Welfare Effects of Publicly Subsidized Crop Insurance Programs: The Sufficient Statistics Approach

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Abstract

This paper first presents a theoretical model to analyze the welfare effect of a publicly subsidized insurance program for a heterogeneous population with information asymmetry and program loads. From the model, we derive the condition for optimal contract and identify key parameters affecting the welfare effects of risk protection, adverse selection, model hazard, and premium subsidy. We then conduct an empirical analysis to measure the welfare effects of the Federal Crop Insurance Program using farm-level Agricultural Census data from the U.S. Heartland region for 2002, 2007 and 2012. We find that although the current risk protection level appears to be appropriate from farmers' perspectives, the net marginal welfare effects of coverage level and subsidy rate are both negative, suggesting that the current coverage level and subsidy rate are above the optimal level from societal perspectives.

Keywords: Federal Crop Insurance Program, sufficient statistics approach, moral hazard, optimal contract, revenue distribution, welfare effects

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1 Introduction

The Federal Crop Insurance Program (FCIP) has evolved into a primary risk management tool for farmers in the United States. It was first authorized in 1938, and experienced rapid development in the recent decades. In 2013, crop insurance covered 295 million acres with federal expenditure of $ 6.0 billion (Shields 2013). The 2014 Farm Bill further expands the FCIP by introducing coverage of deductibles and developing policies for a broader range of commodities (Chite 2014). As crop insurance plays a more vital role in farm programs, it is important to provide theoretical and empirical support for the policy design (Goodwin and Smith 2013). This study conducts a welfare analysis of the FCIP applying the sufficient statistics approach (Chetty and Finkelstein 2013). We first develop a theoretical model to examine the optimal design for the FCIP in terms of the coverage level and the premium subsidy rate. We then perform an empirical assessment of the marginal welfare effect of the program using data from the U.S. Heartland region.

Although the crop insurance literature has discussed different aspects of welfare effects of the Federal Crop Insurance Program, there is a lack of systematic assessments. The sufficient statistics approach (Chetty and Finkelstein 2013) is useful in consolidating different aspects of welfare effects, and connecting the theory and data for welfare analysis of social insurance. The basic concept of this sufficient statistics approach is to derive equations from structural economic models, which could represent the marginal welfare consequences of policy. The equations are functions of a few estimable statistics, such as elasticities; estimating the statistics will be sufficient to quantify the welfare impact of the policy. The sufficient statistic approach has been applied to assess the welfare effect of many social insurance programs, such as, unemployment insurance and health insurance (Chetty and Finkelstein 2013).

Our theoretical model incorporates "real world" features such as, information asymmetry, program loads, and a heterogeneous population. From the model, we derive the condition for optimal contract and identify key parameters that affect the welfare effects of risk protection, adverse selection, moral hazard, and premium subsidy. The results not only provide policy implications and but also suggest the key parameters needed for measuring the welfare effect of publicly provided crop insurance programs empirically. In the empirics, we measure the impact of insurance coverage on the revenue distribution as a representation of the moral hazard effect. A moment-based approach (Antle 1983) is used to estimate the reduced-form equations of the first two moments of revenue distributions using farm-level Agricultural Census data from the U.S. Heartland region for 2002, 2007 and 2012. Our results suggest that increase in coverage level is associated with a lower mean and higher variability of farm revenue per acre, indicating the existence of moral hazard in the federal crop insurance program. Additionally, we collect data on the range of other parameter values affecting welfare effects from the existing literatures, such as the risk attitude parameter, program-loading factor, and marginal deadweight loss associated with government subsidies. We apply the Bootstrap method to deal with uncertainty about parameter values and estimate the marginal welfare effect of the Federal Crop Insurance Program. The results suggest that although the current risk protection level appears to be appropriate from farmers' perspectives, the net marginal welfare effects of coverage level and subsidy rate are both negative, suggesting that the current coverage level and subsidy rate are above the optimal level from societal perspectives.

Much research has evaluated U.S. crop insurance programs. Theoretical papers often examine the first-best and second-best contract schedules under different policy configurations. For example, Mahul and Wright (2003) find that the producers' degree of prudence and basis risks are influential in the optimal contract design in an incomplete insurance market. Bourgeon and Chambers (2003) add the loading factor (systemic risk or transaction cost) and characterize the optimal area-yield contract with information asymmetry.

Many studies also examine the efficiency of crop insurance programs in the presence of information asymmetry, systemic risk, and risk aversion. Welfare benefit of an insurance program can be attributed to risk sharing, which can be further divided to risk spreading and risk pooling (Nelson and Loehman 1987). Welfare cost can result from information problems, such as adverse selection and moral hazard. Moral hazard occurs when insurance encourages farmers to behave in riskier ways (e.g., by applying less pesticides or growing more riskier crops) because production efforts may not be observed by the insurer (Ahsan, Ali and Kurian 1982; Nelson and Loehman 1987). Adverse selection occurs when farmers with higher risks are more likely to select into the program. A major consequence of adverse selection is under-insurance, which causes welfare loss.

Adverse selection and moral hazard are well-documented in the crop insurance literature. Quiggin, Karagiannis and Stanton (1993), Just, Quiggin and Calvin (1999), Goodwin (2001), Makki and Somwaru (2001) provide consistent evidence of adverse selection in early crop insurance programs. As the premium subsidy rate increases and the crop insurance becomes popular, under-insurance due to adverse selection is reduced, other impacts such as moral hazard draw more attentions. For example, a number of empirical studies examine the effects of federal crop insurance on input use, particularly fertilizers and chemicals uses (Horowitz and Litchenberg 1993, Babcock and Hennessy 1996, Smith and Goodwin 1996, Mishra Nimon and El-Olsa 2005, Chang and Mishra 2012, Weber, Key and O'Donoghue 2016). Schoengold, Ding and Headlee (2014) examine the impact of crop insurance on conservation tillage adoption. Wu (1999), O'Donoghue, Roberts and Key (2009), and Walters et al. (2012) examines the effect of crop insurance on land use and induced environmental impacts. A number of empirical studies have also examined the effect of the federal crop insurance on production outcomes, including yield distribution (Quiggin, Karagiannis and Stanton 1993, Roberts, Key and O'Donoghue 2006, Ligon 2012, Cornaggia 2013, Weber, Key and O'Donoghue 2016) and indemnity payment (Coble et al. 1997).

Hennessy, Babcock and Hayes 1997, Wang et al. 1998, Adhikari, Knight and Belasco 2012 estimate welfare gains from a risk protection program by simulating the production outcome. Empirical studies have examined various components of the welfare effect of the FCIP, but the overall welfare effect is still unclear because of a lack of systemic assessments.

This study contributes to the literature in two aspects. First, the theoretical model adds to the literature by integrating various aspects of welfare effects of a publicly subsidized insurance program and bringing in realistic features, such as heterogeneity, self-selection, transaction cost, and deadweight loss associated with government subsidies in a single model. The results can be used to address questions such as: What are the tradeoff relationship between the welfare benefits and costs that defines the optimal coverage level and subsidy rate? What are the key factors affecting the program's welfare effects and how the policy design should be adjusted for regions with different features? Second, our estimation of the impacts of crop insurance coverage on the revenue distribution adds to the literature to understand the welfare implication of the moral hazard. Finally, our empirical analysis provides quantitative results on the welfare effect of the Federal Crop Insurance Program.

2 Background

2.1 Program history

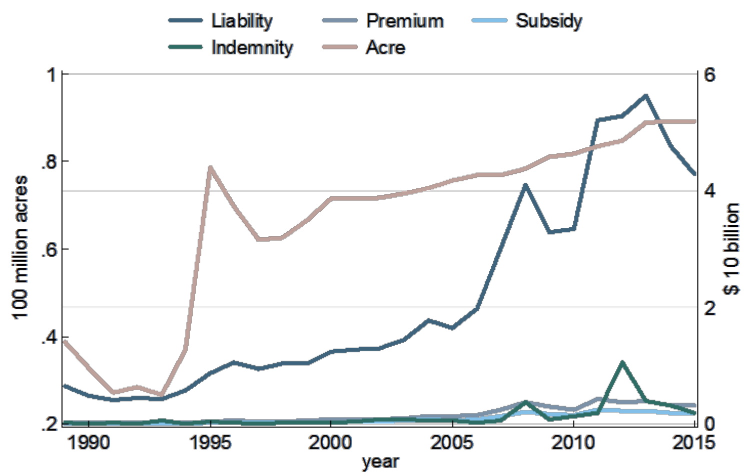


Figure 1: Historical trends of the Federal Crop Insurance Program

The Federal Crop Insurance Program (FCIP) was first authorized in 1938, it remained as an experiment until the passage of the Federal Crop Insurance Act of 1980, which expanded the program to more crops and regions and offered a subsidy equal to 30% of the premium and the 65% coverage level. Now it has become a major government provided risk management tool for farmers. Its rapid expansion follows a few major policy changes in the program history, as shown in Figure 1. In 1994, the Federal Crop Insurance Reform Act created catastrophic coverage (CAT), which covered 50% of a producer's approved yield at 60% of the expected market price and is fully subsidized, and made its participation mandatory to be eligible for price support programs. Congress repealed the mandatory participation in 1996, but the participation remained as an eligibility requirement for ad hoc payments afterwards. In 2000, Congress passed the Agricultural Risk Protection Act, which further increased premium subsidies to encourage participation. Enrollment rose from 182 million acres in 1998 to over 295 million in 2013. The 2014 Farm Bill further shifted the focus of U.S. agricultural policy to risk management by increasing risk management program funding by $5.7 billion in total for the next ten years. The 2014 Farm Bill also introduced Supplemental Coverage Option (SCO) and Stacked Income Protection Plan (STAX), known as shallow loss programs, and these new programs essentially provide coverage for the less deductibles and higher subsidy rate at the county level. The enrolled acreage has risen to 366 million acres by 2015.

2.2 Insurance mechanism

The FCIP, administered by the U.S. Department of Agriculture's (USDA) Risk Management Agency (RMA), provides farmers with risk management tools for about 130 crops (Shields 2015). The policy mechanism is the same as the general form of insurance. At the beginning of a growing season, the farmer selects an insurance contract, and pays a portion of the corresponding premium. The rest will be paid by the subsidies provided by the federal government. Most policies are either yield-based or revenue-based. The coverage level ranges from 50% to 85% at the 5% interval. The selected coverage level times the historical revenue or yield level is referred to as liability. The contract guarantees the farmer's revenue/yield is no lower than the guaranteed liability. If the realized outcome (revenue or yield) is lower than the liability, the farmers will get indemnity payment that equals the gap between the realized level and the guaranteed level.

The actuarial fairness is an important feature of crop insurance premium. Current law requires the actuarial soundness of the entire Federal Crop Insurance Program, that is, indemnities should equal to total premiums. The premium rate varies by crop, region, and coverage level. The revenue policy is generally more expensive than the yield policy. Thus, the actuarial fairness constraint pairs the premium and the contract, which is the source of selection-bias. The loss ratio is often used to indicate the actuarial -fairness of the premium. It is defined as the ratio of the indemnity to the premium, and if the loss ratio equals to 1, then the premium is said to be actuarially fair.

2.3 Study region

The Heartland region is the major production region in the U.S. It covers 544 counties in Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska, Ohio and South Dakota. The region accounts for 22% of the farms, 27% of the cropland, and 23% of the value of production in the nation. At the same time, the region accounts for significant percentage of the program nationwide, around 31% of the insured total acres and 41% of the total liability from 2002 to 2012 on average. The crop insurance is widely adopted in the region, 77% of the cropland are under the insurance coverage in 2012. Corn and soybeans are the major field crops produced in the region, taking account for 47% and 38% of the cropland. Corn and soybeans contribute most insured acres too, accounting for 53% and 42% of the total insured acres in the region, respectively. Figure 2 shows the policy trends. In this region, the revenue policy is the major policy type and becomes even more dominant in recent years. As for the coverage levels, higher coverage levels are more popular. Most farms select coverage levels higher than 70%, and around 30% of enrolled acreage are covered by the highest coverage level in recent years.

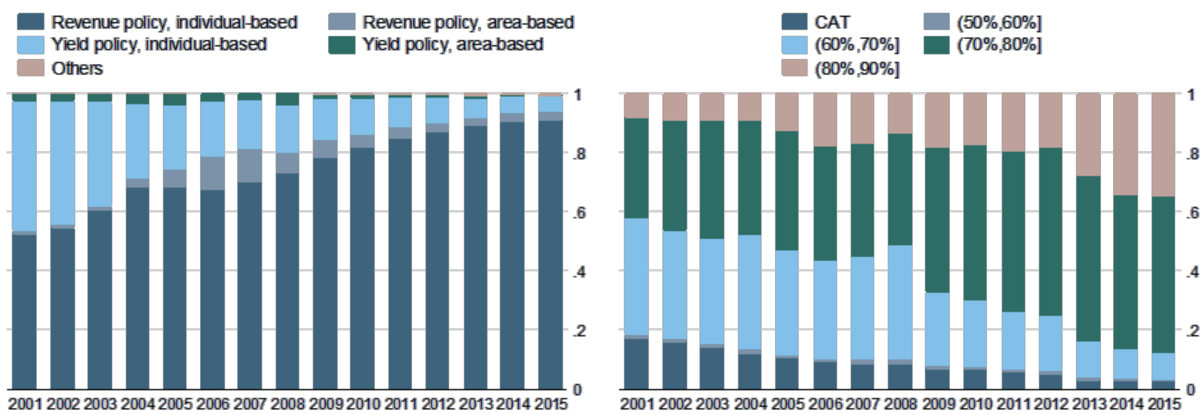
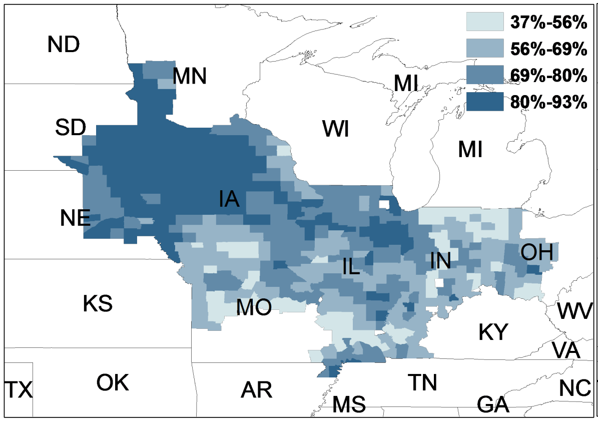
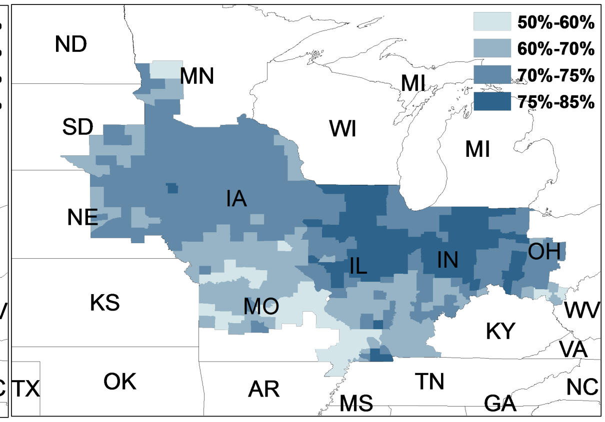


