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Expectations, Index Qualities and Basis Risks in Explaining Famers' Pessimism in Purchasing Weather Index Insurance

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Abstract:

This paper attempts to explain why famers exhibit pessimism in purchasing Weather Index Insurance (WII). Three sources of the pessimism are identified: a) if insurers overestimate or farmers underestimate the possibility of future risks, the farmers tend to buy less WII coverage; b) the lower the quality of the index is, the less coverage the famers will purchase; c) the more their productive characteristics deviate from population mean, the higher basis risk they will have, resulting less coverage to be chosen. The second half of this paper empirically compares three kinds of weather indices in measuring long-run yield variation in China's 26 provinces during 1951 – 2002, and justifies the theoretical findings from releasing the Quality Assumption by simulating hypothesized operations of WII in the last half century in China. The econometric and simulation results corroborate the critical role of the index quality in measuring yield variation and explain the pessimism.

Keywords:
Weather index insurance; Expectation; Index quality; Basis risk; Pessimism; China

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1. Introduction

The increasingly extreme weather events have imposed great threats on agricultural production and farmers' welfare (Field et al., 2012). Especially for poor farmers, they are the most vulnerable group of people facing weather disasters and can be easily trapped in poverty, due to the lack of coping strategies and missing credit market (Carter et al., 2007). To mitigate the impact of weather variation on farmers' welfare, agricultural insurance has been considered as an important adaptation to hedge against the meteorological risks (Hazell et al., 1986). However, crucial constraints in promoting conventional agricultural insurance have been argued, including moral hazard, adverse selection, and the massive cost of monitoring and measuring farmers' agricultural outcomes (Chamber, 1989; Just et al, 1999; Skees and Barnett 2006).

Recent research focuses on a new innovation -- the Weather Index Insurance (WII) (Barnett and Mahul, 2007; Wouter, 2008; Gine et al. 2008). The WII is constructed against specific perils (e.g., drought and flood) by setting certain thresholds in exploited weather indices to identify the occurrence of damages to production and trigger indemnifications. One critical principle in WII is that the index shall precisely capture the relationship between weather conditions and production levels; otherwise, it becomes more like a lottery, in which the payment is independent with agricultural performance (Clarke et. al., 2012; Carter et. al., 2014).

WII has several advantages intrinsically, but it also faces challenges in practices. WII performs well in terms of avoiding adverse selection problems, moral hazard issues and lowering administrative cost (Stoppa and Hess, 2003; Vedenov and Barnett, 2004; Skees and Collier, 2008). However, two empirical puzzles emerge recently (Clarke; 2011). First, demand for WII has been lower than expected, for example, the take-up rate ranges from 4% in 2004 in India (Gine et al., 2007) to 27% in the same region in 2006 (Cole et al., 2013). Second, "demand seems to be particularly low from the most risk averse" (Gine et al., 2008)

Many reasons can explain why farmers feel pessimistic in purchasing WII. First of all, wrong expectations for future weather conditions in either side of contracts may reduce the take-up rate. On the one hand, if insurers overestimate the future risk, they increase premium rates, which dampen farmers' passion to participate the WII. Hill et al. (2013) find that farmers' willingness to pay is decreasing when price of the contract is increasing, using data from Ethiopia. On the other side, if farmers underestimate the future risk, they also lose incentive to purchase insurance.

However, given their expectations are correct, due to the existence of basis risk, famers may still exhibit the pessimism. Note that, usually only two states in the conventional insurance could happen, i.e. a good state (no disaster) without indemnifications and a bad state (disaster) with indemnifications.[1] However in WII, additional two theoretically undesirable states may exist, i.e. a good state with indemnifications and a bad state without indemnifications. Clarke (2011) only defines the existence of the last state as the basis risk. While when considering utility loss, this paper adopts a more general definition of the basis risk, i.e. both of the two undesirable states are defined as the basis risk, since they all contradict with a risk-averse farmer's purpose of income smoothing, resulting his/her distrust and pessimism in purchasing WII. Elabed et al (2013) clearly classifies risks under WII as Figure 1.[2]

Two factors can cause the happening of the two extra states. One is the quality of indices used in WII. Low quality indices perform badly in predicting production reductions, resulting mismatch of the farmers' losses and indemnification triggers. Cai et al. (2009) and Gine and Yang (2009) study the determinants of participation of WII and conclude that the higher the correlation between the index and the yield, the higher the take-up rate. Since a perfect index does not actually exist in real world,

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[1] Assuming insurers strictly execute the conventional insurance contract, i.e. indemnifying farmers when they suffer losses. Otherwise, basis risks also exist in conventional insurance.

[2] If only considering yield reductions as disaster losses, Clarke's definition can be applied to Figure 1. If considering utility losses as disaster losses, my general definition can be applied to Figure 1.

the basis risk of WII, called design risk, always exists due to the mismatch.

The other factor originates from farmers' heterogeneous abilities in resisting weather disasters, which amplify the individual basis risk in Figure 1. Empirical research has found that education and wealth play important roles in affecting farmers' participation decision (Gaurav et al, 2011; Hill et al., 2013). Moreover, to answer the second empirical puzzle that "demand seems to be particularly low from the most risk averse", Karman and Morduch (2009) suggest that the most vulnerable farmers, usually the most risk averse, feel hard to trust the product itself; Binswanger-Mkhize (2012) points out that the poor farmers' credit constraint should be another cause of the empirical puzzle. One significant contribution of this paper is that, in third theoretical part, it provides an alternative explanation for the second puzzle, that the most vulnerable farmer has a different possibility distribution of the four outcome states under WII, and the distribution favors passive reactions to WII.

Although some empirical studies, as list above, have been made to explain where the pessimism comes from, limited attentions have been located to the index quality. Furthermore, most of them focus on single reason, such as farmers' personal characteristic, and luck of theoretical supports. Clarke (2011) provides rich theoretical analysis on rational demand for index insurance, but his analysis centre on the purchaser's utility function form, ignoring the three points that I discussed above, which are farmers' and insurers' expectations, index qualities and farmers' heterogeneous abilities. This paper consistently uses natural logarithm as utility function form and jointly analyzes how these factors affect farmers' decisions.

The purpose of this paper is to identify the source of farmers' pessimistic behavior in purchasing WII. Specifically, I examine why farmers do not choose full insurance when premium rate is set at actuarially fair level by insurers. Three key assumptions imposed in an Ideal Situation will be released one by one to see how famers adjust the coverage. They are: 1) *Expectation Assumption*: both insurers' prediction and farmers' expectation on the possibility of the happening of an extreme weather event in next year are correct. 2) *Quality Assumption*: the index can perfectly measure average agricultural productions. 3) *Homogeneity Assumption*: farmers are assumed to be homogenous in every aspect, i.e. no idiosyncratic risk, and the basis risk just comes from the index quality.

