07	$4,455.90	0.001	0.000	$40,997.69	0.008	0.000
1.00E-06	$4,455.89	0.002	0.000	$40,988.93	0.016	0.000
5.00E-06	$4,455.51	0.009	0.000	$40,848.82	0.076	0.004
1.00E-05	$4,454.44	0.018	0.000	$40,576.04	0.144	0.010
5.00E-05	$4,436.27	0.083	0.004	$38,149.32	0.494	0.070
1.00E-04	$4,401.38	0.156	0.012	$37,061.08	0.686	0.096
5.00E-04	$4,098.07	0.515	0.080	$34,079.62	0.929	0.169
1.00E-03	$3,899.20	0.703	0.125	$33,715.15	0.964	0.178
5.00E-03	$3,606.66	0.933	0.191	$33,423.80	0.993	0.185
1.00E-02	$3,573.53	0.966	0.198	$33,399.22	0.996	0.185

Table 8. SURE vs. Ad-Hoc Indifference and Changes, Spring Wheat

Aversion	Est. Prob.	ΔAcres* (%)	ΔCovg* (%)	ΔEU* (%)
0.00E+00	0.489	0.00%	-0.12%	-0.10%
1.00E-07	0.489	-0.09%	-0.01%	-0.13%
5.00E-07	0.490	-0.12%	-0.02%	-0.12%
1.00E-06	0.490	0.00%	0.00%	-0.13%
5.00E-06	0.495	0.00%	0.00%	-0.12%
1.00E-05	0.500	-0.13%	0.11%	-0.12%
5.00E-05	0.543	-0.41%	0.00%	-0.09%
1.00E-04	0.590	-0.67%	0.00%	-0.06%
5.00E-04	0.825	-1.22%	0.00%	0.00%
1.00E-03	0.942	-0.69%	0.00%	0.00%
5.00E-03	1.000	0.00%	0.00%	0.00%
1.00E-02	1.000	0.06%	0.02%	0.00%

Table 9. SURE vs. Ad-Hoc Indifference and Changes, Corn				
Aversion	**Est. Prob**	**ΔAcres* (%)**	**ΔCovg* (%)**	**ΔEU* (%)**
0.00E+00	0.499	0.00%	0.00%	-0.11%
1.00E-07	0.500	-0.06%	0.07%	-0.11%
5.00E-07	0.504	-0.06%	0.00%	-0.11%
1.00E-06	0.510	0.00%	0.00%	-0.10%
5.00E-06	0.550	0.00%	0.00%	-0.07%
1.00E-05	0.596	-0.59%	0.00%	-0.05%
5.00E-05	0.752	-1.21%	0.00%	-0.28%
1.00E-04	0.938	1.47%	0.00%	0.01%
5.00E-04	1.000	0.00%	0.00%	0.00%
1.00E-03	1.000	0.00%	0.00%	0.00%
5.00E-03	1.000	0.00%	0.00%	0.00%
1.00E-02	1.000	0.00%	0.00%	0.00%

Table 10. Optimization Results, Wheat 70% Ad-hoc Probability

Aversion	Acres*	Covg*	E[Profit]	Std[Profit]	CV
0	67.75	82.81%	$4,588.70	$3,899.39	0.85
1.00E-07	67.73	82.72%	$4,588.70	$3,901.00	0.85
5.00E-07	67.69	82.82%	$4,588.70	$3,896.04	0.85
1.00E-06	67.62	82.88%	$4,588.68	$3,890.18	0.85
5.00E-06	67.21	83.30%	$4,588.26	$3,853.60	0.84
1.00E-05	66.65	83.75%	$4,586.95	$3,807.97	0.83
5.00E-05	63.07	85.00%	$4,563.88	$3,566.28	0.78
1.00E-04	59.55	85.00%	$4,518.85	$3,367.55	0.75
5.00E-04	47.14	85.00%	$4,162.20	$2,665.77	0.64
1.00E-03	42.75	85.00%	$3,962.16	$2,417.38	0.61
5.00E-03	40.02	88.02%	$3,683.48	$2,205.07	0.60
1.00E-02	39.93	88.56%	$3,650.15	$2,189.53	0.60