Figure 2: The program trends in the Heartland region

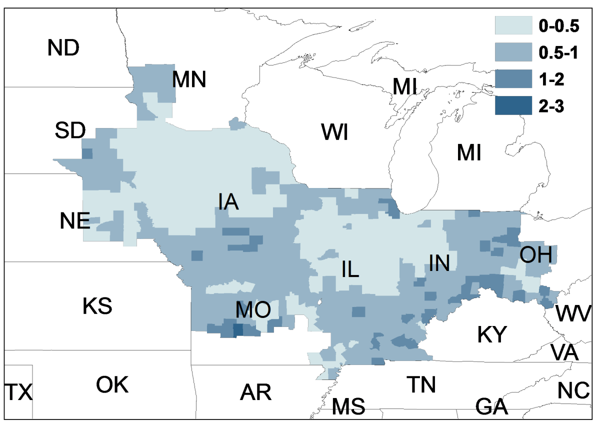
Figure 3 shows features of the program's geographic distribution: percentage of insured acres, coverage level, loss ratio (indemnity/premium), standardized corn and soybean yield. Figure 3(a) (b) and (d) show very similar patterns. In the northern and central counties that are more productive (higher yield, darker area in (d)), crop insurance is more popular, as greater proportion of cropland are covered by the insurance. And at the same time, higher coverage levels are more popular in these areas. Figure (3c) appears to be the opposite, where the loss ratio indicates the actuarial-fairness of the premium, and also shows whether the insurers and the insureds can profit from insurance. In most region the indemnity is less than the premium. For the insurers, they are collecting more premium than their payout to the farmers, especially for those highly productive areas with more insurance coverage. For the insureds, since they are subsidized, they are not necessarily losing money buying insurance, however, in the southern counties that are less productive, the insureds earn more indemnities compared to their premium payment.



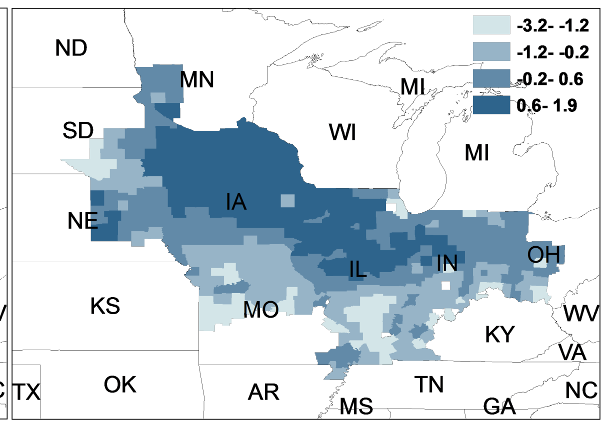
(a) Participation rate



(b) Coverage level



(c) Loss ratio



(d) Yield (corn and soybeans)

Figure 3: Geographic distribution of crop insurance and production yields in the Heartland region

3 Welfare effects of crop insurance: A graphic illustration

Before presenting a formal model, we first illustrate the welfare effects of crop insurance graphically. In a crop insurance market, the demand curve for the insurance contract can be characterized as farmers' willingness to pay (WTP) for the insurance product. First, farmers get indemnified if the realized revenue is lower than the liability. Second, crop insurance also reduces farmers' risk premium for risk averse farmers, which is the cost to farmers for bearing risk. So farmers' WTP for the insurance product depends on the expected indemnity payment plus the reduced risk premium. If the WTP is no less than the contract price τ offered by insurance companies, farmers will choose to insure. Therefore, the demand for the insurance product is a function of its price: $D(\tau)$. In Figure 2[1], y-axis represents the price of the insurance contract τ; x-axis shows the quantity of the insurance contract sold or the number of farmers who choose to insure.

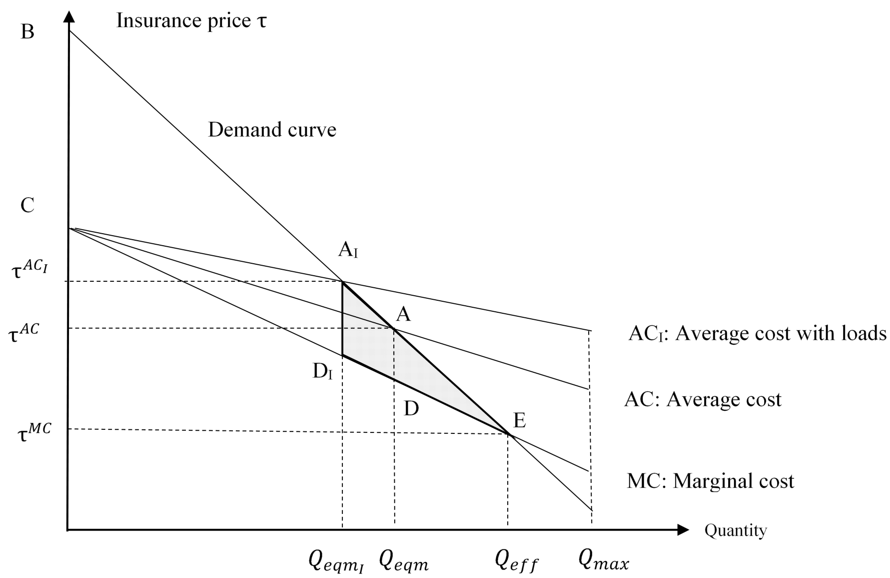


Figure 4: Crop insurance market and its welfare effects

A unique feature of insurance market is the correlation of its demand side and supply side (Chetty and Finkelstein 2013). In a traditional market, the supply side is portrayed as an upward-sloping marginal cost curve, and it is independent of the WTP of the demand side. The negative slope of supply curve in the insurance market is due to the correlation between the farmers' WTP and the insurers' provision cost. The correlation comes from the farmers' risk types that decide the indemnity payment and risk premiums. As discussed in the previous paragraph, farmers' WTP is the total of expected indemnity payment and reduced risk premium from the insurance contract. At the same time, the insurers' provision cost is essentially expected payment to farmers. And then with such correlation, the shape of MC curve depends on the shape of demand curve. In other words, the downward sloping demand curve says, for a given price, the farmers with higher WTP would opt in first. And they are more likely to be the ones who face higher risks and therefore expect higher indemnity payment, if we assume the population holds the same risk attitude . That is, the expected indemnity payment is decreasing

[1]Adapted from Einav, Finkelstein and Cullen (2011)

for marginal insureds as price decreases. Consequently, it corresponds to a decreasing marginal provision cost for the insurers. That is, MC curve is downward-sloping as the demand curve. This link between the supply curve and the demand curve is the most important distinction of the insurance market from traditional markets (Chetty and Finkelstein 2013).

The aggregate surplus is the area between the MC and the demand curve, which essentially comes from the reduced risk premium for farmers, with the risk-averse farmers and the risk-neutral insurers. It is standard to assume the risk aversion for the insureds and the risk neutrality for the insurers in the literature (Ahsan, Ali and Kurian 1982). If farmers are all risk neutral, under actuarially fair condition, farmers do not have incentive to buy insurance. The insurance market cannot exist, and the welfare gain from risk protection disappears. The risk neutrality of the insurers can be justified by the fact that crop insurance companies are reinsured and subsidized by the government. Therefore, it is fair to assume that bearing risks doesn't incur risk premiums for insurance companies. In this setting, the marginal cost is no greater than the WTP of the marginal insureds, that is, the MC curve lies under the demand curve. In practice, the cost of insurance provision also includes transaction cost, which adds a loading factor to marginal cost, moving MC curve upward. Theoretically, it is not certain whether MC curve with transaction cost will cross the demand curve or not. Assuming it does, the efficient equilibrium is Point E in Figure 4. The potential welfare gain from insurance is the area between demand curve and MC curve (ΔEBC). In the insurance literature, the welfare gain is attributed to risk sharing which can be further divided to risk spreading and risk pooling (Nelson and Loehman 1982). Gains from risk spreading arise because of the difference in risk attitudes (Holmstrom 1979), that is, risk is redistributed from risk-averse farmers to risk-neutral insurance companies. Gains from risk pooling are attributed to a reduction in the variance of the total loss, which in turn results in a risk premium reduction (Pauly 1968). Notice that, if farmers are all risk neutral, under actuarially fair condition, farmers don't have incentive to buy insurance. Thus the insurance market will no longer exist, as well as its welfare gain.

In the "real world", there are features that generate welfare costs: for instance, information problems including adverse selection and moral hazard and program loads. We now discuss their implications to welfare effects.

Adverse selection. In crop insurance market, the insurers cannot observe the heterogeneous information on the demand side. Therefore, they could only price the contract at the average cost. The average cost (AC) curve is determined by the provision cost for the farmers who choose to insure. The correlation of the WTP and MC means that the insured's average provision cost is above the provision cost of the marginal insured. In Figure 4, Point A is the equilibrium in the presence of adverse selection. Compared with equilibrium point E in the complete market, adverse selection issue essentially causes underinsurance. And welfare loss due to adverse selection is the triangular area (ΔADE). It is the aggregated surplus of the under-insured group. The fundamental reason to the welfare loss is that the equilibrium with adverse selection is determined by AC and demand curves, whereas the efficient equilibrium is determined by demand and MC curves (Chetty and Finkelstein 2013).

Moral hazard. Moral hazard is defined as an alteration in production behaviors under coverage which deviates from social optimality, and it occurs because production efforts cannot be observed by the insurers (Nelson and Loehman 1987). Now we consider how moral hazard will affect the demand and the supply sides. The farmer's expected utility is optimized before insurance is introduced, that is, there is a balanced tradeoff between the production outcome and corresponding risk premium. When the insurance is introduced, the risk premium decreases due to risk protection, and the original first-order condition no longer holds. As a result, it provides the incentive for the farmers to reevaluate their production effort, and make adjustments to optimize outcome under the insurance coverage. Such behavioral changes directly lead to alterations of the farmers' WTP, that is, the demand curve. As for the supply side, the insurers may also adjust the insurance price based on the observed average changes of the demand side. Therefore, the aggregate welfare gain changes as the supply and demand curves adjust. In this sense, the welfare effect of moral hazard exist at the intensive margin for the current participants. At the extensive margin, there may be marginal un-insureds opt into the program because of the gains brought by the possibility of production behavioral deviations. That is, farmers may also select on their moral hazard behaviors which are also unknown to the insurers, which is one source of heterogeneity that leads to adverse selection. The way that adverse selection and moral hazard are interacting with each other makes it difficult to separate their welfare consequences. To be precise,ΔADE is the welfare loss of adverse selection conditioned on moral hazard.

Program loads. Program loads refer to the factors that increase the insurance provision cost. Systemic risk in agricultural production is primarily from the impacts of geographically extensive unfavorable weather events, such as droughts or extreme temperatures (Miranda and

Glauber 1997). It induces significant correlation among farm-level losses. Consequently, the insurer's average cost to indemnify these losses are correlated and higher than the one where the losses are independent. The average cost curve (AC_I) with program loads lies above the AC curve without program loads. Intuitively, when a marginal insured opts in, the increase of the average cost not only includes the provision cost for the marginal insured but also its correlation with provision costs of existing insureds (often positively correlated in agricultural production). That is, the average cost of crop insurance provision is greater than the one without such correlations. In addition, the transaction cost is another source of program loads. In practice, the insurers usually multiply the average provision cost by a factor, called the program loading factor, to account for the systemic risk, administrative cost and any loads that increase the insurance provision cost. In Figure 4, the equilibrium moves to A_I along the demand curve. The program loads essentially aggravates the underinsurance problem caused by adverse selection, and therefore, leads to more welfare losses (ΔADE to $\Delta A_I D_I E$). Miranda and Glauber (1997) argue that the systemic risk is a major cause of crop insurance market failure. The transaction cost leads to further increases in welfare losses, and may even cause market failure too (Ahsan, Ali and Kurian 1982; Chambers 1989; Skees and Reed 1999).

Premium subsidies. The subsidy is suggested as a solution to the underinsurance problem (Ahsan, Ali and Kurian 1982, Nelson and Loehman 1987). In practice, the FCIP offers subsidy as a proportion of the premium. The subsidy rate ranges from 38% to 80% depending on the coverage level and other options chosen by the farmer for traditional crop insurance, and is fixed at 65% for Supplemental Coverage Option (SCO). The premium subsidy's welfare effect is straightforward: the premium subsidy brings down the price, and more farmers are willing to participate, therefore increases the aggregate welfare by encouraging participation. However, it is well known that government spending may cause deadweight losses (DWL) because of its distortional effects. Whether the net is positive or negative is an empirical question.

In the next section, we present a model to consolidate different aspects of welfare effects of a publicly subsidized insurance program and to bring in realistic features, such as heterogeneity, self-selection, transaction cost, and deadweight loss of government subsidies in a single model. The results will be used to examine the tradeoff relationship between the welfare benefits and costs that defines the optimal coverage level and subsidy rate.

4 The model

In this section, we formally build the theoretical model, and derive a proposition to summarize results of the model. Based on the proposition, we further discuss the welfare effects of insurance coverage and premium subsidies, as well as the key parameters that affect these welfare effects.

Consider a farmer's decision for participating in a revenue insurance program. Following Just and Pope (1978), the reduced form equation for the revenue is specified as $\widetilde{R}(x) = R(x) + \sigma(x)\varepsilon$, where x is a vector of input uses; $R(x)$ and $\sigma(x)$ are revenue's mean and standard deviation; the state of nature represents uncertainties, and follows a standard normal distribution: $\varepsilon \sim N(0, 1)$. When an insurance contract (b, τ, s) is introduced, the farmer's revenue is guaranteed at $bR(x)$ at the expense of paying subsidized premium $\tau_s = \tau(1-s)$, where τ is the actuarially-fair premium, s is the premium subsidy rate, and b is the coverage level as a percent of average revenue. Under the insurance contract, the farmer faces two states: in the high state, the revenue is above the guaranteed level, and the indemnity is not triggered; in the low state, the revenue falls below the guaranteed level, and the indemnity payment is made to the farmer to fill the gap. Assume the probability of the high state is denoted as e, and the probability of the low state is then $1 - e$. Intuitively e can be thought of as the farmer's effort level to get to the high state because it depends on the input level: $e = 1-\Phi[(b-1)R(x)/\sigma(x)]$, where $\Phi(\cdot)$ is the cumulative distribution function (CDF) of the standard normal distribution. Through this definition, the input use can be mapped to the effort level. Hence the revenue can be written as a function of the effort level: $\widetilde{R}(e) = R(e) + \sigma(e)\varepsilon$. Similarly, the production cost is $c(e)$. Then the farmer's profits in the two states with the insurance are: $\pi_L = bR(e)-c(e)-(1-s)\tau$ and $\pi_H = R(e)+\sigma(e)\varepsilon-c(e)-(1-s)\tau$. The profit without the insurance is $\pi_0 = R(e) + \sigma(e)\varepsilon - c(e)$. The farmer's expected utility with the insurance is: $w_1 = \max_e (1 - e)u(\pi_L) + eE[u(\pi_H)]$, where $u(\cdot)$ is the utility function, which is increasing in profit and concave ($u' > 0, u'' < 0$), and state-independent (i.e., the utility functional form is independent of its argument); $E[u(\pi_H)]$ is the farmer's expected utility given that a high state occurs. The farmer's expected utility without insurance is: $w_0 = max_e E[u(\pi_0)]$. Then farmer's valuation of the insurance contract is $v = w_1 - w_0$, and he only participates when the valuation of insurance contract is non-negative.