The following sections are organized as: Section2 introduces the Ideal Situation, where all of three key assumptions hold, to prove that farmers will choose full insurance. Then, releasing the Expectation Assumption to see how incorrect predictions/expectations will cause the coverage changes. In Section3, I further release the Quality Assumption. The model evolves from two-outcome states to four-outcome states. Section4 breaks the Homogeneity Assumption by assuming, given the same possibility of a disaster happening for farmers, low skill (or poor endowment) farmers have higher possibilities to suffer losses than high skill (or rich endowment) farmers. Secion5 empirically tests the goodness of various indices in measuring agricultural productions. Section6 provides simulation results to show how index qualities affect farmer utilities gained from WII. Final section concludes.

2. The Role of Correct Expectations

2.1 Benefits of WII under Ideal Situation

First, pessimism can be defined in many ways, such as low willingness to pay, low demand, low participation rate, etc. In theoretical part of this paper, I define the pessimism as the fact that the chosen insurance coverage is less than the full insurance level.[3] In the empirical part, where I compare different indices, the pessimism is defined as the utility loss due to choosing alternative indices.

Assume all of the three key assumptions hold, called it as Ideal Situation. To demonstrate the benefit of WII, using Uncertainty Theory (Mas-Colell et al. 1995), I assume the probability of an extreme weather event happening is π, and the corresponding agricultural production/income of a representative farmer without

[3] In real world practices, if the chosen coverage is too small, farmers will not participate in the WII, since transaction costs always exist.

buying WII is ω_1, call this *bad* state. Then, the probability of a *good* state is $(1-\pi)$, and the farmer harvest ω_2, where $\omega_2 - \omega_1$ is the amount of the loss if it is positive.

The insurer offers the WII contract with selectable coverage α. If over insurance is allowed, then α can be larger than $\omega_2 - \omega_1$, otherwise, $\alpha \in [0, \omega_2 - \omega_1]$. Full insurance means $\alpha = \omega_2 - \omega_1$. The contract offers a fixed premium rate q for each unit of α, i.e., the total premium is $q\alpha$. For simplicity, through the whole paper, I assume that the insurer always sets the q at the actuarially fair level, i.e. q equals to the insurer's predicted possibility of the weather event in next year, $q \equiv \pi$.

Note that, as long as all the farmers are homogenous (Homogeneity Assumption holds) in every aspect, the Quality Assumption implies that the loss and indemnification can be perfectly matched up by the index, so only two states can appear. I use (x_1, x_2) to denote the final payoff set of the two states, and simply standardize the product price to 1. If the farmer does not buy any WII, his/her payoff is $(x_1, x_2) = (\omega_1, \omega_2)$; otherwise, the payoff in each state should be:

$x_1 = \omega_1 + \alpha - q\alpha$, a disaster happens, and the index reaches the threshold;

$x_2 = \omega_2 - q\alpha$, no disaster happens, and the index does not reach the threshold;

Finally, I assume a representative farmer is strictly risk averse, with Von Neumann–Morgenstern twice differentiable utility function $U(x)$, which satisfies $U'(x) > 0,\ U''(x) < 0$.[4] The farmer's Utility Maximization Problem with 2 possible states (UMP2) is:

$$\underset{\alpha}{Max}\, U(x_1, x_2) = \pi U(x_1) + (1-\pi) U(x_2) \tag{1}$$

$$\text{Subject to: } x_1 \leq \omega_1 + \alpha - q\alpha$$

$$x_2 \leq \omega_2 - q\alpha$$

Rearranging the constraints, and drop the α:

[4] In next section, I will explicitly assume $U(x) = Ln(x)$

$$\frac{q}{1-q}x_1 + x_2 \leq \frac{q}{1-q}\omega_1 + \omega_2 \qquad (2)$$

The $\frac{q}{1-q}$ can be thought as the value of x_1 in bad state, in term of x_2 in good state. Treat $\frac{q}{1-q}$ as the price of x_1, so the price of x_2 equal to 1, equation (2) becomes the traditional budget constraint (BC), and can be interpreted as how many goods at good state the farmer want to sacrifice to increase the consumption at the bad state. Also know that as premium rate (q) increases, the price of consumptions in bad state increases. The interior solution to (1) must be located on the BC.

Under differentiability assumption, the FOC of (1) for an interior maximum is:

$$\frac{\pi U'(x_1)}{[1-\pi]U'(x_2)} = \frac{q}{1-q} \qquad (3)$$

Substitute with $q = \pi$, we find that $U'(x_1) = U'(x_2)$. Since the utility function is concave, the solution must satisfies that $x_1 = x_2$, which implies the $\alpha = \omega_2 - \omega_1$, i.e. *a strictly risk averse decision maker facing actuarially fair insurance must choose to be fully insured.* Solve out the UMP2: $\tilde{x}_1 = \tilde{x}_2 = q\omega_1 + (1-q)\omega_2$, where $\tilde{x}_1$ and $\tilde{x}_2$ are optimal solutions in this Ideal Situation. Denote $U(\tilde{x}_1, \tilde{x}_2) = U^M$, and $U(\omega_1, \omega_2) = U^O$. U^M is maximized utility level, and U^O is the original utility level.

The "iso-expected-outcome" (IEO) lines of the farmer can be defined by this equation:

$$\pi x_1 + (1-\pi)x_2 = constant \qquad (4)$$

Given different constant values, they are a group of parallel lines, with slope $\frac{dx_2}{dx_1} = -\frac{\pi}{1-\pi}$ in Figure 2. Note that, given any point at an IEO line, the corresponding utility level obviously cannot be higher than the point at the intersection with 45 degree line, because the farmers is assumed to be risk averse. The 45 degree line is also called "Certainty Line". Under the Ideal Situation, Figure 1 shows that the WII can provide a feasible transaction from original state *A* to the utility maximized state *B*. Note that $\omega_2 - \tilde{x}_2$ is the premium αq, and $\omega_1 - \tilde{x}_1$ is the chosen coverage minus premium $\alpha - \alpha q$.