Table 11. Optimization Results, Corn, 70% Ad-hoc Probability					
Aversion	**Acres***	**Covg***	**E[Profit]**	**Std[Profit]**	**CV**
0	205.33	82.83%	$42,114.19	$35,734.98	0.85
1.00E-07	204.88	82.96%	$42,114.10	$35,621.59	0.85
5.00E-07	203.76	83.38%	$42,110.85	$35,319.73	0.84
1.00E-06	202.23	83.71%	$42,101.84	$34,970.76	0.83
5.00E-06	192.21	85.00%	$41,921.91	$32,915.38	0.79
1.00E-05	182.39	85.00%	$41,571.07	$31,233.58	0.75
5.00E-05	147.26	85.00%	$38,737.64	$25,218.49	0.65
1.00E-04	135.00	85.00%	$37,798.58	$23,118.74	0.61
5.00E-04	125.58	87.64%	$34,713.91	$21,060.22	0.61
1.00E-03	125.20	88.27%	$34,366.08	$20,888.92	0.61
5.00E-03	125.08	88.75%	$34,113.99	$20,784.93	0.61
1.00E-02	125.08	88.83%	$34,072.95	$20,770.16	0.61

Table 12. Optimized Risk Premiums, Wheat and Corn, 70% Ad-hoc Probability						
	Spring Wheat Farmer			***Corn Farmer***		
Aversion	**E-Profit**	**RP-BCF**	**RP-Actual**	**E-Profit**	**RP-BCF**	**RP-Actual**
0	$4,588.70	0.000	0.000	$42,114.19	0.000	0.000
1.00E-07	$4,588.70	0.000	0.000	$42,114.10	0.002	0.000
5.00E-07	$4,588.70	0.001	0.000	$42,110.85	0.009	0.000
1.00E-06	$4,588.68	0.002	0.000	$42,101.84	0.017	0.000
5.00E-06	$4,588.26	0.010	0.000	$41,921.91	0.082	0.005
1.00E-05	$4,586.95	0.019	0.000	$41,571.07	0.154	0.013
5.00E-05	$4,563.88	0.089	0.005	$38,737.64	0.512	0.080
1.00E-04	$4,518.85	0.165	0.015	$37,798.58	0.704	0.102
5.00E-04	$4,162.20	0.530	0.093	$34,713.91	0.934	0.176
1.00E-03	$3,962.16	0.717	0.137	$34,366.08	0.967	0.184
5.00E-03	$3,683.48	0.937	0.197	$34,113.99	0.993	0.190
1.00E-02	$3,650.15	0.968	0.205	$34,072.95	0.997	0.191

Table 13. Optimization Results, Wheat 100% Ad-hoc Probability					
Aversion	**Acres***	**Covg***	**E[Profit]**	**Std[Profit]**	**CV**
0	69.16	82.81%	$4,787.64	$4,000.97	0.84
1.00E-07	69.16	82.79%	$4,787.64	$4,000.96	0.84
5.00E-07	69.16	82.86%	$4,787.64	$3,999.18	0.84
1.00E-06	69.06	82.85%	$4,787.63	$3,994.07	0.83
5.00E-06	68.62	83.18%	$4,787.22	$3,959.90	0.83
1.00E-05	68.04	83.66%	$4,785.85	$3,914.33	0.82
5.00E-05	64.35	85.00%	$4,761.13	$3,668.60	0.77
1.00E-04	60.64	85.00%	$4,711.61	$3,457.14	0.73
5.00E-04	47.56	85.00%	$4,317.34	$2,711.37	0.63
1.00E-03	42.94	85.00%	$4,096.53	$2,448.23	0.60
5.00E-03	40.02	87.98%	$3,801.96	$2,234.20	0.59
1.00E-02	39.91	88.50%	$3,768.29	$2,219.44	0.59