For a heterogeneous population, denote a farmer's valuation of the insurance contract as $v(z)$, where z is a vector of characteristics that affect the agent's valuation of the program. Without loss of generality, we assume z is a scalar to simplify notations and $v(z)$ increases with z. The

CDF of z is $F(z)$. Then participation rate is $I = 1 - F(z_b)$, where z_b indicates the marginal insureds, defined by $v(z_b) = 0$. The actuarial-fair condition is defined as: $\tau = \frac{1+\iota}{I}\int_{z_b}^{\infty} \tau(b)\, dF(z)$, where $\tau(z)$ is the expected indemnity payment for farmers with characteristics z, and ι is the loading factor that represents any factor that might add to the insurance provision cost.

The government chooses the coverage level and the subsidy rate to maximize social welfare, subject to the actuarially-fair condition:

$$\max_{b,s} W - V = \int_{-\infty}^{z_b} w_0\ dF + \int_{z_b}^{\infty} w_1(b)\ dF - U \quad s.t. \quad \tau = \frac{1+\iota}{I}\int_{z_b}^{\infty} \tau(b)\ dF(z) \tag{1}$$

where $U(\cdot)$ is the welfare cost of government subsidies, φ is the marginal deadweight loss (DWL) associated with government subsidy transfers. The optimization problem is conditioned on farmers' choices of their effort levels. The choice of (b, τ, s) may affect both the effort level (because of moral hazard) the participation rate (because of self-selection). The actuarial-fairness condition is imposed because the legislation requires the FCIP to be actuarially fair[2].

In the following proposition, we characterize the solution to the governemnt's problem. For notational simplicity, we assume farmers exhibit constant absolute risk aversion (CARA). In section 6, we also discuss the case of constant relative risk aversion (CRRA).

Proposition. *Suppose farmers exhibit constant absolute risk aversion (CARA). The insurance program can improve the social welfare if*

$$\underbrace{\gamma_2\overline{e\Delta}}_{risk\ spreading} + \underbrace{\frac{-\gamma_2\overline{\pi}_L\rho_2}{1+\eta_{IA}}}_{risk\ pooling} \geq \underbrace{\frac{\eta_{IA}}{1+\eta_{IA}}}_{information\ asymmetry} + \underbrace{(1+\iota)\left(s^* + \frac{s^*}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)}_{DWL} + \underbrace{\iota(1-\gamma_2\overline{e\Delta})}_{program\ loads} \tag{2}$$

The government subsidies can improve the social welfare of the crop insurance if

$$\underbrace{(\gamma_2\overline{e\Delta}+\varphi)(1+\eta_{\tau,s})}_{Marginal\ intensive\ effect} - \underbrace{\frac{\eta_{\tau,s}}{s}\left(1 - \gamma_2\overline{e\Delta} - \frac{1+\gamma_2\overline{\pi}_L\rho_2}{(1+\iota)(1+\eta_{IA})}\right)}_{Marginal\ extensive\ effect} \geq 0 \tag{3}$$

The definition of each of the parameters in (2) and (3) is given in table 1.

[2]For the purpose of our model, the role of insurance companies is suppressed in this study. It makes sense because the policy provisions and the major part of ratings are conducted by RMA and the crop insurance companies essentially act as intermediates in the market. In addition, we focus on the surplus from the insurance market. Potential welfare effects outside the insurance market may include environmental impacts induced by changes in input use and land allocation and impacts on the food market which may lead to food consumers' welfare changes.

Table 1: Definitions of the parameters in Proposition

Parameters	Definitions
$\bar{\cdot}$	The average of the insureds
$\gamma = -u^{''}/u^{'}$	Arrow-Pratt coefficient of absolute risk aversion
e	The probability of the high state (not getting indemnified)
$\Delta = \pi_H - \pi_L$	The gap between profits at the high state and the low state
$\eta_{IA} = \eta_A + \eta_M$	The composite term representing the effect of information asymmetry
η_A	The adverse selection effect
η_M	The average moral hazard effect
η_m	The individual moral hazard effect
$\eta_{R,b} =, \eta_{\sigma,b} =$	The elasticities of the revenue's mean and standard deviation with respect to the coverage level
λ_L	Inverse Mill's ratio of the revenue distribution
$c_v = \sigma/R$	The revenue's coefficient of variation
$\eta_{I,\tau}$	The price elasticity of insurance demand
$\rho_1 = corr[(1-e)R, \eta_m]$	The correlation coefficient of marginal indemnity payment $(1-e)R$ and individual moral hazard effect η_m
$\rho_2 = corr[(1-e)R, \pi_L]$	The correlation coefficient of marginal indemnity payment $(1-e)R$ and individual moral hazard effect π_L
τ_b	The expected indemnity payment of the marginal insureds
$\eta_{\tau,s}$	The elasticity of the insurance premium with respect to the subsidy rate
ι	The program loading factor
φ	The marginal deadweight loss due to subsidy transfer

The proof of the proposition is presented in the Appendix A1. Condition (2) and (3) are derived from the first-order conditions of the maximization problem (1) with respect to the coverage and subsidy rate, respectively. Together they determine the optimal coverage level of these two policy variables and show the marginal benefits and marginal costs in adjusting these variables. In the following we discuss the intuitions and welfare consequences represented by different terms in (2) and (3).

4.1 Marginal benefits of insurance coverage

The literature attributes the benefit of insurance to risk sharing, which can be further divided into risk spreading and risk pooling (Nelson and Loehman 1987). These two benefits are represented by the two terms on the left-hand side (LHS) of (2).

Risk spreading. In the social insurance literature (e.g. Gruber 1997, Chetty 2006), the risk spreading effect is interpreted as the marginal benefit from consumption smoothing. Analogously, in the context of the FCIP, it can be understood as the marginal benefit from profit smoothing, since the insurance brings the expected outcomes of the two states closer. It can also be thought of as the reduced risk premium due to a smoother distribution of profit. Hence, the expression becomes very intuitive that the marginal spreading effect depends on the risk attitude parameter and a "smoothness" parameter Δ.

Risk pooling. The risk pooling effect (the second term) arises because farms with different risks place their risk levels in a common pool, and the variance (risk) of the pool becomes smaller which leads to a reduction in premium. In short, the welfare effect of pooling is the utility change due to reduced insurance premium. Then the marginal welfare effect of pooling depends on correlation of the marginal utility and the marginal insurance premium. Under the actuarially fair constraint, the marginal insurance premium equals the marginal indemnity. The marginal utility can be represented by a risk attitude parameter and the profit. Assuming a constant risk attitude parameter, the marginal pooling effect depends on the correlation coefficient between the marginal indemnity payment and the low-state profit ρ_2.

4.2 Marginal costs of insurance coverage

The three terms on the right-hand side of (2) represent the three marginal costs of insurance coverage: the cost of information asymmetry, the deadweight loss of government subsidy, and the program loads.

Information asymmetry. The marginal welfare cost of information asymmetry is represented by first term on right-hand side of (2). Technically, it arises because the actuarially fair condition is imposed on the government, but is not internalized by farmers when adjusting their effort levels in response to insurance coverage. The welfare cost of information asymmetry can be further divided into a moral hazard effect and an adverse selection effect. The moral hazard effect is the wedge between the private and social returns to production effort. It would disappear if the government could observe the farmer's effort level, and incorporate the responses into the actuarially fair condition. The moral hazard effect is represented by a composite elasticity term $\eta_m = \frac{b-1}{b}\eta_{R,b} + \frac{1}{b}\lambda_L c_v \eta_{\sigma,b}$. It consists of two elasticities measuring the responsiveness of the revenue mean ($\eta_{R,b}$) and the standard deviation ($\eta_{\sigma,b}$) to the coverage level. It shows the net impact on the revenue distribution, as opposed to the structural parameters that account for each potential behavioral responses separately and then aggregate. The advantage of the reduced-form parameters is that it is convenient when it comes to empirical estimation. Because they can be estimated by reduced-form models, instead of behavioral models which require more complicated structural specifications and are demanding in data. Because the farmers' production decisions are optimized individually, and given in the government's optimization problem. The envelope theorem enables us to write the marginal value of raising coverage level in terms of the reduced-form response of production outcome.

The adverse selection (η_A) arises because of the difference between marginal cost and average cost of providing insurance due to the unobserved heterogeneity. The triangle area ($\Delta A_I D_I E$ in Figure 4) showing the welfare loss of adverse selection depends on the slope of demand curve ($\eta_{I,\tau}$) and the gap between the marginal cost (τ_b) and the average cost (τ) of providing insurance coverage. As shown by the effect of adverse selection: $\eta_A = (\eta_M + 1)\left[\frac{1}{1+[1-(1+\iota)\tau_b/\tau]\eta_{I,\tau}} - 1\right]$, a greater gap between the marginal cost and average cost increases the adverse selection welfare effect, and so does a more elastic demand curve ($\eta_{I,\tau} < 0$). Since the moral hazard effect affects the slopes of demand and supply curves, it is difficult to separate the moral hazard effect and the adverse selection effect from each other. Therefore, the moral hazard effect (η_M) also appears in η_A. It is convenient to use a composite term to represent the effect of information asymmetry from both the moral hazard and the adverse selection as: $\eta_{IA} = \eta_A + \eta_M$.

Program loads and DWL. The second term represents the marginal welfare cost associated with government subsidy transfers, and the third term is the marginal welfare cost of program loads that increase insurance provision costs, such as transaction costs and systemic risk loads. In equation (2), when the marginal welfare benefits are greater than the marginal welfare costs, then increasing insurance coverage would further improve the social welfare. When the equality holds in equation (2), it implicitly defines the optimal coverage level.

4.3 Marginal benefits and costs of premium subsidy

The premium subsidy not only benefits the existing participants, but may also bring in new insureds. We thus distinguish its welfare effects into the one at the intensive margin for existing insureds and the one at extensive margin for new insureds. At the intensive margin, premium subsidy has a direct effect on the existing participants: reduce the marginal risk premium and increase the deadweight loss of government subsidies. At the extensive margin, premium subsidy brings in new insureds. The elasticity of the premium payments with respect to the subsidy rate $\eta_{\tau,s}$ measures the relative magnitude of the intensive- and extensive-margin effects. The terms in the bracket for the extensive marginal effect is essentially a simplified version of (2) representing the marginal welfare effect of increasing insurance coverage. When the equality holds in (3), it defines the optimal subsidy rate:

$$s^* \;=\; \frac{\left(\gamma_2\overline{e\Delta} + \frac{1+\gamma_2\bar{\pi}_L\rho_2}{(1+\iota)(1+\eta_{IA})} - 1\right)\eta_{\tau,s}}{(\gamma_2\overline{e\Delta}+\varphi)(1+\eta_{\tau,s})} \tag{4}$$

4.4 Key Parameters

Equations (2) and (3) characterize the marginal welfare effects of insurance and implicitly define the optimal coverage level and the subsidy level. They also identify the key parameters that affect the marginal welfare effects: 1) reduced-form elasticities that represent the policy impacts by information asymmetry, 2) risk attitude parameters, 3) program loading factors and the marginal DWL, and 4) summary statistics. We conduct a comparative statics analysis to examine how changes in some of the parameters affect the optimal coverage level and the optimal subsidy rate (Table 2). Conditions (5a) and (5b) determine the directions of impacts on the optimal coverage level and subsidy rate. In Appendix A2, we present the detailed derivations.

$$\overline{e\Delta}(1+\eta_{IA})(1+\iota)\left[1 - s^*(1+1/\eta_{\tau,s})\right] - \bar{\pi}_L\rho_2 \geq 0 \tag{5a}$$

$$1 - \gamma\overline{e\Delta} + s^*(1+1/\eta_{\tau,s})(\gamma_2\overline{e\Delta}+\varphi) \geq 0 \tag{5b}$$

Table 2: Comparative statics analysis

Variables	Sign $\partial b^*/\partial\alpha$	Sign $\partial s^*/\partial\alpha$
Risk attitude parameter γ	(+) if (5a) holds	(+) if $\eta_{\tau,s} > 0$
Information asymmetry η_{IA}	(-) if (5b) holds	(-) if $\eta_{\tau,s} > 0$
Demand elasticity $\eta_{I,\tau}$	(+) if (5b) holds	(+) if $\eta_{\tau,s} > 0$
The effect on the mean $\eta_{R,b}$	(+) if (5b) holds	(+) if $\eta_{\tau,s} > 0$
The effect on the variability $\eta_{\sigma,b}$	(-) if (5b) holds	(-) if $\eta_{\tau,s} > 0$
Loading factor ι	(-) if (5b) holds	(-) if $\eta_{\tau,s} > 0$
DWL parameter φ	(+) if $\eta_{\tau,s} > 0$	(+) if $\eta_{\tau,s} > 0$

Notes:Differentiate the first-order conditions (2) and (3) with respect to parameter α : $F(x^*, s\alpha) = 0 \Rightarrow \frac{\partial F}{\partial \alpha} + \frac{\partial F}{\partial x}\frac{\partial x}{\partial \alpha} = 0$, and assum the second-order condition is negative $D = \frac{\partial F}{\partial x} < 0 \Rightarrow \frac{\partial x}{\partial \alpha} = -D^{-1}\frac{\partial F}{\partial\alpha = sign(\frac{\partial F}{\partial \alpha})}$. The detailed derivation is presented in Appendix A.

The population's risk attitude is critical in the welfare evaluation and policy design, as the welfare benefit of the crop insurance is from the risk protection. The risk parameters are represented by the shape of utility function. Condition (5a) shows the marginal risk sharing welfare with respect to risk attitude parameters γ. From Table 2, if (5a) holds, the optimal coverage level should be higher in areas where populations are more risk averse. The premium subsidies affect the marginal risk-sharing benefit at the extensive margin, and it depends on the sign of $\eta_{\tau,s}$ representing the extent of extensive margin. If $\eta_{\tau,s}$ is positive, the subsidy rate should be higher to encourage farmers to participate and select higher coverage level for farmers who are more risk averse.