2.2 Insurers Incorrectly Predict the Possibility

To distinguish the Expectation Assumption and the Quality Assumption in predicting future risk, two important roles of the index used in WII are worth to be revealed and emphasized. On the one hand, the index is used to identify the triggers of the indemnification, using happened weather data in the end of a production circle. The Quality Assumption means that there is not mismatch between triggers and yield reductions, i.e. perfect identification. On the other hand, the insurer uses the index to predict the possibility of future disasters for pricing the contract (premium rate q). For the second role, the insurer has to use forecasted weather data to calculate the possibility.[5] Note that, if the quality of the index is perfect, the prediction may still be wrong, because of using unreliable forecasted weather data. If the quality of the index is poor, there is no way to believe the prediction will be correct, even using a reliable forecasted future weather data.[6]

Now loosen the Expectation Assumption for insurer side. Assume the insurer incorrectly predicts the possibility of future risks, because of using forecasted weather data. Denote $\hat{\pi} = \pi + \varepsilon$ as the insurer's predicted probability of the extreme weather event, where π is the true probability, and ε is the prediction error, which can be systematically positive, negative, or randomly disturbed. So by actuarially fair assumption, $\hat{q} \equiv \hat{\pi} = \pi + \varepsilon$.

Farmers are still assumed to have correct expectations on future risks. As Figure 3 shows, compared with the Ideal Situation (Figure 2), the IEO line of a farmer does not change at all, because the true disaster possibility (π) does not change and the Quality Assumption still holds, i.e. the possibility of triggering the indemnification is still π, even the insurer's prediction is $\hat{\pi}$. However, due to the change of $\hat{q}$, the

[5] If insurers use historical weather data to decide the future contract prices, they are implicitly treating current weather data as forecasted future weather data.

[6] In other word, if the Quality Assumption holds, the Expectation Assumption for insurer side may holds; reversely, if the Expectation Assumption for the insurer side holds, the Quality Assumption must hold.

farmer's budget constraint changes.

Assume the insurer overestimates the risk before production circle begins, i.e. $\varepsilon > 0$, $\hat{q} > \pi$, then the BC line will be steeper than the IEO line, which will lead the farmer to choose point C to maximize his/her expected utility, *so the pessimism happens due to the insurer's overestimation on the future risk*. The utility level declines from U^M to U^1.

On the contrary, assume the insurer neglects the potential weather risk (underestimate), i.e. $\varepsilon < 0$, $\hat{q} < \pi$, then the BC line would be flatter, i.e. segment AD in Figure 2. If the policy allows over-insurance (coverage > loss), the farmer will choose D. If over-insurance is banned, he/she will choose E. Although it seems that farmers reach a higher utility level, such famer-favoring situation may not lasts very long, because no insurer will run the business in negative net profit situation for long-run, except that the WII is subsidized for encouraging farmers to participate the project. Therefore, the result from Figure 3 shows how the subsidy (lowering the premium rate) works in WII. Since the point D and E both offer higher utility than point B, the subsidy spurs potential purchasers to increase the coverage.

2.3 Farmers' Wrong Expectations on Future Weather Risks

This subsection assumes the Expectation Assumption does not hold for farmer side, i.e. farmers have wrong expectations on the possibility of future risks, while insurers are now assumed to be able to correctly predict the possibility. Usually farmers in developing country do not use any index to predict the future weather conditions, but they do have personal expectations based on their own agricultural experiences. The accuracy of such expectation depends on many things, such as years of growing crops, education level, local weather information accessibility or weather channels in TV. Denote $\bar{\pi} = \pi + \mu$ as a farmer's expectation about the disaster possibility for next year, where μ is the estimation error. Note that $q = \pi$ in this case, since the insurer is assumed to correctly predict the possibility.

Figure 4 shows that the farmer who inclines to overestimate the weather risk ($\mu > 0$) will intend to be over insured. He/she attempts to maximize his/her own expected utility with wrong probability $\bar{\pi}$, which results in his/her imagined IEO line ($\widehat{IEO}$) being steeper than the real one, but remember that the real IEO can only be affected by the true π. Correspondingly, his/her imagined utility curves rotate clockwise around the 45 degree line. Suppose the purchased coverage can be larger than loss (over-insurance), then he/she will choose point C in Figure 4, reaching imagined utility level U^2. However, the contingent payoff is based on real π， which will give him/her a utility level of U^R, which is substantially lower than the utility level U^M.

The other direction is that the farmer underestimates the risk ($\mu < 0$). He/she uses $\bar{\pi} < \pi$, resulting his/her imagined IEO line ($\widehat{IEO}$) becomes flatter than the real one (Figure 5), and the imagined indifference curves rotate counterclockwise around 45 degree line. He/she will choose point C in Figure 5, reaching imagined utility level U^2. But eventually he/she obtains the utility U^R, which is lower than U^M. *In this case, the pessimism happens again due to famers' underestimating the future risks.*

One significant policy implication in practicing WII can be draw from the analysis in this scenario, which is the over-insurance should be ban. In Figure 4, banning the over-insurance will decrease the incentive for farmers to participate the WII, since $U^1 < U^2$, but the ban actually brings higher utility level for farmers. In Figure 5, the ban does not have same practically effect on farmers' behavior, since the over-insurance is not the optimal choice for them. One extreme example is that, in some WII pilots, people purchase coverage even they do not grow crops, then, the WII because a lottery for them, which is not the purpose of operating WII.

3. The Index Quality

In real world practices, the index used in WII certainly cannot fully capture the relationship between weather variation and yield variation, since agricultural outputs can be affected by many factors rather than precipitation and temperature. So it is undoubted that the perfect quality index does not exist in real world, even all farmers are identical.

In this section, I release the Quality Assumption, while still keep the Homogeneity Assumption holds. To be simple, the Expectation Assumption will be partially released. Specifically, because of the imperfect quality of the index, the insurer wrongly predicts the disaster possibility, however, for simplicity and focusing on the quality issue, the farmers are assumed to have right expectations.

Denote D as the event that a disaster happens, L as the event that a farmer suffers a loss due to the disaster, and T as the event that the indemnification is triggered. Since the Homogeneity Assumption holds, in this section, I assume $P(D) = P(L) = \pi$ without losing generality. To model the quality degree of the index, assume $P(T|D) = \rho$, and $P(\bar{T}|\bar{D}) = \gamma$, where $\bar{T}$ and $\bar{D}$ are opposite events of T and D, and both ρ & γ $\in [0,1]$. The intuition is that, if a disaster has happened in the past contract year (D is true), the imperfect quality index can only has possibility ρ to trigger the indemnification, while when there was not disaster ($\bar{D}$ is true), there is still possibility $1 - \gamma$ to trigger the indemnification due to the imperfect quality of the index.

The parameter ρ and γ essentially capture the performance of the index in representing the weather conditions. If $\rho = \gamma = 1$, the index is perfect, and there exist only two states (*good* and *bad* states) as defined in the Section 2 (under Homogeneity Assumption). If $\rho = \gamma = 0$, the index is terribly bad. It oppositely reflects what happened in the past contract circle, since only two theoretically undesirable states appear: no disaster actually happened, but insured farmers receive indemnification, call this state as *over-good*; or a disaster happened, while insured farmers do not receive indemnification, call this state as *over-bad*. If both ρ & γ do not take their polar values, four states coexist with all positive possibilities.[7] Table 1 shows the payoff distribution of WII in real world practices. Denote the payoff under over-good state as $x_2{}'$, and payoff under over-bad state as $x_1{}'$.