Table 14. Optimization Results, Corn, 100% Ad-hoc Probability					
Aversion	**Acres***	**Covg***	**E[Profit]**	**Std[Profit]**	**CV**
0	209.40	82.86%	$43,847.94	$36,834.34	0.84
1.00E-07	208.99	82.98%	$43,847.71	$36,738.48	0.84
5.00E-07	207.87	83.24%	$43,844.90	$36,484.01	0.83
1.00E-06	206.16	83.63%	$43,834.45	$36,099.58	0.82
5.00E-06	195.73	85.00%	$43,637.59	$33,986.53	0.78
1.00E-05	185.38	85.00%	$43,248.53	$32,188.56	0.74
5.00E-05	148.39	85.00%	$40,108.02	$25,766.43	0.64
1.00E-04	135.00	85.00%	$38,927.53	$23,441.35	0.60
5.00E-04	125.59	87.53%	$35,815.87	$21,453.05	0.60
1.00E-03	125.21	88.20%	$35,446.23	$21,291.20	0.60
5.00E-03	125.08	88.76%	$35,153.09	$21,187.51	0.60
1.00E-02	125.11	88.82%	$35,128.95	$21,184.38	0.60

Table 15. Optimized Risk Premiums, Wheat and Corn, 100% Ad-hoc Probability						
	Spring Wheat Farmer			*Corn Farmer*		
Aversion	**E-Profit**	**RP-BCF**	**RP-Actual**	**E-Profit**	**RP-BCF**	**RP-Actual**
0	$4,787.64	0.000	0.000	$43,847.94	0.000	0.000
1.00E-07	$4,787.64	0.000	0.000	$43,847.71	0.002	0.000
5.00E-07	$4,787.64	0.001	0.000	$43,844.90	0.009	0.000
1.00E-06	$4,787.63	0.002	0.000	$43,834.45	0.018	0.000
5.00E-06	$4,787.22	0.010	0.000	$43,637.59	0.085	0.005
1.00E-05	$4,785.85	0.020	0.000	$43,248.53	0.158	0.014
5.00E-05	$4,761.13	0.091	0.006	$40,108.02	0.519	0.085
1.00E-04	$4,711.61	0.170	0.016	$38,927.53	0.708	0.112
5.00E-04	$4,317.34	0.536	0.098	$35,815.87	0.935	0.183
1.00E-03	$4,096.53	0.720	0.144	$35,446.23	0.967	0.192
5.00E-03	$3,801.96	0.938	0.206	$35,153.09	0.993	0.198
1.00E-02	$3,768.29	0.969	0.213	$35,128.95	0.997	0.199

Table 16. Input % Change, Corn, Relative to Crop Ins Only						
	SURE		Adhoc70		Adhoc100	
Aversion	**ΔAcres**	**ΔCovg**	**ΔAcres**	**ΔCovg**	**ΔAcres**	**ΔCovg**
0.00E+00	3.67%	0.02%	5.12%	-0.03%	7.20%	0.01%
1.00E-07	3.64%	-0.09%	4.99%	-0.10%	7.10%	-0.09%
5.00E-07	3.65%	-0.19%	5.01%	-0.14%	7.13%	-0.31%
1.00E-06	3.70%	-0.22%	4.95%	-0.37%	6.99%	-0.46%
5.00E-06	3.85%	0.00%	4.43%	0.00%	6.34%	0.00%
1.00E-05	3.92%	0.00%	3.90%	0.00%	5.60%	0.00%
5.00E-05	4.74%	0.00%	3.34%	0.00%	4.13%	0.00%
1.00E-04	2.86%	0.00%	2.86%	0.00%	2.86%	0.00%
5.00E-04	-0.04%	-0.31%	-0.05%	-0.18%	-0.04%	-0.31%
1.00E-03	0.01%	-0.14%	0.01%	-0.07%	0.01%	-0.14%
5.00E-03	0.00%	-0.01%	0.00%	-0.03%	0.00%	-0.01%
1.00E-02	0.03%	-0.01%	0.00%	0.00%	0.03%	-0.01%

Table 17. Input % Change, Wheat, Relative to Crop Ins Only						
	SURE		Adhoc70		Adhoc100	
Aversion	ΔAcres	ΔCovg	ΔAcres	ΔCovg	ΔAcres	ΔCovg
0.00E+00	3.70%	0.07%	5.27%	0.04%	7.47%	0.03%
1.00E-07	3.81%	-0.03%	5.34%	-0.18%	7.57%	-0.09%
5.00E-07	3.72%	0.06%	5.26%	0.09%	7.54%	0.14%
1.00E-06	3.66%	-0.09%	5.25%	-0.11%	7.49%	-0.15%
5.00E-06	3.82%	-0.12%	5.28%	-0.13%	7.49%	-0.28%
1.00E-05	3.85%	-0.31%	5.17%	-0.35%	7.36%	-0.45%
5.00E-05	4.13%	0.00%	4.79%	0.00%	6.92%	0.00%
1.00E-04	4.30%	0.00%	4.28%	0.00%	6.18%	0.00%
5.00E-04	3.52%	0.00%	1.89%	0.00%	2.79%	0.00%
1.00E-03	1.98%	0.00%	0.91%	0.00%	1.37%	0.00%
5.00E-03	0.05%	-0.21%	0.04%	-0.16%	0.05%	-0.21%
1.00E-02	-0.03%	-0.16%	0.02%	-0.10%	-0.03%	-0.16%