On the welfare cost side, the parameters for information asymmetry and program loads increases means higher cost to increase the coverage level, the optimal coverage level should be lower and the subsidy level should be lower too if (5b) holds and $\eta_{\tau,s} > 0$. Specifically, for different effects of information asymmetry, the demand elasticity is negative, if the demand is more elastic, the loss due to adverse selection would be higher. Under such circumstances, the optimal coverage level should be lower, so does the subsidy rate. The two moral hazard elasticities have opposite welfare implications, as the welfare impacts by the revenue's mean and variability have opposite signs. An increase in the marginal DWL φ decreases the optimal coverage level and the subsidy rate unless an increase in the subsidy rate leads to a sufficiently large reduction in the total insurance premium.

With estimates of all three categories of key parameters, equations (2) and (3) enable us to make welfare statements about the policy parameters. The elasticities can be found in the impact assessment literature; the summary statistics can be easily found in publicly available data; and the parameters in the third category are not necessarily specific to the crop insurance program, and can be found in existing literatures. Next section focus on empirical estimation for the moral hazard effect.

5 The econometric model of the moral hazard effect

The theoretical model indicates that it is sufficient to represent the welfare effect of moral hazard by the impacts of insurance coverage on the revenue distribution. In this section, we apply the moment-based approach (Antle 1983) to estimate the impacts of crop insurance on the first two moments of revenue distributions. As Woodard (2016) and Weber, Key and O'Donoghue

(2016) pointed out, a critical issue for the estimation is to control for self-selection in insurance coverage, which could lead to biased estimates because farmers choosing different coverage level may have different characteristics that confound the effect of insurance coverage. Without controlling for the heterogeneous characteristics, especially the unobserved ones, the estimated effect of insurance coverage would be biased. Fixed effect models can be used to capture the time-invariant component of the confoundedness such as risk preferences and soil quality that are correlated with production outcomes and insurance decisions. However, they cannot control for time-variant component of the confoundedness, such as farming experience that may affect both production decisions and the insurance decision and farmers' capabilities of taking advantage of insurance coverage by deviating from production behaviors.

In this study, we address the confoundedness of the insurance coverage variable by controlling for the farm-fixed effects and by applying the control function approach (Wooldridge 2010, Section 4.3.2) to address the endogeneity issue of the insurance coverage [3]. Heckman and Robb (1985) describes a control function (CF) as a variable that, when conditioned on, makes an endogenous variable "exogenous" in a regression equation. For instance, the Heckman-type correction term is essentially a CF for the discrete choice case. In the following we formally lay out the model specification and the estimation strategy.

5.1 Model specification

To measure the impact of coverage level on the revenue distribution, we estimate the following equation:

$$Y_{mit} = \delta_m b_{it} + X_{it}\beta_1 + \theta_{mi} + u_{mit} \quad E(Xu) = 0 \quad E(bu) \neq 0 \quad m = 1,2 \quad i = 1,2,3...N, \quad t = 1,2,...,T \tag{6}$$

where Y_{mit} is the mean ($m = 1$) and standard deviation ($m = 2$) of the revenue per acre for individual farm i in year t, b_{it} is the endogenous coverage level, δ is the coefficient of our interest, X_{it} is a vector of explanatory variables, θ_{mi} is the farm fixed effect, and u_{mit} is the error term.

To separate the unobservable factor in u_{mit}, we introduce a correction term ν_{it}, which is the

[3] A few recent studies apply instrumental variable (IV) approach to control for the endogeneity of insurance participation, and their identification strategies often rely on exogenous insurance supply, such as introduction of new programs (Cornaggia 2013), changes in subsidy rates (Roberts, Key and O'Donoghue 2009, Yu and Sumner 2016), or the upper bound of the coverage level imposed by the policy structure (Weber, Key and O'Donoghue 2016).

control function obtained from modeling the coverage level selection:

$$b_{it} = X_{it}\alpha + Z_{it}\gamma + \nu_{it} \quad E(X\nu) = 0 \quad E(Z\nu) = 0 \quad i = 1, 2, 3...N, \ t = 1, 2, ..., T \tag{7}$$

The CF is a latent factor which relates to the unobserved component that assigns each individual into different coverage levels. Equation (7) is a regression of endogenous insurance coverage on exogenous controls X_{it} from Equation (6) and excluded instrumental variables Z_{it}. A valid CF requires instrumental variables to provide exogenous variations from Z_{it} for identification. Then the correlation between the error terms u_{it} and ν_{it} from equation can be captured using a linear relationship:

$$u_{it} = \rho\nu_{it} + e_{it} \quad E(\nu e) = 0 \quad i = 1, 2, 3...N, \ t = 1, 2, ..., T \tag{8}$$

Plug (7) into (6) we obtain (8). Because both u and ν are uncorrelated with Z, it follows that e is uncorrelated with Z, and then e is also uncorrelated with b. Therefore, estimating equation (9) could provide consistent estimates on δ.

$$\begin{aligned} Y_{mit} = \delta_m b_{it} + X_{it}\beta_1 + \theta_{mi} + \rho_m\nu_{mit} + e_{mit} \quad E(Xe) = 0 \quad E(be) = 0 \quad E(\nu e) = 0 \\ m = 1, 2 \quad i = 1, 2, 3...N, \quad t = 1, 2, ..., T \end{aligned} \tag{9}$$

The control function approach is inherently an instrumental variables method. The idea is to bring in separate variation ν introduced by exogenous variation of excluded instrument variables Z. The control function ν controls for the endogeneity of b as a proxy for the unobserved factors in u that are correlated with b. Adding appropriate control function yields a new error term e, that is uncorrelated with all explanatory variables including b by construction. Therefore, we obtain consistent coefficient for b.

The vector X_{it} consists of a set of variables that affect farm revenue. We include farm and operator characteristics, such as farm size, operation type, tenure, asset value, and gender, experiences and age of the principal operator, in vector X_{it}. To capture potential non-linear relationship, both linear and quadratic term for operator's age and experience are included. These farm and operator's characteristics may also affect risk preferences. We control for production practices such as irrigation, farm diversification, and crop mixes. Irrigation may affect both the production outcome and the insurance decision. To account for farm diversity, we use the ratio of livestock sales. Including the share of acres in each of major crops helps control for any effect that crop rotation patterns may have on changes in insurance coverage and input decisions. We use the county-level yield to control for the variations of local productivity and physical conditions across time and space. For instance, the heat wave in 2012 has great impact on the production in the Heartland region, the county-level yield could control the impact of such incidence. And farm-level yield is included to reflect individual variations on those factors. Farm-level yield and county-level yield are weighted yields for corn, soybean and wheat by their acreage shares. Commodity prices for corn, soybean and wheat with one year lag and variations across states and year are included to control for the revenue variation due to price changes. Dummy variables for state and year are included to control for the relevant policy changes and differences across states and time.

The CF approach has several attractive features (Wooldridge 2015). First, comparing to the IV approach, the CF approach uses more information and therefore estimates are more precise, although they may be less robust (Wooldridge 2015). Second, the CF approach can parsimoniously handle models that are nonlinear in endogenous explanatory variables. Third, by regressing the endogenous variable, it allows us to study the nature of self-selection. Finally, the CF approach provides a simple test to compare OLS and 2SLS, which is robust to heteroscedasticity and cluster correlation.

However, the construction of a valid CF requires exogenous instruments that are correlated with the coverage level but not with the error term in the revenue equation. It is not easy to separate the factors that affect the insurance decision exclusively but are irrelevant to other production decision in the agricultural setting. Commonly used strategy is to explore the feature of the crop insurance and exogenous policy changes. For instance, Cornggia (2013) exploits the introduction of new insurance policies in some counties and not others. Yu and Sumner (2016) use the information of subsidy changes from the Farm Bills. Weber, Key and O'Donoghue (2016) employ the constraint of maximum coverage level imposed by the policy construction as a source of exogenous information. Woodward (2016) explores the rate making process of the program, and simulates parameters to represent features of the supply curve and use them as instruments. Our data set only includes farm-level observations for three census years. Thus, it is infeasible to use identification strategies relying on subsidy rate changes or new coverage levels or new policies introduction. Based on our data structure, we follow the strategy by Woodward (2016) that relies on exogenous insurance price variations. Next, we describe our identification strategy.

5.2 Identificaiton

Woodard (2016) proposes an identification strategy to estimate the price elasticity of the insurance demand. The standard way is to instrument the demand equation using the supply shifters. In the FCIP, the supply is essentially inelastic given the mandatory offer requirement. Woodard (2016) uses rate curves in the rating system as a proxy of the supply curve, which represents premium rate as a function of coverage level and is upward sloping in coverage. The rate curve tends to shift from year to year in response to changes in the base methodology or new experience data. Although the rate curve is not a supply curve technically, the similar logic behind it shows that information about the rate curve can be used as instruments to identify the insurance coverage demand equation. Woodard (2016) proposes to simulate the rate curve as a log equation, as shown by equation (10):

$$ln(rate_{jt}) = \alpha_{0j} + \alpha_{1j} ln(b_{jt}) + \alpha_{2j} ln(b_{jt})^2 + \phi_{jt} \tag{10}$$

where ϕ_{jt} is a normally distributed error term; α_{0j} can be interpreted as a rate curve shifter, α_{1j} the slope, and α_{2j} a measure of curvature. Also the rate schedules are published prior to the sales period, and thus are exogenous to the actual choice of coverage level in a given year. Woodard (2016) proposes to use the parameters related to shifters, slopes, and curvatures of the rate curve as exclusive instruments Z. The construction of instruments from parameters in equation (10) are detailed in the data section. The estimation procedures are summarized as:

Step1. Fit the coverage equation (7) with exogenous variation of prices Z_{it} as well as control variables X_{it}, and generate the control function from the predicted residual of equation (7): $\hat{\nu}_{it}$;

Step2. Fit the mean revenue equation (8): regress the revenue per acre over the coverage level b_{it}, the control function $\hat{\nu}_{it}$, and the set of controls X_{it}, and predict the residual terms of the mean equation $\hat{e}_{1it}$.

Step3. Fit the second-order moment equation: regress $Y_2 it = ln(\hat{e}^2_{1it})$ over the coverage level b_{it}, the control function $\hat{\nu}_{it}$, and the set of controls X_{it}, and generate predicted value $\hat{Y}_{2it}$.

Step4. Use $\hat{e}^2_{1it}$ to construct weight matrix and then estimate the mean equation using the

Feasible Generalized Least Square (FGLS) to control for heteroscedasticity, and repeat step2 and step3.

5.3 Data

The primary data source for this study is the farm-level Census of Agriculture. The data contain information on land use and ownership, farm and operator characteristics, production practices, income and expenditure for all U.S. farms and ranches. The census is taken for every five years, we use the data from 2002, 2007 and 2012 to construct the panel structure. The original data set includes 245,231 farms and 423,461 observations (observations with missing values for the key variables are excluded). We narrow the range of the data set in the following steps. We are more interested in the behaviors of standard farms and therefore exclude farms with cropland less than 50 acres (considered as hobby farms) and extremely large corporate farms (with cropland greater than 5000 acres). We focus on the crop insurance, and farms that have only livestock revenue but no crop revenue are excluded. In the Heartland region, corn, soybeans and wheat are the main crops that cover 85% of cropland, and account for 98% of insured acreages in 2012. We focus on the farms that grow corn, soybeans or wheat. Therefore, farms that don't grow corn, soybean or wheat are excluded. Next, we delete observations that are obvious outliers (e.g., farms with irrigated land greater than cropland, or corn yield greater than 300 bushels per acre). Finally, the estimation strategy requires the panel structure. Farms with only one observation are excluded. It is normal to have farms entering or exiting the business since there are five years gap between two census years. This leaves us with 180,550 observations and 74,463 farms and the panel structure is shown in Table 3.

Table 3: Panel structure of the data set

Panel structure	Number of farms	Percentage of observations
Year 2002 and 2007	17,621	19.5%
Year 2002 and 2012	11,295	12.5%
Year 2007 and 2012	13,923	15.5%
Year 2002, 2007 and 2012	31,624	52.5%
Total	74,463	180,550 (100%)

The construction of the panel data brings great benefits, though it bears certain limitations. First, the farm-level dataset enables us to control for individual variations, which is lost in more prevalent county-level analyses. Second, with the panel structure, we can use fixed effects models to control for farm-fixed effects and therefore avoids biases from time-invariant unobservable factors and missing variables. However, because there is a five-year gap between each two census years, many farms change owners. As a result, many farms have only one observation, which must be excluded because of the panel data requirement.

Another major limitation of the farm-level census data is that it doesn't include crop insurance information for individual farms. To avoid this limitation, we follow O'Donoghue, Roberts and Key (2009) to construct farm level insurance variables using farm-level crop shares and the county-level data on coverage level, premium payment, subsidy, and liability for individual crops. For example, the farm-level coverage level is constructed as a weight coverage of county-level crop-specific coverage levels by the farm level crop-shares: $b_i = \sum_m b_{jm} s_{im}$, where b_{jm} is the average coverage level for crop m (corn, soybeans, or wheat) in county j, s_{im} is the acreage share of crop m in farm i. Original coverage levels are discrete, from 50% to 85% by 5% increment, and after being weighted by crop shares, b_i becomes a continuous variable. Other insurance variables, insurance premiums and subsidies are also constructed in the same way for each farm. The county-level crop insurance data are taken from the USDA Risk Management Agency (RMA)'s Summary of Businesses (SOB) for 1989-2015. The SOB data contain annual summaries by crop, insurance product, and coverage level, and include data on the number of policies sold, acreage insured, premiums, subsidies, losses, and liabilities.

Several adjustments are made when preparing the data for the analysis. First, to make regression coefficients less affected by scales of variables, we normalize some variables by their mean, including, yield, asset value per acre, farm size and principal operator's age and experience. Second, all the monetary variables are adjusted to the dollar value in 2012 with farm producer price index (PPI)[4]. Third, to indicate the farm productivity level, a farm yield variable is constructed as the normalized yields of different crops weighted by their acreage shares. We include sales from corn, soybean, wheat, and the rest of crops and livestock sales when constructing the yield index. The summary statistics of dependent and explanatory variables are presented in the Appendix A3.

The parameters of the rate curve are required for identification. Following Woodard (2016) we simulate the rate curve equation (9) with the SOB data. For each coverage level, the premium rate is calculated by dividing premium minus subsidy by liability. Counties that do not have at

[4]The source of producer price index (ERS USDA): http://www.ers.usda.gov/data-products/food-price-outlook.aspx40298

least one thousand acres for at least three coverage levels are omitted. In SOB data, we have a time series of 27 years for most of 523 counties, with a total of 1552 observations. The rate curve is simulated for each county and each year. The average R^2 statistics across all rate curve models is 0.69.