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[7] Any of ρ or γ takes the polar value will eliminate one of corresponding states.

This paper only analyzes the actuarially fair WII contracts, i.e. insurers set the premium rate q equal to their predicted possibilities, even the predictions are wrong, and trigger the indemnification according to the imperfect indices. Therefore, $q \equiv P(T) = P(Bad) + P(Over - good)$. Using Possibility Theory, the $P(Bad)$ can be calculated: $P(Bad) = P(LT) = P(T|L)P(L) = \rho\pi$. The possibility distribution for the rest of three states can be processed in the same way (see Appendix I). Table 2 shows the possibility distribution for WII when farmers are assumed to be homogenous.

Know that, I decompose the performance of the index into two parts, using two parameters $\rho \,\&\, \gamma$ to measure the performance under disaster and no disaster situations. However such decomposition seems give us unclear information about the general performance of the index. Two questions could be asked: does the index systematically tend to overestimate or underestimate the disaster possibility? If there is not systematical bias, whether the index carries estimation error with zero expected mean? Based on Table 2, answers to these questions can be achieved. Note that, $P(T) = P(TL) + P(T\bar{L}) = \rho\pi + (1 - \gamma)(1 - \pi)$. Compare $P(T)$ with π, the following conditions describe the general quality of the index.

$$\begin{cases} \dfrac{1-\gamma}{1-\rho} > \dfrac{\pi}{1-\pi} & \text{The index systematically overestimates the disaster possibility} \\ \dfrac{1-\gamma}{1-\rho} = \dfrac{\pi}{1-\pi} & \text{The index has zero expected estimation error term} \\ \dfrac{1-\gamma}{1-\rho} < \dfrac{\pi}{1-\pi} & \text{The index systematically underestimates the disaster possibility} \end{cases}$$

Figure 6 illustrates the relationships between ρ, γ and index quality, assuming $\pi = 0.3$. Perfect index point appears at the point $\rho = \gamma = 1$. If $\rho \,\&\, \gamma$ satisfy $\rho = \frac{7}{3}\gamma - \frac{4}{3}$, then the expectation of calculated disaster possibility, using the index, equal to real possibility, $E[P(T)] = \pi \equiv 0.3$, but the measurement error exists. Otherwise, the index biases.

The inaccurate estimation of the index for a happened disaster gives positive values to the possibilities of the two theoretically undesirable states, and results the famers decrease the coverage for globally increase their expected utilities. To see how this happens, set up the new farmer Utility Maximization Problem with 4 possible states (UMP4) :

$$\underset{\alpha}{Max}\ \begin{aligned} U(x_1, x_2', x_1', x_2) = P(Bad)U(x_1) + \ P(Over-good)U(x_2') \\ +P(Over-bad)U(x_1') + \ P(Good)U(x_2) \end{aligned} \tag{5}$$

$$\text{Subject to: } x_1 \leq \omega_1 + \alpha - q\alpha$$

$$x_2' \leq \omega_2 + \alpha - q\alpha$$

$$x_1' \leq \omega_1 - q\alpha$$

$$x_2 \leq \omega_2 - q\alpha$$

Where the payoffs are shown in Table 1 and possibilities are shown in Table 2. The FOC of (5) for an interior maximum is:

$$\frac{P(Bad)U'(x_1) + \ P(Over-good)U(x_2')}{P(Over-bad)U'(x_1') + \ P(Good)U'(x_2)} = \frac{q}{1-q} \tag{6}$$

The two states in the numerator (*Bad* and *Over-good*) both refer to the states that the insurer indemnifies the farmer whatever there was a disaster or not; the states in the denominator ($Over - bad$ and $Good$) stand for the situations that no indemnifications are triggered whatever the disaster happened or not. Therefore the right-hand-side of (6) is the marginal substitution rate (MRS) of consuming one goods between the states where the insurer pays the indemnification and the states where the insurer does not pay the indemnification. The equation (6) essentially expresses the same idea as equation (3): the farmer chooses a coverage that guarantees the marginal substitution rate (MRS) equal to the “price ratio” ($\frac{q}{1-q}/1$) between two kinds of states of the insurer’s behaviors (“price” at the states where insurers do not pay is 1, as I discussed for equation (2)).

However, the equation (6) cannot be solved mathematically. To see how the quality of index affects the farmer’ choice, I use numerical method to find the optimal solutions of the coverage α^*, letting ρ and γ vary. Define $U(x) = Ln(x)$. The simulated parameter set is: $\omega_1 = 300$, $\omega_2 = 800$, $\pi = 0.3$, so the full insurance coverage is $\omega_2 - \omega_1 = 500$.[8] Remember that the actuarially fair premium rate (q) is set to be equal with $P(T)$. Figure 7 shows the numerical simulation results.

One important finding of this paper is shown in the Panel A in Figure 7: farmers decrease the coverage as long as the quality of the index decrease, *i.e. low quality index explains the farmers' pessimistic behavior*. Note that, in Panel A, the highest value of α^* (full insurance) appeals when ρ & γ both equal to 1 (perfect index). Then, whatever ρ or γ goes down, the optimal α^* decreases.

When both ρ and γ fall below 0.5, the possibilities of the *Over-good* state and the *Over-bad* state dominate the possibilities of the *Good* state and the *Bad* state, respectively (see Table 2). Therefore, a risk-averse farmer will not purchase any WII for avoiding exacerbating the differences between two polarized states and the middle states, since the polarized states already obtain too much weights in possibilities. That explains why the α^* in the left-down corner are all zero-value.[9]

Panel B in Figure 6 shows the farmer's utility changes when the index quality is getting worse. The result is very similar with the coverage change: the maximized utility is a decreasing function of ρ or γ. When the farmer does not purchase any coverage, the changes of the quality parameters do not affect the utility anymore.

4. Farmers' Basis Risks

Knowing the wrong expectations and the low index quality can explain farmers' pessimistic behavior is still not enough. The conceptual framework in this paper provides us an approach to investigate how farmers' basis risks affect their index insurance choices. This section also provides an alternative explanation to the second

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[8] Roughly speaking, Chinese farmers' rice/corn/wheat yield is about 800-1000 Jin/mu (2 Jin = 1 Kg, 15 mu=1 hectare).

[9] Actually, as long as $\rho + \gamma \le 1$, $\alpha^* = 0$.

empirical puzzle that most vulnerable farmers tend to passively response to WII contract.