Table 18. Wheat: Optimal Coverage, Acres Constrained					
Aversion	**Acres**	**Covg-CI**	**Covg-SURE**	**Covg-Hoc70**	**Covg-Hoc100**
0.00E+00	64.4	82.80%	82.86%	82.86%	82.86%
1.00E-07	64.3	82.90%	82.92%	82.92%	82.92%
5.00E-07	64.3	82.70%	83.02%	83.02%	83.02%
1.00E-06	64.2	83.00%	83.19%	83.19%	83.19%
5.00E-06	63.8	83.40%	***84.34%***	***84.18%***	***84.04%***
1.00E-05	63.4	84.00%	***84.98%***	***84.98%***	***84.97%***
5.00E-05	60.2	85.00%	85.00%	85.00%	85.00%
1.00E-04	57.1	85.00%	85.00%	85.00%	85.00%
5.00E-04	46.3	85.00%	85.00%	85.00%	85.00%
1.00E-03	42.4	85.00%	***86.91%***	***87.05%***	***86.91%***
5.00E-03	40.0	88.20%	88.41%	88.46%	88.41%
1.00E-02	NA	NA	NA	NA	NA

Table 19. Corn Optimal Coverage, Acres Constrained					
Aversion	**Acres**	**Covg-CI**	**Covg-SURE**	**Covg-Hoc70**	**Covg-Hoc100**
0.00E+00	195.3	82.90%	82.87%	82.87%	82.87%
1.00E-07	195.1	83.00%	82.95%	82.95%	82.95%
5.00E-07	194.0	83.50%	83.36%	83.36%	83.21%
1.00E-06	192.7	84.00%	83.75%	83.72%	83.52%
5.00E-06	184.1	85.00%	85.00%	85.00%	85.00%
1.00E-05	175.5	85.00%	85.00%	85.00%	85.00%
5.00E-05	142.5	85.00%	85.00%	85.00%	85.00%
1.00E-04	131.3	85.00%	85.00%	85.00%	85.00%
5.00E-04	NA	NA	NA	NA	NA
1.00E-03	125.2	88.30%	88.20%	88.25%	88.20%
5.00E-03	125.1	88.80%	88.71%	88.74%	88.71%
1.00E-02	125.1	88.80%	88.85%	88.85%	88.85%

Table 20. RMA Schedule of Crop Insurance Premium Subsidies

Premium Subsidy Schedule

Effective for all 2009 reinsurance year crops filed 4/30/08 and later. **Premium** subsidy factors apply to all policies. When the coverage enhancement option is applicable and elected, the **premium** subsidy factor is based on the coverage enhance option coverage level.

	Subsidies									
Coverage level	**CAT**	**50**	**55**	**60**	**65**	**70**	**75**	**80***	**85***	**90***
Premium subsidy factor**	1.00	.67	.64	.64	.59	.59	.55	.48	.38	NA
GRP **premium** subsidy factor	1.00	NA	NA	NA	NA	.59	.59	.55	.55	.51
GRIP **premium** subsidy factor	NA	NA	NA	NA	NA	.59	.55	.55	.49	.44

Enterprise and Whole Farm Unit Premium Subsidy Factors***

Coverage level	**50**	**55**	**60**	**65**	**70**	**75**	**80***	**85***
Enterprise unit factors*	.80	.80	.80	.80	.80	.77	.68	.53
Whole farm unit factors*	NA	NA	NA	.80	.80	.80	.71	.56

* Where applicable.
**Applies to all plans of insurance except GRP and GRIP, and livestock.
***See http://www.rma.usda.gov/news/2008/11/1104wholefarm.html for more information on Enterprise and Whole Farm Unit subsidies.