5.4 Results

We report two sets of results in Table 4: The fixed-effect model estimated using the instrumental variables approach (FE+IV), and the fixed-effect model estimated using the control function approach (FE+CF). We believe the results from FE+CF is preferable for several reasons. First, as mentioned above, the CF approach uses more information and therefore should provide more precise estimates than the IV approach (Wooldridge 2015). In this study, the IV approach directly applies the excluded variables to instrument the insurance coverage, while the CF approach uses the instruments to introduce the exogenous insurance price variations, which is then used to partial out the effect of the confounding factors. Second, tests reject over-identification in the FE+IV model, but not in the first-stage regression in the FE+CF model. It indicates that instrumental variables representing the supply change of insurance are correlated with error terms in the revenue equation, and therefore are not valid IVs for the revenue equation (FE+IV model). The over-identification test cannot deny the validity of IVs for coverage selection equation which chooses the estimates from FE+CF model over the estimates from FE+IV model. Finally, the Wald test rejects the hypothesis that coverage level is endogenous in the FE+IV model, while the significance of control function in the FE+CF model suggests that the existence of self-selection.

The FE+CF estimates show that insurance coverage has a negative effect on revenue mean, but a positive effect on revenue variance. Intuitively, the risk protection from insurance coverage may dis-incentivize farmers to put effort to reduce risk, such as application of pesticides, at the same time, it provides incentives to pursue practices that bring higher returns and higher risks, for instance, fertilizer application, allocating more land into corn production. In addition, the indemnity payment may encourage farmer to grow on marginal land which usually suggests high risks and low productivities, as they can report low output and collect indemnity payment. Overall, these possible behavioral changes suggest the risk-increasing effect by insurance coverage, which is consistent with the empirical results. As for the mean effect, their impacts are not in the same direction. The empirical result suggests a negative mean effect. Although previous studies have analyzed various effects of crop insurance, to our knowledge, only Weber, Key and O'Donoghue (2016) estimated the effect of insurance coverage on revenue using data for 2000-2013. They first estimate a FE model without controlling for self-selection of coverage level and find a positive relationship between coverage level and revenue. We find a similar result for our FE model without controlling for self-selection of insurance coverage. After controlling for insurance coverage selection, Weber, Key and O'Donoghue (2016) find the relationship between coverage level and revenue become statistically insignificant.

Table 4: Estimates of impacts of crop insurance coverage on the revenue distributions

	(2) FE+IV		(3) FE+CF	
	Mean	Std. Dev.	Mean	Std. Dev.
Coverage level b	-279.2	-0.550*	-282.3***	2.421***
	(185.8)	(2.310)	(1.20)	(0.546)
Control function ν			526.6***	-1.869***
			(1.479)	(0.655)
Observations	180,346	180,346	180,346	180,346
Number of farms	74,385	74,385	74,385	74,385
R-squared	0.598	0.003	0.600	0.003

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses, and they are robust to heteroskedasticity and clustering on farms. Other explanatory variables include farm size, operators' gender, age, experience, percentage of rented acreages, percentage of incorporated acres, crop prices (state-level), percentage of irrigated acreages, percentage of livestock sales, and dummy variables for states and years. The full regression results are presented in the Appendix A3.

The results in Table 4 have some welfare implications. All the production behavioral adjustments generate the welfare impacts through the impacts on the revenue distribution[5]. Therefore, we could use the impacts on the revenue distribution as a representation for the moral hazard

[5]Our discussion of welfare refers to the welfare of the farmers and insurers in the insurance market. Secondary welfare impacts, such as the impact by environmental outcomes and the impact on consumer's welfare in food market caused by price changes, are not included.

effect. As discussed earlier, moral hazard behaviors may have counteractive effects on welfare, and not all of them induce welfare losses. As they may have counteractive effects, it is an empirical question whether the production behavioral changes generate welfare gain or loss. The CF estimates indicate welfare losses by the mean-reducing and risk-increasing production behavioral changes, such as converting marginal land and possible less fertilizer use.

6 Implementing the sufficient statistics approach

6.1 Paramtrization

In this section, we describe the parametrization process for the marginal welfare effects of subsidized crop insurance. In equation (2) and (3), there are four elasticities. $\eta_{R,b}$ and $\eta_{\sigma,b}$ show the impacts of insurance coverage on the revenue distribution's parameters, and they represent the reduced-form of the moral hazard effect. $\eta_{I,\tau}$ is the price elasticity of insurance demand, and it represents the slope of demand curve which affects the level of adverse selection. $\eta_{\tau,s}$ measures how the subsidy rate affects actuarially fair premium. Other parameters in (2) and (3) include summary statistics of revenue distribution parameters, risk attitude parameter γ, program loading factor ι and the marginal DWL parameter φ. Table 5 summarizes the methods, sources and assumptions for the parametrization.

Moral hazard and adverse selection $\eta_{R,b}$, $\eta_{\sigma,b}$and $\eta_{I,\tau}$

In Section 5, we estimate the impacts of crop insurance coverage on the revenue distribution as a reduced-form representation of the moral hazard effect. It is estimated that in the Heartland region, during the year 2002 to 2012, increasing the coverage level by 1% is associated with 0.82% decrease in the mean of farm revenue distribution, and 0.24% increase in its standard deviation. In our estimation, the first stage is to model the coverage level demand (equation (7)). We model the insurance demand with a Probit model with the same identification strategy. In the Probit model, the dependent variable is a binary choice variable, and the instrumental variables representing the supply changes are used to instrument the endogenous insurance price. The crop insurance demand elasticity ($\eta_{I,\tau}$) with respect to price is -0.096. It is interpreted as 1% increase of the insurance premium is associated with a 0.096% decrease of the participation probability.

Table 5: Estimates of various components of the effects of Federal Crop Insurance Program

Parameter		Distribution Assumption	Distribution parameters		Sources/Methods
Risk attitude					
CARA	γ	Uniform	a=0.00001	b=0.00005	Hennessy and Babcock (1997)
CRRA	$\bar{\gamma}$	Normality	μ=0.77	σ=0.64	Barham et al. (2014)
Loading factor					
CAT loads	ι_1	Uniform	a=0.07	b=0.46	Coble et al. (2010)
A&O loads	ι_2	Normality	μ=0.170	σ=0.0138	Bootstrapping
Elasticities			Mean	Std.Err.	
Moral Hazard	$\eta_{R,b}$		-0.817	0.001	
	$\eta_{\sigma,b}$		0.241	0.183	
Adverse selection	η_A		-0.0966	0.0464	
Effect of subsidy rate	$\eta_{\tau,s}$		2.83	442	O'Donoghue (2014)
Summary statistics					
Profit of low state	$\bar{\pi}_L$		390.348	0.378	
Coefficient of variance	c_v		0.134	0.009	
Profit gap between two states	$\bar{\Delta}$		147.143	0.117	
Inverse mill's ratio of the low state	λ_L		2.690	0.003	
Probability of the high state	$\bar{e}$		0.949	0.000	
Correlation coefficient	ρ_1		0.003	0.002	
Correlation coefficient	ρ_2		-0.009	0.002	
Indemnity of the marginal insureds	τ_b		26.623	0.048	

Subsidy rate elasticity $\eta_{\tau,s}$

The elasticity of premium with respect to the subsidy rate $\eta_{\tau,s}$ measures the extent of the indirect marginal effect relative to the direct marginal effect. O'Donoghue (2014) measures the effect of premium subsidies on demand for crop insurance. The elasticity of premium payment with respect to the subsidy payment is estimated using the subsidy rate change introduced by Agriculture Risk Protection Act of 2000 (ARPA). County-level data is used in the estimation for several production regions in the U.S. For the Midwest states, it is estimated that one percent in subsidy change per acre leads to 0.91% change of premium per acre for corn in the Midwest region and 0.90 % for soybeans (Midwest states IL, IN, IA, OH are slightly different to the study target in this study, by has majority overlaps, overlapped counties). We transform the estimate to the elasticity of premium per acre with respect to the subsidy rate $\eta_{\tau,s}$, and obtain $\eta_{\tau,s} = 10.11$[6].

Other parameters

The third category includes risk attitude parameter γ, the marginal DWL parameter φ, and the loading factor τ. We draw evidence on their values from the existing literature.

For risk attitude parameters, we assume two utility functions that represent risk aversion: the negative exponential utility function $1 - e^{-\gamma x}$ that exhibits CARA, and the Power utility function $[sign(1 - \bar{\gamma})x^{1-\bar{\gamma}}]$ that exhibits CRRA. For CARA, Hennessy and Babcock (1997) use the low and high risk-aversion coefficients of 0.00001 and 0.00005, respectively from Babcock, Choi and Feinerman (1993). The two levels imply that the risk premium is between 10% and 50% of the standard deviation of farm revenue. Assume γ follows uniform distribution, varying between these two levels. For CRRA, We use the results from Barham et al. (2014), and assume $\bar{\gamma}$ follows a normal distribution with mean 0.77 and standard deviations 0.64.

We consider the program loads from systemic risk and transaction costs. The RMA uses the catastrophic risk loads in the rate-making process, and we take their values (Coble et al. 2010) and transform it to the form we use in our model. The CAT risk that contributes to the total loading factor takes the range of (0.07, 0.46). The program's Administrative and Operational cost (A&O) includes reimbursement cost, federal salaries of USDA's Risk Management Agency and various research and development initiatives mandated by the Agriculture Risk Protection

[6] Using our notation, the elasticity estimated in O'Donoghue (2014) can be written as: $\eta_{O'Donoghue} = \frac{d\tau/\tau}{d(\tau s)/(\tau s)} = \frac{s}{\left(s+\tau\frac{ds}{d\tau}\right)} = \frac{1}{\left(1+\frac{ds/s}{d\tau/\tau}\right)} = \frac{1}{\left(1+\frac{1}{\eta_{\tau,s}}\right)}$

Act of 2000. The ratio of A&O cost to the premium is used to proxy the transaction cost load, which measure the A&O cost for \$1 transfer between the high and low states. We perform a simple bootstrap procedure of regressing the A&O cost over the premium payment and obtain the Normal-based 95% confidence interval of the ratio as (0.143, 0.197).

As for the marginal welfare cost of DWL, Alston and Hurd (1990) discuss the social cost of government spending in farm policies, and suggest that the deadweight loss of U.S. federal government spending is more likely to be in the range of 20% to 50% after discussing estimates from several studies. This suggested rage covers the estimates of most other studies, and we will parameterize from this range.

6.2 Results

With the parameters estimated in Section 5 and collected from other studies, we perform the Bootstrap method to estimate each component of (2) and (3), that is, the marginal welfare effects. We present the results in Table 6 and 7, and discuss the welfare implications.

The coverage level

The welfare benefit is from risk sharing, including risk spreading and risk pooling. The risk spreading effect is originated from reducing the variability of the revenue distribution, represented by $\gamma\overline{e\Delta}$. The sign of the marginal effect from risk pooling depends on the correlation between the marginal indemnity payment and the profit at the low state ($\rho_2 = corr[(1-e)R, \pi_L] < 0$). Both the marginal risk spreading and pooling effects are positive, and the marginal pooling effect is trivial relative to the marginal spreading effect due to a small ρ_2. When the coverage level increases farmers put greater proportion of their risks into the pool, the marginal benefit from insurance premium reduction is limited. Overall, the positive marginal benefits suggest when increasing the coverage level, the welfare benefits from risk sharing also increase.

Table 6: Estimates of various components of the effects of Federal Crop Insurance Program

	CARA			CRRA		
	Mean	Std. Dev.	95% Conf. Interval	Mean	Std. Dev.	95% Conf. Interval
Marginal benefit						
Risk spreading	5.41E-03	1.58E-03	(2.30E-03, 8.51E-03)	0.385	0.005	(0.375, 0.395)
Risk pooling	8.94E-05	3.71E-05	(1.68E-05, 1.62E-04)	5.56E-04	4.51E-03	(8.29E-03, 9.40E-03)
Marginal cost						
Information asymmetry	0.306	0.041	(0.224, 0.387)	0.306	0.041	(0.224, 0.387)
DWL of subsidy	0.267	0.098	(0.074, 0.459)	0.296	0.268	(-0.229, 0.822)
Program Loads	0.232	0.177	(-0.116, 0.58)	0.225	0.165	(-0.098, 0.547)
Net marginal effect	-0.799	0.241	(-1.271, -0.327)	-0.790	0.266	(-1.312, -0.268)

Table 7: Estimates of the marginal benefit and cost of premium subsidies

	CARA			CRRA		
	Mean	Std. Dev.	95% Conf. Interval	Mean	Std. Dev.	95% Conf. Interval
The intensive margin	-0.275	0.085	(-0.442, -0.108)	-0.306	0.258	(-0.812, 0.2)
The extensive margin	-0.535	0.175	(-0.879, -0.192)	-0.497	0.427	(-1.334, 0.341)
Net marginal effect	-2.877	612.3	(-1203.0, 1197.3)	-2.846	511.7	(-1005, 1000)
Optimal subsidy rate s^*	-1.148	0.428	(-1.987, -0.309)	-0.958	2.180	(-5.231, 3.314)

The welfare cost consists of costs from the information asymmetry, deadweight loss of subsidy transfer, and the program loads. The cost of information asymmetry are further attributed to moral hazard and adverse selection. For the marginal effect of moral hazard, the increase of insurance coverage is associated with a lower mean and a higher variability of revenue distribution. Risk-averse farmers' utilities decrease due to such variation of revenue distribution. The marginal effect of adverse selection depends on both the moral hazard effect and insurance demand elasticity. The total marginal effect of information asymmetry is positive, indicating that the welfare cost increases with a higher coverage level. The marginal welfare effects of DWL associated with the subsidy transfer and program loads are both positive, the magnitude of which primarily depend on the parameter φ and ι.

The tradeoff relationship between the marginal benefit and marginal cost defines the optimal coverage level. In Table 6, the negative net welfare effect suggests that the marginal cost is greater than the marginal benefit given the current coverage level and subsidy rate. With the assumption of negative second-order condition in maximization problem (1), the current insurance coverage is greater than its optimal level given the subsidy rate.

As the comparative statics analysis indicate that the parametrization of the exogenous parameters affects the welfare evaluation. For instance, in the evaluation of risk protection effect, the risk parameter plays a dominant role. The empirical estimates of risk attitude parameter covers a broad range. Different parametrization may lead to different results. In our case, the net welfare effect is negative. In the comparative statics analysis in Section 4.4, condition (5) is satisfied. That is, if the "real" risk attitude parameter is greater than the one parametrized here, both the optimal coverage level and the optimal subsidy rate should be higher. Intuitively, the marginal welfare benefit of risk protection increases with a greater "real" risk-averse parameter, and it is beneficial to provide higher coverage level and subsidy rate.