Before moving on, it is worth to clear the relationships between the second and the third key assumptions with the risk classification in the Figure 1. First, if the Quality Assumption holds, there is not “Design Risk” in Figure 1. Furthermore, if all the farmers are homogenous, there is not “idiosyncratic Risk”. Hence, if both the second and third key assumptions hold, all farmers share the same risk, which is the “Correlated Risk” in Figure 1, and it is also equal to the “Insured Risk”. For investigating the farmers’ basis risk, I release all of the three key assumptions, except partially keeping the Expectation Assumption, as the last section did, i.e. farmers’ expectations on disaster possibility in next year are correct. Now, farmers’ basis risks are jointly determined by index qualities and their own disaster-resisting abilities.

For being simple but without losing generality, I assume there are three types of farmers: high skill or rich endowment farmers, called *Strong Farmer*; low still or poor endowment farmers, called *Weak Farmer*; and normal skill or modest endowment farmers are called *Normal Farmer*. Also assume learning effect for realizing their abilities exists, i.e. after years of agricultural activities, farmers know their own types. First, I introduce the baseline possibility assumption for the Normal Farmer: $\begin{cases} P(L^N|D) = 1 \\ P(L^N|\bar{D}) = 0 \end{cases}$, where L^N stands for the event that the Normal Farmer suffers a loss. It is obvious that the Normal Farmer’s possibility distribution is exactly identical to the representative farmer in the Section 3 (Table2). The following analysis will focus on the Strong Farmer and the Weak Farmer.

As I release the Homogeneity Assumption, farmers have different possibilities of suffering losses given the same exogenous possibility of a weather disaster happening. Assuming Strong Farmer: $\begin{cases} P(L^S|D) = S \\ P(L^S|\bar{D}) = 0 \end{cases}$, $S \in [0,1]$.

Where L^S stands for the event that the Strong Farmer suffers a loss. Therefore:

$P(L^S) = S\pi$; $P(\overline{L^S}) = 1 - S\pi$. This setting means, even a disaster happens, the Strong Farmer does not necessarily suffer a loss. After conditioning on a disaster happens, the possibility of the Strong Farmer suffering a loss is S, $0 \leq S \leq 1$. The less the S is, the stronger the Strong Farmer will be.

Assuming Weak Farmer: $\begin{cases} P(L^W|D) = 1 \\ P(L^W|\overline{D}) = W \end{cases}$, $W \in [0,1]$.

Where L^W stands for the event that the Weak Farmer suffers a loss. Therefore: $P(L^W) = \pi + W(1 - \pi)$; $P(\overline{L^S}) = (1 - W)(1 - \pi)$. This setting means even there is not disaster, the Weak Farmer still may suffer a loss due to misoperations. The possibility of suffering a loss condition on no disaster happens is W, $0 \leq W \leq 1$. The bigger the W is, the weaker the Weak Farmer will be.

The Strong Farmers always can adopt better methods to fight disasters, such as having money/loan to install bumps for underground water, or their plots may locate closer to rivers than others, so they have better resisting ability for fighting a drought. The logic for the Weak Farmer is similar, but in a reverse direction. Since the Weak Farmers is vulnerable to any shock, when disaster happens, they certainly suffer losses, but when there is not disaster, they may also have production declines due to their constrained budgets, low operation skills (mistakes), so W can be bigger than 0.

For calculating their possibility distribution of the four states under WII, one critical assumption has to be imposed here, which is ***Conditional Independent Assumption****:* assume that, given the disaster has happened, the possibility of a farmer suffers a loss is independent with the possibility of the index triggers the indemnification. In mathematical expression: $(L^M, L^S, L^W) \perp T|D$. This assumption is understandable, since it is the main logic that explains how WII avoids the moral hazard and the adverse selection problems.

Given the conditional possibility setting, their possibility distribution of the four states in WII can be calculated. As I still assume the index quality is not perfect, the final possibilities are affected by many factors $(\rho, \gamma, \pi, S, W)$. For tractability but without losing generality, I assume $\rho = \gamma$ for the rest analysis. Table 3 shows the possibility distributions. See the Appendix II for the detailed process of calculations.

The intuition from Table 3 is quite simple. Compare with Table 2, which turns out to be the possibility distribution of the Normal Farmer, the Strong Farmers definitely are getting better off, since they get more possibility weights in the *Over-good* and *Good* states, while the Weak Farmers are absolutely getting worse off after introducing the heterogeneous setting. However the payoff distributions for the all three types of farmers remain unchanged (Table 1).

The structure of the Strong Farmer's Utility Maximization Problem is some as the Weak Farmer, just substituting the possibility distributions in Table 3 to the equation (5). Nevertheless, there is no close form solution, so I apply the numerical method again. The parameter set and the utility function form are same as in the Section 4. Figure 8 shows the optimal solutions of the Strong Farmers and corresponding utility change, allowing the index quality (ρ) and Strong Farmers' individual basis risk parameter (S) change simultaneously in Figure 8.

The results from Figure 8 are also simple and consistent with our expectation. According to the Panel A in Figure 8, as the index quality decreases, the Strong Farmer tends to choose less coverage, and *as his/her individual basis risk decreases* $(S \rightarrow 0)$*, he/she also presents more pessimistic on purchasing WII.* Panel B shows that as his/her operation ability or available resource increases, i.e. S decreases, he/she reaches higher utility level.

The Weak Farmer's results are presented in Figure 9. Remember that, since I set $P(L^W|\overline{D}) = W$, the bigger the W is, the weaker the Weak Farmer will be. First, I focus on a more intuitive result in the Panel B of the Figure 9, that as the farmer becomes more and more vulnerable, i.e. individual basis risk parameter W increases, his/her utility level decreases.

Second, the result from Panel A in Figure 9 is worth to be discussed in more details. What the result tells us is that *as the Weak Farmer becomes weaker, he/she shows more pessimistic on purchasing WII, which explains why most vulnerable farmers have particularly low demand for WII (the second empirical puzzle)*. First to check the extreme case, when $W = 1$, $P(Over - good) = P(Good) = 0$, i.e. the farmer has no way to conduct a successful agricultural operation, he/she “unfortunately” only has two possible payoff states, which are *Over-bad* and *Bad*. Given these two outcomes, the farmer definitely has no incentive to purchases any coverage, since payoff in *Bad* states $(x_1 = \omega_1 + \alpha - q\alpha)$ is already larger than payoff in *Over-bad* states $(x_1{}' = \omega_1 - q\alpha)$. Purchasing more coverage will decreases the payoff $x_1{}'$ in the worst state, and increase payoff x_1 in the relatively better state. Such transaction is not a risk-averse farmer’s reasonable choice.