The subsidy rate

The intensive marginal effect $-(\gamma\overline{e\Delta}+\varphi)$ is negative, referring to the effect on the existing participants. The extensive marginal effect refers to the marginal effect caused by changes of selection in participation and coverage levels induced by subsidy changes. The marginal effect of increasing subsidy rate at the intensive margin is smaller than the marginal effect at the extensive margin. It makes sense, since the goal of providing subsidies is to encourage participation. $\eta_{\tau,s}$

is a measure of the extent of extensive marginal effect relative to the intensive margin. We use the estimates from O'Donoghue (2014), which suggests that the current participants selecting higher coverage levels encouraged by higher subsidy rate plays a dominant role.

Both the marginal effects at the intensive margin and extensive margin are negative, indicating the marginal welfare effect of higher subsidy decreases the program welfare. Given the current coverage level, the program is over subsidized and the optimal subsidy rate should be zero given the negative s^* in Table 6.

In the optimal policy setting, the coverage level and subsidy rate are jointly defined by equation (2) and (3). The marginal welfare effects with respect to the coverage level and subsidy level suggest both the coverage level and subsidy level are greater than the social optimal. Furthermore, considering the objective of the crop insurance program is to provide the "safety net" for farmers, we narrow our discussion to the agricultural sector. The welfare benefit of risk protection roughly equals to the marginal cost of information asymmetry under the assumption of CRRA. That is, with the current subsidy rate, the risk protection level is appropriate from the farmers' perspective.

However, in this study, there are a few problems that may impose some limitations to the results. First, in implementing the sufficient statistics approach, the parameters should be exogenous in order to identify the optimal policy parameter. In this case, we use the observed summary statistics which are conditioned on the current policy setting. Therefore, the results show the current welfare status of the program, instead of identify the optimal contract. Second, the conceptual model in Section 4 is developed based on the revenue insurance, and the empirical estimation of the crop insurance impacts does not identify policy types due to the data limitation. It may cause some bias by parametrizing the moral hazard effect of revenue insurance with estimates of general crop insurance.

7 Conclusion

The FCIP protect farmers from income losses due to weather and price risks. As the program expands, more attentions have been focused on its unintended impacts on input uses, land allocations, and associated environmental externalities. These unintended effects may compromise the program's benefits from risk protection. Theoretically, how different impacts interact, and empirically, whether the program's welfare gains outweigh its welfare costs are key questions for researchers and policy makers.

Our theoretical analysis suggests that the optimal design of a publically subsidized insurance program must consider the tradeoff relationship between welfare benefits from risk protection and welfare costs of information asymmetry, government subsidy, and program loadings. Our empirical analysis of the U.S. FCIP in the Heartland region suggests the current insurance coverage level and premium subsidy rate are greater than the optimal levels even without consider the welfare costs outside of the insurance market such as environmental costs caused by changes in input use and land allocation induced by crop insurance. In addition, the government starts to provide the shallow loss programs after the 2014 Farm Bill, which essentially increase the coverage level and the subsidy rate. These changes may cause additional welfare losses in the Heartland region. However, considering only farmers' welfare, the marginal welfare benefit from risk protection roughly equals to the marginal welfare cost of moral hazard and adverse selection. This suggests that the current risk protection level and the current subsidy level are appropriate from farmers' perspectives.

The RMA should consider the key parameters identified in the conceptual model in the program design. First, it is important to accurately measure the risk attitude parameter because it plays a key role in determining the optimal coverage level and subsidy rate. If the targeted population is more risk averse, insurance coverage will bring more welfare benefit from risk protection. The welfare cost of the information asymmetry originates from the gap between public knowledge and individual knowledge. The RMA will have more individual information as more farms participate in the program and report their production history. It is essential for the RMA to incorporate private information into the premium rate-making process to reduce the welfare cost from information asymmetry. The marginal deadweight loss and program loadings are sufficient statistics exogenous to the program, and in policy design, it is also essential to incorporate these effects: higher marginal deadweight losses or program loadings suggest a lower coverage level. Furthermore, the parameters that affect the marginal welfare effects may vary across crops and policy types. The marginal welfare effects in the conceptual model give guides to incorporate crop-specific and policy-specific attributes in policy design. Some parameters such as systemic risks that add to the program loads also vary across regions.

This study contributes to the literature by deriving the conceptual model that integrates different components of welfare effects of the crop insurance. This conceptual model increases our understanding of the interactions between different components of welfare effects of the crop insurance and provides guidance for the empirical analyses of the welfare effect of the program. However, there are certain limitations in the application. First, the conceptual model is derived for the revenue insurance and a few assumptions are imposed to make the model tractable, such as the normality assumption of the production output. Also the conceptual model focuses on the effects in the insurance market. Other impacts, such as environmental externalities associated with input use changes and the impact on commodity prices and food consumers' welfare, are not incorporated in the framework. Furthermore, it is a static model. It is more precise to describe the insurance program with a dynamic model, since in a longer run, the production behaviors get updated based on their production and insurance history. Second, in the empirics, the measurement of moral hazard behaviors are for the general crop insurance, instead of revenue insurance which the conceptual model is developed for. And in parametrizing the net marginal welfare effects, we collect some summary statistics which are endogenous to the policy setting. That is, when there are adjustments to the policy, these statistics might change accordingly. This limits the conceptual model's power in predicting the optimal policy design. Extending the present study to overcoming these limitations offers directions for future research.

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Appendix

A1. The Proof of the Proposition

The social planner maximizes the aggregate welfare of the economy with the insurance program: the aggregate welfare of participants and non-participants subject to the actuarially fair constraint.

$$\max_{(b,s)} W = \int_{-\infty}^{z_b} w_0\, dF + \int_{z_b}^{+\infty} w_1(b)\, dF \ - U[(1+\varphi)s\tau], \qquad s.t.\ \tau = \frac{1+\iota}{I}\int_{z_b}^{+\infty} \tau(z)\, dF(z) \quad \text{(A1)}$$

First derive the first-order condition with respect to the coverage level:

$$\frac{dW}{db} = \frac{dW_0}{db} + \frac{dW_1}{db} - \frac{\mathrm{d}U}{\mathrm{db}}$$

$$= \int_{-\infty}^{z_b} \frac{dw_0}{db} dF + w_0(z_b) f(z_b) \frac{dz_b}{b} + \int_{z_b}^{+\infty} \frac{dw_1}{db} dF - w_1(z_b) f(z_b) \frac{dz_b}{b} - \frac{\mathrm{d}U}{\mathrm{db}}$$

w_0 is the welfare of non-participants, which is not a function of b, and for the marginal insureds who are indifferent to participate or not participate, $w_0(z_b) = w_1(z_b)$. It reduces to:

$$\frac{dW}{db} = \frac{dW_0}{db} + \frac{dW_1}{db} - \frac{\mathrm{d}U}{\mathrm{db}} = \int_{z_b}^{+\infty} \left(\frac{\partial w_1}{\partial b} + \frac{\partial w_1}{\partial \tau}\frac{d\tau}{db} + \frac{\partial w_1}{\partial s}\frac{ds}{db}\right) dF - \frac{\mathrm{d}U}{\mathrm{db}} = 0 \quad \text{(A2)}$$

And similarly, the first-order condition with respect to the subsidy level is:

$$\frac{dW}{ds} = \frac{dW_0}{ds} + \frac{dW_1}{ds} - \frac{\mathrm{d}U}{\mathrm{ds}} = \int_{z_b}^{+\infty} \left(\frac{\partial w_1}{\partial s} + \frac{\partial w_1}{\partial \tau}\frac{d\tau}{ds} + \frac{\partial w_1}{\partial b}\frac{db}{ds}\right) dF - \frac{\mathrm{d}U}{\mathrm{ds}} = 0 \quad \text{(A3)}$$

Farmers' utility and the government's utility are not comparable. We derive the four terms $\frac{dW_0}{db} + \frac{dW_1}{db}, \frac{\mathrm{d}U}{\mathrm{db}}, \frac{dW_0}{ds} + \frac{dW_1}{ds}\ and\ \frac{\mathrm{d}U}{\mathrm{ds}}$ in (A2) and (A3) separately, and make normalization for comparison.

(1) For the first-order condition with respect to the subsidy rate, the marginal welfare effects of the farmers is $\int_{z_b}^{+\infty} \left(\frac{\partial w_1}{\partial b} + \frac{\partial w_1}{\partial \tau}\frac{d\tau}{db} + \frac{\partial w_1}{\partial s}\frac{ds}{db}\right) dF$. It is easy to obtain $\frac{\partial w_1}{\partial b} = (1-e)R(e)u_L'$ and $\frac{\partial w_1}{\partial \tau} = -\frac{d[(1-s)\tau]}{d\tau}u' = -u'(1-s) = -u'(1-s)$, $\frac{\partial w_1}{\partial s} = \tau u'$, $\frac{ds}{db} = \frac{d\tau/db}{d\tau/ds} = \frac{s}{\tau\eta_{\tau,s}}\frac{d\tau}{db}$, where $\eta_{\tau,s} = \frac{d\tau/\tau}{ds/s}$, then it yields:

$$\int_{z_b}^{+\infty} \left(\frac{\partial w_1}{\partial b} + \frac{\partial w_1}{\partial \tau}\frac{d\tau}{db} + \frac{\partial w_1}{\partial s}\frac{ds}{db}\right) dF = \int_{z_b}^{+\infty} [(1-e)Ru_L']\, dF - \int_{z_b}^{+\infty} \left[\left(1 - s - \frac{s}{\eta_{\tau,s}}\right)u'\right]\frac{d\tau}{db} dF =$$
$$\overline{(1-e)Ru_L'} - \frac{d\tau}{db}\left(1 - s - \frac{s}{\eta_{\tau,s}}\right)\overline{u'} \quad \text{(A4)}$$

In the second step, the subsidy rate and premium payment are exogenous to individual farmers, therefore can be taken out of the integral, $\bar{\cdot}$ stands for the average of the participants' group. Now derive $\frac{d\tau}{db}$, where $\tau = \frac{1+\iota}{I}\int_{z_b}^{+\infty} \tau(z)\, dF(z)$.

$$\frac{d\tau}{db} = \frac{1+\iota}{I}\int_{z_b}^{+\infty} \frac{d[\tau(z)f(z)]}{db} dz - \frac{1+\iota}{I}\tau(z_b) f(z_b)\frac{dz_b}{db} - \frac{\tau I}{I^2}\frac{dI}{db}$$

$$= \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z) + \frac{1+\iota}{I}\int_{z_b}^{+\infty}\tau(z)\frac{df(z)}{db}dz - \frac{1+\iota}{I}\tau(z_b)\frac{dF(z_b)}{dz_b}\frac{dz_b}{db} - \frac{\tau}{I}\frac{dI}{db}$$

$$= \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z) + \frac{1+\iota}{I}\int_{z_b}^{+\infty}\tau(z)\frac{df(z)}{db}dz - \frac{1+\iota}{I}\tau(z_b)\frac{dF(z_b)}{db} - \frac{\tau}{I}\frac{dI}{db} \quad \text{(A5)}$$

For four terms in (A5). In the first term of (A5), we can apply the result in Appendix 1, that is, $\frac{d\tau(z)}{db} = (1-e)R(1+\eta_m)$. For the second term, assume $\frac{df(z)}{db} = 0$, that is, the coverage level change won't affect the order of the insureds' valuation of insurance contract. In the third term, $F(z_b)$ defines the participation rate as: $F(z_b) = 1 - I$. Apply these changes to (A2-2), and it reduces to:

$$\frac{d\tau}{db} = \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z) + \frac{(1+\iota)\tau_b}{I}\frac{dI}{db} - \frac{\tau}{I}\frac{dI}{db}$$

$$= \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z) - \frac{\tau-(1+\iota)\tau_b}{I}\frac{dI}{db}$$

$$= \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z) - \frac{\tau-(1+\iota)\tau_b}{I}\frac{dI}{d\tau}\frac{d\tau}{db} \quad \text{(A6)}$$

$\frac{d\tau}{db}$ appears at both sides of (A6), rearrange terms it yields:

$$\frac{d\tau}{db} = \frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z)\Big/\left[1 + \frac{\tau-(1+\iota)\tau_b}{I}\frac{dI}{d\tau}\right] = \frac{\frac{1+\iota}{I}\int_{z_b}^{+\infty}\frac{d\tau(z)}{db}dF(z)}{1+(1-(1+\iota)\tau_b/\tau)\eta_{I,\tau}} \quad \text{(A7)}$$

where $\eta_{I,\tau}$ is the price elasticity of insurance demand. The $\frac{d\tau(z)}{db}$ in the numerator is the marginal indemnity payment for individual with characteristics z. It represents the moral hazard effect. Now we derive the moral hazard effect. Further expand the term as

$$\frac{d\tau(z)}{db} = \frac{\partial\tau(z)}{\partial b} + \frac{\partial\tau(z)}{\partial(1-e)}\frac{d(1-e)}{db} \quad \text{(A8)}$$

It is easy to obtain: $\frac{\partial\tau(z)}{\partial b} = (1-e)R(z)$. Now we derive the term $\frac{\partial\tau(z)}{\partial(1-e)}$.

$$\frac{\partial\tau(z)}{\partial(1-e)} = (b-1)R + \sigma\lambda_L + (1-\mathrm{e})\left[(b-1)\frac{dR}{d(1-e)} + \lambda_L\frac{d\sigma}{d(1-e)} + \sigma\frac{d\lambda_L}{d(1-e)}\right]$$

$$= (b-1)R + \sigma\lambda_L + (1-e)(b-1)R\frac{dR}{d(1-e)} + \lambda_L\frac{d\sigma}{d(1-e)} + \sigma(1-e)\frac{d\lambda_L}{d(1-e)} \quad \text{(A9)}$$

The last term in (A9):

$$\frac{d\lambda_L}{d(1-e)} = \frac{d\left(\frac{\phi}{1-e}\right)}{d(1-e)} = -\frac{\phi}{(1-e)^2} + \frac{1}{1-e}\frac{d\phi}{d(1-\mathrm{e})} = \frac{1}{1-e}\left[-\lambda_L + \frac{d\phi}{d\Phi}\right]$$

$$= \frac{1}{1-e}\left[-\lambda_L + \frac{d\phi(\Phi^{-1})}{d\Phi}\right] = \frac{1}{1-e}\left[-\lambda_L + \frac{\phi'}{\phi}\right]$$

$$= \frac{1}{1-e}\left[-\lambda_L - (b-1)R/\sigma\right] \quad \text{(A10)}$$

Plugging (A10) into (A9) obtains:

$$\frac{\partial\tau(z)}{\partial(1-e)} = (b-1)R + \sigma\lambda_L + (1-e)\left[(b-1)\frac{dR}{d(1-e)} + \lambda_L\frac{d\sigma}{d(1-e)}\right] + \sigma[-\lambda_L - (b-1)R/\sigma]$$

$$= (1-e)\left[(b-1)\frac{dR}{d(1-e)} + \lambda_L\frac{d\sigma}{d(1-e)}\right] \quad \text{(A11)}$$

Plugging (A11) into (A8) yields:

$$\frac{d\tau(z)}{db} = (1-e)R + (1-e)(b-1)\frac{dR}{d(1-e)}\frac{d(1-e)}{db} + \lambda_L(1-e)\frac{d\sigma}{d(1-e)}\frac{d(1-e)}{db}$$

$$= (1-e)R[1 + \frac{b-1}{R}\frac{dR}{db} + \frac{\lambda_L}{R}\frac{d\sigma}{db}]$$

$$= (1-e)R\left(1 + \frac{b-1}{b}\eta_{R,b} + \frac{1}{b}\lambda_L c_v\eta_{\sigma,b}\right) \quad \text{(A12)}$$

In (A12), $\eta_{R,b} = \frac{dR}{db}\frac{b}{R}$ and $\eta_{\sigma,b} = \frac{d\sigma}{db}\frac{b}{\sigma}$ are elasticities of revenue's mean and standard deviation with respect to coverage level, $c_v = \sigma/R$ is the coefficient of variation of revenue. We use $\eta_m = \frac{b-1}{b}\eta_{R,b} + \frac{1}{b}\lambda_L c_v\eta_{\sigma,b}$ as a composite elasticity term that represents how the coverage level affect the revenue's mean and variability. The individual moral hazard effect can be written as $\frac{d\tau(z)}{db} = (1-e)R\eta_m$, and plug it into (A7):

$$\frac{d\tau}{db} = \frac{(1+\iota)\overline{(1-e)R\eta_m}}{1+(1-(1+\iota)\tau_b/\tau)\eta_{I,\tau}} = \frac{(1+\iota)\overline{(1-e)R}(1+\eta_M)}{1+(1-(1+\iota)\tau_b/\tau)\eta_{I,\tau}} = (1+\iota)\overline{(1-e)R}(1+\eta_M+\eta_A) \quad \text{(A13)}$$

where $\eta_M = \bar{\eta}_m(\rho_1+1)$, represents the average moral hazard effect $\rho_1 = corr[(1-e)R, \eta_m]$, and τ_b is the expected indemnity payment for the marginal insureds, where $\eta_A = -\frac{(1+\eta_M)[1-(1+\iota)\tau_b/\tau]\eta_{I,\tau}}{1+[1-(1+\iota)\tau_b/\tau]\eta_{I,\tau}}$ represents the adverse selection effect. We use $\eta_{IA} = \eta_M + \eta_A = \frac{1+\eta_M}{1+[1-(1+\iota)\tau_b/\tau]\eta_{I,\tau}} - 1$ to represent the marginal effect of information asymmetry (both adverse selection and moral hazard).

Plugging $(A13)$ into (A4) obtains:

$$\frac{dW_0}{db} + \frac{dW_1}{db} = \overline{(1-e)Ru'_L} - (1+\iota)\overline{(1-e)R}(1+\eta_{IA})\left(1-s-\frac{s}{\eta_{\tau,s}}\right)\bar{u}'$$

$$= \overline{(1-e)R}\left[\rho\bar{u}'_L + \bar{u}'_L - (1+\iota)(1+\eta_{IA})\left(1-s-\frac{s}{\eta_{\tau,s}}\right)\bar{u}'\right]$$

$$= \overline{(1-e)R}\left[\rho\bar{u}'_L + \bar{u}'_L - (1+\eta_{IA})\bar{u}' + (1+\iota)(1+\eta_{IA})\left(s+\frac{s}{\eta_{\tau,s}}\right)\bar{u}' - \iota(1+\eta_{IA})\bar{u}'\right]$$

$$= \overline{(1-e)R}\bar{u}'_L\left\{(1+\eta_{IA})\left(\frac{\overline{eu'_L}-\overline{eu'_L}}{\bar{u}'_L}\right) + \rho - \eta_{IA} + (1+\eta_{IA})\left[\left(s+\frac{s}{\eta_{\tau,s}}\right)(1+\iota) - \iota\right]\left(1-\frac{\overline{eu'_L}-\overline{eu'_H}}{\bar{u}'_L}\right)\right\} \quad \text{(A14)}$$

Normalize (A14) by the marginal welfare from a lump-sum subsidy transfer which equals to the indemnity payment in the low state: $\overline{(1-e)R}\bar{u}'_L$, and obtain:

$$M_{W_1}(b)=\frac{\frac{dW_0}{db}+\frac{dW_1}{db}}{(1-e)R\bar{u}_L'}=(1+\eta_{IA})\left(\frac{\overline{eu}_L'-\overline{eu}_L'}{\bar{u}_L'}\right)+\rho-\eta_{IA}+(1+\eta_{IA})\left[\left(s+\frac{s}{\eta_{\tau,s}}\right)(1+\iota)-\iota\right]\left(1-\frac{\overline{eu}_L'-\overline{eu}_H'}{\bar{u}_L'}\right) \quad \text{(A15)}$$

The marginal welfare of increasing coverage level for the government is

$$\frac{\mathrm{d}U}{\mathrm{db}}=\frac{dU[(1+\varphi)s\tau]}{db}=U'(1+\varphi)\frac{d\tau}{db}\left(s+\tau\frac{ds/db}{d\tau/db}\right)=U'(1+\varphi)\left(s+\frac{s}{\eta_{\tau,s}}\right)(1+\iota)\overline{(1-e)R}(1+\eta_{IA})$$

Also normalize $\frac{\mathrm{d}U}{\mathrm{db}}$ by the marginal utility of the lump-sum subsidy transfer in the low state $\overline{(1-e)R}U'$and obtains:

$$M_U(b)=\frac{dU/db}{\overline{(1-e)R}U\prime}=(1+\varphi)(1+\iota)(1+\eta_{IA})\left(s+\frac{s}{\eta_{\tau,s}}\right) \quad \text{(A16)}$$

The first-order condition with respect to the coverage level b is then:

$$M_W(b)=M_{W_1}(b)-M_U(b)=(1+\eta_{IA})\left(\frac{\overline{eu}_L'-\overline{eu}_H'}{\bar{u}_L'}\right)+\rho-\eta_{IA}-\iota(1+\eta_{IA})\left(1-\frac{\overline{eu}_L'-\overline{eu}_H'}{\bar{u}_L'}\right)$$

$$-(1+\eta_{IA})(1+\iota)\left(s+\frac{s}{\eta_{\tau,s}}\right)\left(\frac{\overline{eu}_L'-\overline{eu}_H'}{\bar{u}_L'}+\varphi\right)=0 \quad \text{(A17)}$$

$M_W(b)$ is derived from the first-order condition. Assume the second-order condition holds, that is the marginal welfare effect $M_W(b)$ is decreasing in b, $M_W(b)\geq 0$ indicates the net marginal welfare effect of increasing the coverage level is non-negative, in other words, $M_W(b)\geq 0$ is a sufficient condition to for the government to provide the crop insurance program, which gives inequality (2) in the Proposition. And $M_W(b)=0$ implicitly defines the optimal coverage level, where the marginal welfare of adjusting the coverage level b^* is zero.

(2) For the first-order condition with respect to the subsidy rate, the marginal welfare effects of the farmers are

$$\frac{dW_0}{ds}+\frac{dW_1}{ds}=\int_{z_b}^{+\infty}\left(\frac{\partial w_1}{\partial s}+\frac{\partial w_1}{\partial \tau}\frac{d\tau}{ds}+\frac{\partial w_1}{\partial b}\frac{db}{ds}\right)dF \quad \text{(A18)}$$

where $\frac{\partial w_1}{\partial s}=\tau u'$, $\frac{\partial w_1}{\partial \tau}\frac{d\tau}{ds}=-(1-s)u'\frac{d\tau}{ds}=-\frac{1-s}{s}\tau\eta_{\tau,s}u'$ and $\frac{\partial w_1}{\partial b}\frac{db}{ds}=(1-e)Ru_L'\frac{db}{ds}=(1-e)Ru_L'\frac{d\tau/ds}{d\tau/db}=(1-e)Ru_L'\frac{\tau\eta_{\tau,s}}{sd\tau/db}$. Plug these three terms into (A2-9):

$$\frac{dW_0}{ds}+\frac{dW_1}{ds}=\tau\left[1-\frac{1-s}{s}\eta_{\tau,s}\right]\int_{z_b}^{+\infty}u'\,dF+\frac{\tau\eta_{\tau,s}}{\frac{sd\tau}{db}}\int_{z_b}^{+\infty}(1-e)Ru_L'\,dF$$

$$=\tau\bar{u}_L'\left[\left(1-\frac{1-s}{s}\eta_{\tau,s}\right)\left(1-\frac{\overline{eu}_L'-\overline{eu}_H'}{\bar{u}_L'}\right)+\frac{(1+\rho)\eta_{\tau,s}}{s(1+\iota)(1+\eta_{IA})}\right] \quad \text{(A19)}$$

Normalize it by the marginal utility of a direct lump-sum subsidy for the farmers respectively, and rearranging terms obtain:

$$M_{W_1}(s) = \frac{\frac{dW_0}{ds}+\frac{dW_1}{ds}}{\tau\bar{u}'_L} = \left(1 - \frac{1-s}{s}\eta_{\tau,s}\right)\left(1 - \frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L}\right) + \frac{(1+\rho)\eta_{\tau,s}}{s(1+\iota)(1+\eta_{IA})} \quad \text{(A20)}$$

The marginal welfare effects of the government is:

$$\frac{\mathrm{d}U}{\mathrm{d}s} = \frac{dU[(1+\varphi)s\tau]}{ds} = U'(1+\varphi)\left(s\frac{d\tau}{ds}+\tau\right) = U'(1+\varphi)\tau\left(1+\eta_{\tau,s}\right) \quad \text{(A21)}$$

$$M_U(s) = \frac{dU/ds}{\tau U\prime} = (1+\varphi)\left(1+\eta_{\tau,s}\right) \quad \text{(A22)}$$

The first-order condition with respect to the subsidy rate is

$$M_W(s) = M_{W_1}(s) - M_U(s)$$

$$= \left(1 - \frac{1-s}{s}\eta_{\tau,s}\right)\left(1 - \frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L}\right) + \frac{(1+\rho)\eta_{\tau,s}}{s(1+\iota)(1+\eta_{IA})} - (1+\varphi)\left(1+\eta_{\tau,s}\right)$$

$$= -\left(\frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L} + \varphi\right)\left(1+\eta_{\tau,s}\right) - \frac{\eta_{\tau,s}}{s}\left[1 - \frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L} - \frac{1+\rho}{(1+\iota)(1+\eta_{IA})}\right] = 0 \quad \text{(A23)}$$

The government can improve the social welfare by providing premium subsidies when the marginal welfare effect with respect to the subsidy level is greater than zero, that is, $M(s) \geq 0$. Rearrange terms we then obtain inequality (2) in the Proposition.

The optimal subsidy rate is defined by $M(s) = 0$, when the marginal welfare benefit equals the marginal welfare cost: $s^* = \frac{\left[\frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L} + \frac{1+\rho}{(1+\iota)(1+\eta_{IA})} - 1\right]\eta_{\tau,s}}{\left(\frac{\overline{eu}'_L - \overline{eu}'_H}{\bar{u}'_L} + \varphi\right)(1+\eta_{\tau,s})}$.

Q.E.D.

A2. Comparative statics analysis

Equation (2) and (3) are the first-order conditions derived from maximization problem (1), they implicitly define the optimal coverage level and subsidy rate. We perform comparative statics analysis to investigate how the key factors would affect the optimal policy parameters b^* and s^*. Differentiating the first-order condition ($F(x^*, \alpha) = 0$ where x^* is b^* or s^*) with respect to factor α, we get:

$$\frac{\partial F}{\partial \alpha} + \frac{\partial F}{\partial x}\frac{\partial x}{\partial \alpha} = 0 \quad \text{(A24)}$$

Assuming the objective function is concave, that is, the second-order condition is negative ($D = \frac{\partial F}{\partial x} < 0$), we get the direction of impact of α on x is the same as the sign of $\frac{\partial F}{\partial \alpha}$.

$$\frac{\partial x}{\partial \alpha} = -D^{-1}\frac{\partial F}{\partial \alpha} = sign\left(\frac{\partial F}{\partial \alpha}\right) \quad \text{(A25)}$$

We examine the impacts of some factors on the optimal coverage level and the subsidy rate, namely, risk preferences, price elasticity of insurance demand, the level behavioral responses, the DWL and the loading factor.

(1) Risk attitude parameters γ:

$$\frac{\partial b}{\partial \gamma_2} \sim \frac{\partial M_W(b)}{\partial \gamma_2} = \overline{e\Delta}(1+\iota)\left[1 - s\left(1 + \frac{1}{\eta_{\tau,s}}\right)\right] - \frac{\overline{\pi}_L \rho_2}{1+\eta_{IA}} \tag{A26a}$$

$$\frac{\partial s}{\partial \gamma_2} \sim \frac{\partial M_W(s)}{\partial \gamma_2} = \frac{\eta_{\tau,s}}{s(1+\iota)}\left\{\overline{e\Delta}(1+\iota)\left[1 - s\left(1 + \frac{1}{\eta_{\tau,s}}\right)\right] - \frac{\overline{\pi}_L \rho_2}{1+\eta_{IA}}\right\} \tag{A26b}$$

From (A26a) and (A26b), if $\overline{e\Delta}(1+\iota)\left[1 - s\left(1 + \frac{1}{\eta_{\tau,s}}\right)\right] - \frac{\overline{\pi}_L \rho_2}{1+\eta_{IA}} > 0$ holds, the coverage level increases as population are more risk averse ($\frac{\partial b}{\partial \gamma_2} > 0$); the subsidy rate increases with risk averse coefficient ($\frac{\partial s}{\partial \gamma_2} > 0$ if $\eta_{\tau,s} > 0$).