Second, a common sense that “a vulnerable person should buy more insurance to prevent being stroked by bad things” is not right in WII, since the possibility of getting indemnification from insurers has nothing to do with farmer’s individual basis risks (given the natural disaster is exogenous). Note that, according to Table 3, $P(T) = \rho\pi + (1-\rho)(1-\pi)$ for both Strong Farmers and Weak Farmers, and the formula does not include the individual basis risk parameters S and W.[10] Furthermore, the statement doesn’t consider the cost of purchasing insurance. Not only because the strict budget constraint or credit constraint, but because the fact that purchasing more coverage will further misbalance the possibility weighted payoffs from different states, resulting expected utility decreasing.

[10] It is not saying that the trigger is independent with the loss, since the *P(T)* and $P(L^S)$($P(L^W)$) still share the parameter ρ and π. Trigger and loss are connected by weather conditions.

Combining the results from Figure 8 and Figure 9, one interesting result can be found: *the more the farmer' ability or endowment deviates from population mean (e.g. the Normal Farmer), the less coverage he/she will purchase.* The economic explanation for this finding is that the individual deviation changes the possibility distribution among four possible WII payoff states, resulting optimal coverage changes.

5. Empirically Compare Index Qualities in Measuring Yield Variations

As I showed in theoretical part, the quality of the underlying weather index in WII plays a critical role in determining farmers' purchasing behavior. In the following two empirical sections, I first provide evidence that several weather indices can be used to measure yield variations, using historical weather data. Then, I simulate the impact WII would have had on farmers' utilities in China over the past half century. Using these simulations, I attempt to explain why farmers exhibit pessimism to WII. The simulations verify the finding from the Section 2 and 3.

5.1. Three Indices

There are many factors to consider when choosing an index and assessing index quality. Basic questions are that which index works better or what the threshold of triggers should be chosen? Is using one single parameter in the index enough or should more weather variables should be exploited? This paper examines three different types of weather indices: Precipitation Percentiles Index (PPI) (Klein Tank and Konnen, 2003), Precipitation Anomalies Index (PAI) (Barring and Hulme, 1991) and Ped Drought Index (PDI) (Ped, 1975; Mason and Goddard 2001).

The PPI is the simplest among them. It is a binary dummy variable in which critical values set at certain percentiles of long historical weather data, for example 5%, if the precipitation in a certain year is lower than this value, then PPI is set to 1, otherwise the PPI is set to 0.

PAI is another commonly used weather index to measure rainfall. It also only requires precipitation data. The formula is:

$$PAI = \frac{D_p}{M_p} = \frac{P - M_p}{M_p}$$

where D_p is precipitation deviation, M_p is the average precipitation in a long period in history, and P is precipitation in one year.

PDI is first constructed by Ped in 1975, and has been used by many researchers and turns out to be a relatively simple and useful drought index (Shame 1997; Breustedt et al. 2008). It requires two weather indicators, precipitation and temperature. It is formulated as:

$$PDI = \frac{D_T}{SD_T} - \frac{D_p}{SD_p}$$

where D_T is the temperature deviation, SD_T is the standard variation of temperature and SD_p is the standard variation of precipitation in long historical data.

5.2. Data

The weather data come from the Chinese National Meteorological Bureau stations, and are reported monthly from 1951 to 2002. The agricultural data come from the Chinese National Statistics Bureau, covering 26 provinces yearly from 1949-2012. In order to match the weather data, only 1951-2002 production data are used.

Since the agricultural data is collected at province level year by year, the weather data is also processed at the same dimensions (i.e. yearly at province level), and thus the sample size is 1352. See Appendix III for summary statistics of the data.

5.3. Model

Using the weather data, I construct the three indices. Appendix IV shows the Kernel density distribution of precipitation (used for constructing PPI), PAI and PDI. Since too little or too much rainfall for crop could be both bad shocks, the relationship between the indices and the agricultural production may not be linear.[11] When using

[11] Directly using PAI and PDI to run regression does not give us many significant results.

PPI to fit the variation of agricultural production, one question is how to set the thresholds. This paper explores several trials. Denote PPIs5 as setting the threshold in single side -- 5th percentile. Denote PPId10 as setting the threshold in double sides – 5th and 95th percentiles, i.e. if precipitation is less then 5th or more then 95th, PPId10=1; otherwise is 0. Denote PPId20 as setting the threshold in double sides – 10th and 90th percentiles.

For PAI and PDI, the more deviation from the mean of the indices, the higher the weather risk will be imposed to agricultural production. I first consider using the squared PAI and PDI to run econometric models (denoted as SqPAI and SqPDI). Second, because both of the two indices have zero means (distributions are almost symmetric), I also use absolute values of PAI and PDI to estimate the effect of weather condition on agricultural production (denoted as AsPAI and AsPDI).

The regression model is:

$$Y_{it} = \alpha + \beta \cdot Index_{it} + \gamma \cdot year_t + \delta \cdot province_i + \varepsilon_{it}$$
$$i = 1, \dots, 26; \quad t = 1951, \dots, 2002$$

Y_{it} is the annual grain yield per unit (Kg/mu) in province i , year t. Logarithm form of yields will also be tried.

$Index_{it}$ is a weather index, it could be one of PPIs5, PPId10, PPd20, SqPAI, SqPDI, AsPAI, and AsPDI.

$year_t$ is the time control. Three forms of time variables are applied. First, directly using actual year number (1951-2002) in the regression, i.e. it is assuming that there is linear technical progress effect (the corresponding model results are marked as "Linear"). Second, using 51 yearly dummies (results are marked as "Dummy"); Third, four dummies that respectively represent four periods: 1951-1979, 1980-1989, 1990-1999, 2000-2002 (marked as "Period")[12]. A figure in Appendix V shows the production increase trends over the last half century in China across all 26 provinces.

[12] Since China started the Economic Reform and Open Policy in 1978-1979, agricultural productivity sharply increased after the reform.

$province_i$ is regional dummies, used to control other unobserved potential effects on yields, like terrain (plain area or high altitude area), water resources, soil types, etc.

For concerns about bias of the estimations of the index coefficients, one thing we should know that, although the agricultural yield depends on lots of factors, such as inputs and farmer characteristics, the β in my regressions can still be consistently estimated, since the $Index_{it}$, using weather data, is independent with the error term ε_{it}. Know that, the weather condition is highly exogenous to any other unobservable factors that can affect the agricultural yield. Only time and space may have some correlations with the weather, but I have controlled years and provinces in the model.[13]

5.4. Regression Result

The OLS regression results show weather indices can be significantly correlated with the production variations, but the strengths of the correlations depend on the design (quality) of the indices and the thresholds chosen. Table 4 shows that even the simplest weather index may have significant correlations with agricultural outcomes, but it still requires careful inspection of the thresholds. The interpretation of the estimated coefficients of PPId10 is that, given other conditions unchanged, if the precipitation in a certain year is less than 5^{th} percentile or higher than 95^{th} percentile of historical precipitation records, then the average production at province level in this year will decrease by approximately 68 to 105 Kg per Hectare, or about 2%-4% of total yield. The PPId10 performs better than PPIs5 and PPId20, since the estimated coefficients on PPId10 are statistically significant for regression (2) – (5), while most of the estimation on PPIs5 and PPId20 fail to past t-test.