(2) Information asymmetry effect η_{IA} is decided by the price elasticity of insurance demand $\eta_{I,\tau}$, and the behavioral responses $\eta_{R,b}$ and $\eta_{\sigma,b}$. We first derive $\frac{\partial M_W(b)}{\partial \eta_{IA}}$ and $\frac{\partial M_W(s)}{\partial \eta_{IA}}$, and then how the three elasticities affect information asymmetry effect:

$$\frac{\partial M_W(b)}{\partial \eta_{IA}} = -\left[1 - \gamma_2 \overline{e\Delta} + \left(s + \frac{s}{\eta_{\tau,s}}\right)(\gamma_2 \overline{e\Delta} + \varphi)\right](1+\iota) \tag{A27a}$$

$$\frac{\partial M_W(s)}{\partial \eta_{IA}} = -\frac{\eta_{\tau,s}}{s}\frac{1+\rho}{(1+\eta_{IA})^2(1+\iota)} \tag{A27b}$$

$$\frac{\partial \eta_{IA}}{\partial \eta_{I,\tau}} = -\frac{(1+\eta_{IA})\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]}{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}} < 0 \tag{A27c}$$

$$\frac{\partial \eta_{IA}}{\partial \eta_{R,b}} = \frac{1}{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}}\frac{\partial \eta_M}{\partial \eta_{R,b}} = \frac{(1+\rho_1)(b-1)}{b\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} < 0 \tag{A27d}$$

$$\frac{\partial \eta_{IA}}{\partial \eta_{\sigma,b}} = \frac{1}{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}}\frac{\partial \eta_M}{\partial \eta_{\sigma,b}} = \frac{\lambda_L c_v (1+\rho_1)}{b\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} > 0 \tag{A27e}$$

From equation (A27a)-(A27e) we can obtain the following:

(2.1) Price elasticity of insurance demand $\eta_{I,\tau}$

$$\frac{\partial b}{\partial \eta_{I,\tau}} \sim \frac{\partial M_W(b)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{I,\tau}} = \frac{(1+\iota)(1+\eta_{IA})\left[1-\gamma_2\overline{e\Delta}+\left(s+\frac{s}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)\right]\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]}{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}} \tag{A28a}$$

$$\frac{\partial s}{\partial \eta_{I,\tau}} \sim \frac{\partial M_W(s)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{I,\tau}} = \frac{\eta_{\tau,s}(1+\rho)\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]}{s(1+\iota)\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} > 0, if\ \eta_{\tau,s} > 0 \tag{A28b}$$

(2.2) Behavioral responses

$$\frac{\partial b}{\partial \eta_{R,b}} \sim \frac{\partial M_W(b)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{R,b}} = \frac{(1+\iota)(1+\rho_1)(1-b)\left[1-\gamma_2\overline{e\Delta}+\left(s+\frac{s}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)\right]}{b\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} \tag{A29a}$$

$$\frac{\partial b}{\partial \eta_{\sigma,b}} \sim \frac{\partial M_W(b)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{\sigma,b}} = -\frac{(1+\iota)(1+\rho_1)\lambda_L c_v\left[1-\gamma_2\overline{e\Delta}+\left(s+\frac{s}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)\right]}{b\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} \tag{A29b}$$

$$\frac{\partial s}{\partial \eta_{R,b}} \sim \frac{\partial M_W(s)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{R,b}} = \frac{\eta_{\tau,s}(1+\rho)(1+\rho_1)(1-b)}{sb(1+\iota)(1+\eta_{IA})^2\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} > 0, if\ \eta_{\tau,s} > 0 \tag{A29c}$$

$$\frac{\partial s}{\partial \eta_{\sigma,b}} \sim \frac{\partial M_W(s)}{\partial \eta_{IA}}\frac{\partial \eta_{IA}}{\partial \eta_{\sigma,b}} = -\frac{\eta_{\tau,s}\lambda_L c_v(1+\rho)(1+\rho_1)}{sb(1+\iota)(1+\eta_{IA})^2\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}} < 0, if\ \eta_{\tau,s} > 0 \tag{A29d}$$

There are a few terms requiring some explanation. First, $\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}$, in empirical studies, the insurance demand is usually inelastic, takes the range of (-1,0), and also the premium for the marginal insureds is lower than the average premium. Therefore, the condition $1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}>0$ generally holds. Second, $\eta_{\tau,s}$ is the responsiveness of actuarially fair condition to the subsidy rate, representing the extent of subsidy effect at the extensive margin. In the policy design, the subsidy rate is inversely linked to the coverage level, and the premium increases as coverage level increases. In practice, due to actuarial fairness, the subsidies encourage participation and possibly higher coverage levels, and due to actuarial fairness, the premium payments will change consequently. Based on O'Donoghue (2014), $\eta_{\tau,s}$ is positive. Third, in $\left[1-\gamma_2\overline{e\Delta}+s\left(1+\frac{1}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)\right]$, $1-\gamma_2\overline{e\Delta}=\frac{\bar{u}'}{\bar{u}'_L}>0$ and $\gamma_2\overline{e\Delta}+\varphi>0$. If $\eta_{\tau,s}>0$ or $\eta_{\tau,s}<-1$, then $\left[1-\gamma_2\overline{e\Delta}+s\left(1+\frac{1}{\eta_{\tau,s}}\right)(\gamma_2\overline{e\Delta}+\varphi)\right]>0$.

(3) The loading factor ι

The loading factor affect the insurance premium which affect the selection, and therefore it appears in the information asymmetry elasticity η_{IA}, we derive: $\frac{\partial\eta_{IA}}{\partial\iota}=\frac{\tau_b\eta_{I,\tau}(1+\eta_{IA})}{\tau\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}}$, and use (A28a) and (A28b) we obtain the following:

$$\frac{\partial b}{\partial\iota}\sim\frac{\partial M_W(b)}{\partial\iota}+\frac{\partial M_W(b)}{\partial\eta_{IA}}\frac{\partial\eta_{IA}}{\partial\iota}=-\left[(\gamma_2\overline{e\Delta}+\varphi)\left(s+\frac{s}{\eta_{\tau,s}}\right)+(1-\gamma_2\overline{e\Delta})\right]\left[(1+\eta_{IA})+(1+\iota)\frac{\partial\eta_{IA}}{\partial\iota}\right]=-\frac{(1+\eta_{IA})(1+\eta_{I,\tau})\left[(\gamma_2\overline{e\Delta}+\varphi)\left(s+\frac{s}{\eta_{\tau,s}}\right)+(1-\gamma_2\overline{e\Delta})\right]}{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}} \quad \text{(A30a)}$$

$$\frac{ds}{d\iota}\sim=\frac{\partial M_W(b)}{\partial\iota}+\frac{\partial M_W(s)}{\partial\eta_{IA}}\frac{\partial\eta_{IA}}{\partial\iota}=-\frac{\eta_{\tau,s}}{s}\frac{1+\rho}{(1+\iota)^2(1+\eta_{IA})}-\frac{\tau_b\eta_{\tau,s}\eta_{I,\tau}(1+\rho)}{s\tau(1+\iota)(1+\eta_{IA})\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}}=-\frac{\eta_{\tau,s}(1+\eta_{I,\tau})(1+\rho)}{s(1+\iota)^2(1+\eta_{IA})\left\{1+\left[1-\frac{(1+\iota)\tau_b}{\tau}\right]\eta_{I,\tau}\right\}}<0,\ if\ \eta_{\tau,s}>0 \quad \text{(A30b)}$$

If $\left[(\gamma_2\overline{e\Delta}+\varphi)\left(s+\frac{s}{\eta_{\tau,s}}\right)+(1-\gamma_2\overline{e\Delta})\right]>0$ then $\frac{\partial b}{\partial\iota}<0$.

(4) Deadweight loss of collecting funds for subsidies φ

$$\frac{\partial b}{\partial\varphi}\sim\frac{\partial M_W(b)}{\partial\varphi}=-(1+\iota)\left(s+\frac{s}{\eta_{\tau,s}}\right)=-\frac{s(1+\iota)(1+\eta_{\tau,s})}{\eta_{\tau,s}}<0,\text{if }\ \eta_{\tau,s}<-1\text{ or }\eta_{\tau,s}>0 \quad \text{(A31a)}$$

$$\frac{\partial s}{\partial\varphi}\sim\frac{\partial M_W(s)}{\partial\varphi}=-(1+\eta_{\tau,s})<0,\text{if }\eta_{\tau,s}>-1 \quad \text{(A31b)}$$

A3. Summary statistics and regression results

Table A1. Summary statistics of control variables

	2002	2007	2012
Coverage level (%)	70.04(4.17)	73.34(4.98)	76.31(3.79)
Farm size (acre)	650.01(584.35)	689.57(605.23)	678.85(654.16)
Cropland (acre)	597.38(552.52)	638.62(580.23)	640.49(638.77)
Percentage of operations incorporated under state law (%)	0.06(0.24)	0.08(0.27)	0.09(0.28)
Asset per acre ($/acre, including value of land and machines)	2777.01(2812)	3145.71(3215)	4170.29(4502)
Percentage of rented land (%)	0.52(0.39)	0.53(0.38)	0.51(0.38)
Percentage of female operators (%)	0.03(0.16)	0.03(0.16)	0.03(0.17)
Experience (years)	26.04(13.56)	28.84(13.74)	29.2(14.67)
Age of principal operator	53.27(13.03)	55.35(12.76)	56.82(13.06)
Household size	2.82(1.38)	2.69(1.31)	2.62(1.3)
Percentage of irrigated land (%)	0.04(0.15)	0.04(0.16)	0.03(0.15)
Percentage of livestock sales (%)	0.17(0.27)	0.14(0.25)	0.09(0.21)
Crop revenue ($/acre)	0.25(0.43)	0.33(0.47)	0.32(0.47)
Total expenditure ($/acre)	0.3(0.46)	0.95(0.21)	0.94(0.23)
Seed	622.33(1045.74)	458.38(582.75)	561.76(2738.28)
Fertilizer	6.72(12.72)	35.86(20.95)	69.19(44.05)
Chemicals	7.92(15.1)	52.5(33.54)	94.6(63.5)
Yield (bu/acre)	5.13(11.45)	24.14(19.8)	40.5(34.34)
Corn	43(7.98)	47.33(7.5)	42.74(8.81)
Soybeans	136.16(33.58)	159.71(22.14)	118.71(39.47)
Wheat	50.09(11.07)	51.93(9.72)	59.48(12.22)
Acreage share			
Corn	0.44(0.18)	0.49(0.18)	0.49(0.21)
Soybeans	0.45(0.18)	0.41(0.17)	0.42(0.2)
Wheat	0.02(0.07)	0.03(0.08)	0.02(0.07)

Standard deviations are in parenthesis.

Table A2. Estimation of impacts of insurance coverage on the revenue distribution

	(1) FE		(2) IV+FE		(3)CF+FE	
VARIABLES	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Coverage level	115.3***	1.006***	-279.2	-0.550	-282.3***	2.421***
	(0.279)	(0.224)	(185.8)	(2.310)	(1.196)	(0.546)
Control function					526.6***	-1.869***
					(1.479)	(0.655)
Farm size	-5.15***	-0.00998	-5.06***	-0.0132	-5.087***	-0.0111
	(0.0435)	(0.0092)	(0.768)	(0.0092)	(0.0161)	(0.0091)
Tenure	-9.11***	0.105***	-9.20***	0.090***	-8.921***	0.100***
	(0.0711)	(0.0265)	(2.188)	(0.0268)	(0.0552)	(0.0262)
Corporation	8.46***	0.0377	8.90***	0.0353	7.814***	0.0442
	(0.0269)	(0.0400)	(3.366)	(0.0405)	(0.0440)	(0.0386)
Farm yield	415.0***	0.073***	409.1***	0.089***	414.6***	0.081***
	(0.0541)	(0.0270)	(2.606)	(0.0277)	(0.0515)	(0.0273)
Female	-1.78***	-0.0567	-0.0817	-0.0372	-1.109***	-0.0653
	(0.215)	(0.0522)	(4.373)	(0.0501)	(0.276)	(0.0537)
Age	29.30***	-0.101	35.08	-0.0473	26.80***	-0.130
	(0.590)	(0.327)	(29.66)	(0.326)	(0.739)	(0.329)
Age square	-10.4***	0.0680	-13.99	0.0478	-9.478***	0.0972
	(0.273)	(0.166)	(14.82)	(0.165)	(0.401)	(0.167)
Experience	1.015***	-0.00293	0.10***	-0.00274	1.031***	-0.00187
	(0.0037)	(0.0023)	(0.191)	(0.0022)	(0.0032)	(0.0023)
Experience square	-0.02***	5.05e-05	-0.02***	5.07e-05	-0.017***	3.20e-05
	(5.46e-05)	(3.7e-05)	(0.003)	(3.7e-05)	(5.6e-05)	(3.7e-05)
Lagged corn price	-80.16***	-0.157*	-106.6***	-0.263*	-101.3***	-0.00211
	(0.0776)	(0.0895)	(11.97)	(0.159)	(0.150)	(0.0934)
Lagged soybean price	89.42***	0.0609	98.47***	0.109	97.92***	-0.00315
	(0.0902)	(0.0538)	(5.334)	(0.0740)	(0.112)	(0.0558)
Lagged wheat price	6.335***	-0.0234	2.579	-0.0652**	2.197***	-0.0157
	(0.0443)	(0.0177)	(2.461)	(0.0300)	(0.0445)	(0.0186)
CRP participation	-4.902***	-0.00421	-4.395***	0.00184	-4.592***	-0.0129
	(0.0255)	(0.0170)	(1.299)	(0.0168)	(0.0365)	(0.0169)
Direct payment and CCC payment	-2.317***	-0.00213	-1.803	-0.00179	-1.614***	-0.0148
	(0.0168)	(0.0157)	(1.280)	(0.0162)	(0.0418)	(0.0158)
Share of irrigated acreage	12.22***	0.0901	9.362	0.0789	5.904***	0.113
	(0.145)	(0.0879)	(9.395)	(0.0896)	(0.414)	(0.0867)
Share of livestock sales	-210.2***	0.273***	-209.9***	0.251***	-209.4***	0.266***
	(0.0613)	(0.0359)	(3.742)	(0.0369)	(0.0794)	(0.0358)

Share of corn acreage	382.4***	0.0349	387.5***	0.0833	387.4***	0.0334
	(0.115)	(0.0561)	(5.957)	(0.0612)	(0.107)	(0.0567)
Share of soybean acreage	253.3***	-0.142**	252.2***	-0.128**	253.1***	-0.115**
	(0.134)	(0.0557)	(5.503)	(0.0570)	(0.0942)	(0.0560)
Share of wheat acreage	178.2***	-0.263***	161.9***	-0.374**	160.3***	-0.247**
	(0.266)	(0.100)	(12.01)	(0.146)	(0.307)	(0.108)
County-level yield	57.01***	0.0877	66.79***	0.0514	65.34***	0.0120
	(0.113)	(0.0584)	(6.089)	(0.0744)	(0.113)	(0.0594)
Constant	-928.3***	7.117***			-672.7***	5.894***
	(11.73)	(0.672)			(1.936)	(0.805)
Observations	180,550	180,550	180,346	180,346	180,346	180,346
R-squared	1.000	0.003	0.589	0.002	1.000	0.003
Number of poid	74,463	74,463	74,385	74,385	74,385	74,385

*** p<0.01, ** p<0.05, * p<0.1, Robust standard errors in parentheses, and they are robust to heteroscedasticity and clustering on farms.