Both of PAI and PDI are good indices in capturing the relationship between weather

[13] The estimated coefficients should be interpreted as overall "effect" of the indices on production. Inputs may interact with weather conditions, but the interactions are single direction, i.e. inputs cannot affect weather, but weather may affect the productivities of the inputs.

conditions and agricultural yields (Table 5). Most of the estimated coefficients of squared and absolute PAI or PDI are significantly different from zero. The interpretations are follows: take regression (10) – (12) with absolute PAI and PDI as examples, if the AsPAI increases by 1 unit, the agricultural production will decrease by 10.6% - 20.2% (Note that, Mean of PAI is 0, with Standard Deviation 0.17; Mean of AsPAI is 0.13, with Standard Deviation 0.11); for PDI, if the absolute value of PDI increases by 1 unit, the agricultural production will decrease by 1.4% - 2.1% (Note that, Mean of PDI is 0, with Standard Variance 1.46; Mean of AsPDI is 1.16, with Standard Deviation 0.88).

6. Empirical Evidences of Pessimism from Using Low Quality Indices

This section provides empirical evidences to confirm the findings from the Section 2 and Section 3. If an index performs well in identifying the loss of the yield, using this index in WII should be able to smooth the outcome variation. As Section 2 theoretically promised, given insurance premium is set at actuarial fair level, WII can increase the expected risk-averse utility by smoothing the outcome variation. For Section 3, if more than one kind of indices exists, the higher quality index can bring more utility gain for farmers than lower quality index (Panel B in Figure 7), which provides evidences for explaining farmers' pessimism in facing low quality index WII.[14]

I treat each province data as the representative farmer's yield data in past 1951-2002 from the province. The top blue fine in Figure 10 shows the national average yield trend (original outcome, not simulated by WII). The logic of six simulations are that assuming there were WII programs in China during the 52 years, subtracting a fixed amount of yields as premium from every observation, then compensating the "bad" years with insurance indemnifications, where the "bad" years are identified by the index triggering the specified thresholds.

[14] Due to lack of household production and WII coverage data, I cannot justify the findings from Section 4. But by using weather data to construct weather indices, parts of findings about index qualities can be justified.

There are two critical steps in running simulations. One is how to specify the coverage that farmers purchase, the other one is how to specify the threshold for indices to trigger the indemnification. For first step, I impose a full-insurance restriction in my simulations, which mean the coverage is set to be equal to the loss. Since China has experienced a great advance of productive in the data period, yield reductions caused by weather disasters were compromised by the production increasing trend. Moreover, since the agricultural data is at province level, the variation is much smaller than individual household level data. Both of the two reasons lead to difficulties in calibrating the *loss* of disasters.[15]

To conquer the difficulty, I use a double detrend method to find the conservative measurement of losses. Recall that Y_{it} is the yield of province i in year t. First I detrend the time trend using national average yields: define $Y_{it}^{DeTime} = Y_{it} - \sum_{i=1}^{26} Y_{it}$, so Y_{it}^{DeTime} is province idiosyncratic production variation (technical progress effect is sweep out). However, the negative values of Y_{it}^{DeTime} cannot be directly considered as losses, since some provinces are systematically less productive than other provinces. So define $Y_{it}^{Double} = Y_{it}^{DeTime} - \sum_{t=1}^{52} Y_{it}^{DeTime}$, where Y_{it}^{Double} is the double detrend yield variation, which further excludes the provincial fixed effect. The negative values of Y_{it}^{Double} can be considered as conservative losses result from negative weather shocks, since it is the negative yield variation compared with its historical level, precluding the national technical progress effect. The reason to call it "conservative" measurement of losses is because for sweeping out the technical progress effect, the first step of the detrend (obtaining Y_{it}^{DeTime}) also eliminates the national weather covariation shock, so the loss is underestimated. The sample mean (n=1352) of negative $Y_{it}^{Double} = -333$, since it's the conservative measurement, I define the *loss* as mY_{it}^{Double}, m is a multiplier, $m \geq 1$. In my reported simulation results (Figure 10 and Table 6), I use $m = 3$, which mean the Coverage $\equiv$ | Loss |

[15] In real world, the coverage is a variable as I discussed throughout Section2-4. In simulations, for simplicity, I directly compare the utility change for using different indices, assuming the coverage is fixed for all provinces.

$\equiv$ 1000. I also try other values of m, from 1 to 10, the findings do not change as long as $m \leq 6$, i.e. Coverage = Loss $\leq$ 2000; if coverage is set to be too large, the findings may change, because by indemnifying observations with a too large coverage, it is actually introducing more outcome variations.

The second step is to identify the triggered years. I continue using PPId10 and PPId20 from Section 5 as two indices in first two simulations, e.g. PPId10=1 means if the precipitation in a certain year and province is less than 5% percentile or higher than 95% percentile, than province in this year obtain indemnification, which is 1000 unit. For PAI and PDI, I directly specify the thresholds in their original values to identify the trigger years, instead of the squared or the absolute values. For 3rd and 4th simulations, I use PAId10 and PAId20 (notations "d10" and "d20" follow the rule of PPId10 and PPId20); for 5th and 6th simulations, I use PDId10 and PDId20.

Figure 10 shows the simulation results of assuming there are six kinds of WII that run in China in the last half century. Because the magnitude of the production change is largely dominated by technical progress, the effect of WII is not obvious. So I present the quantitative results of the simulations in Table 6.

Because the premium is set at actuarial fair level, the expected outcomes (yields) shall be same whatever purchasing WII or not (see Column 2 in Table 6). As I have shown in Section 5, all of three indices can be used to capture the variation of yields, so they supposedly can be used in WII to smooth the production variation, i.e. standard deviations should be smaller (see Column 3 in Table, all of simulated results have smaller SD than the original yield). The last column in Table 6 calculates the utility gain from participating in the WII, using $Ln(.)$ as utility function form, and normalizes the utility of original yield as zero and multiplies 10^5.[16]

First finding from Table6 is that it verifies the conclusion from Subsection 2.1 that

[16] Signs and orders of the utility gains are much more meaningful than their magnitudes.

the WII can increase risk-averse farmers' utility level, since all the values in Column 4 are non-negative. The second important finding from the simulation is that it confirms the results from Section 3. Focusing on the 1st and 2nd simulations, utility gain from PPId10 is higher than utility gain from PPId20. Recall that, in Table 4, when using PPId10 and PPId20 to measure the production variation, the former performs better than the later, since the significant levels of the former are much bigger than the later. Therefore, the result of Section 3 is justified, that higher index quality will do better in motivating farmers to participate in WII, since higher quality brings more utility gain than the relatively poorer quality index.

Results from PAI and PDI are not exactly comparable with PPI, since the regressions in Section5 do not use dummy variable forms of PAI or PDI. But, general conclusion can be deduced, that better indices generally perform better in increasing insured representative farmers' utilities, especially for the last simulation (PDId20), but how to specify the threshold points for triggers remains an open question, which is worth to be investigated furthermore.

7. Conclusion

This paper theoretically identifies three factors that can discourage farmers to purchase WII. In details, first, the insurers' overestimation and farmers' underestimation will result farmers to choose less insurance coverage; second, the lower the index quality is, the less coverage the farmers will purchase; last, despite of index quality, the more the farmers' individual basis risks deviate from population mean, the less coverage the they will choose. The possibility distribution of the four possible payoff states plays a very important role in farmers' decisions, which explains why most vulnerable farmers shows little incentive to participate in WII.

Empirical sections verify parts of theoretical findings. First, three kinds of indices are econometrically tested to be capable of capturing the relationship between weather conditions and yield variations, using grain yield data and weather station data from 26 provinces in China during 1951- 2002. Second, by simulating WII to be applied in the data period, the paper shows that the WII can smooth the outcome series, and the higher the index quality is, the better performance for the index to connect the loss and the indemnification, so the higher utility level can be achieved, which explains why low index quality can be a reason for farmers' pessimism.

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Table 1. The Payoff Distribution of Weather Index Insurance

		Farmer Side	
		Loss (L)	No Loss ($\bar{L}$)
Insurer Side	Trigger (T)	*Bad:* $x_1 = \omega_1 + \alpha - q\alpha$	*Over-good:* $x_2{}' = \omega_2 + \alpha - q\alpha$
	No Trigger ($\bar{T}$)	*Over-bad:* $x_1{}' = \omega_1 - q\alpha$	*Good:* $x_2 = \omega_2 - q\alpha$

Table 2. The Possibility Distribution of WII When Farmers are Homogenous

		Farmer Side	
		Loss (L)	No Loss ($\bar{L}$)
Insurer Side	Trigger (T)	$P(Bad) = \rho\pi$	$P(Over-good) = (1-\gamma)(1-\pi)$
	No Trigger ($\bar{T}$)	$P(Over-bad) = (1-\rho)\pi$	$P(Good) = \gamma(1-\pi)$

Table 3. Possibility Distributions for Strong and Weak Farmers with Imperfect Index

Panel A:		Strong Farmer	
		Loss (L^S)	No Loss ($\overline{L^S}$)
Insurer Side	Trigger (T)	$P(Bad) = \rho S\pi$	$P(Over-good) = \rho(1-S)\pi + (1-\rho)(1-\pi)$
	No Trigger ($\bar{T}$)	$P(Over-bad) = (1-\rho)S\pi$	$P(Good) = (1-\rho)(1-S)\pi + \rho(1-\pi)$

Panel B:		Weak Farmer	
		Loss (L^W)	No Loss ($\overline{L^W}$)
Insurer Side	Trigger (T)	$P(Bad) = \rho\pi + (1-\rho)(1-\pi)W$	$P(Over-good) = (1-W)(1-\rho)(1-\pi)$
	No Trigger ($\bar{T}$)	$P(Over-bad) = (1-\rho)\pi + \rho(1-\pi)W$	$P(Good) = (1-W)(1-\pi)\rho$

Table 4 Regression Results of Precipitation Percentage Index (PPI) in Measuring Production Variation

Models	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Y	Y	Y	LnY	LnY	LnY
PPIs5	-99.54*	-59.84	3.663	-0.00564	0.0111	0.0378
	(51.69)	(47.87)	(63.56)	(0.0163)	(0.0168)	(0.0256)
Adj-R2	0.874	0.903	0.839	0.894	0.921	0.815
PPId10	-57.75	-67.98*	-105.3**	-0.0279*	-0.0234*	-0.0441**
	(39.02)	(37.34)	(47.51)	(0.0150)	(0.0140)	(0.0211)
Adj-R2	0.874	0.903	0.839	0.895	0.921	0.815
PPId20	-19.98	-31.91	-28.45	-0.0143	-0.0107	-0.0138
	(32.24)	(29.42)	(37.90)	(0.0115)	(0.0104)	(0.0158)
Adj-R2	0.874	0.902	0.839	0.895	0.921	0.815
Type of Year Variable	Linear	Dummy	Period	Linear	Dummy	Period

Note:1)Robust standard errors in parentheses; 2)*** p<0.01, ** p<0.05, * p<0.1
3)Coefficients of constant term, year, and province variables are not reported; 4)Simple Size 1352

Table 5 Regression Results of Using PAI and PDI in Measuring Production Variation

Models	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	Y	Y	Y	LnY	LnY	LnY
SqPAI	-409.2***	-556.5***	-817.7***	-0.269***	-0.296***	-0.425***
	(152.8)	(162.6)	(205.1)	(0.077)	(0.077)	(0.114)
Adj-R2	0.875	0.903	0.840	0.895	0.922	0.817
AsPAI	-75.93	-199.1	-349.6**	-0.106**	-0.125**	-0.202***
	(133.1)	(131.4)	(163.2)	(0.053)	(0.050)	(0.072)
Adj-R2	0.874	0.903	0.839	0.895	0.922	0.816
SqPDI	-4.031	-13.91***	-15.36***	-0.004**	-0.005***	-0.008***
	(5.249)	(5.341)	(5.731)	(0.002)	(0.002)	(0.002)
Adj-R2	0.874	0.903	0.840	0.895	0.922	0.816
AsPDI	-16.63	-47.25***	-45.57**	-0.014**	-0.017***	-0.021***
	(16.74)	(16.30)	(18.69)	(0.006)	(0.006)	(0.008)
Adj-R2	0.874	0.903	0.840	0.895	0.922	0.816
Type of Year Variable	Linear	Dummy	Period	Linear	Dummy	Period

Note:1)Robust standard errors in parentheses; 2)*** p<0.01, ** p<0.05, * p<0.1
3)Coefficients of constant term, year, and province variables are not reported; 4)Simple Size 1352

Table 6. Simulation Results of Outcome Smoothing

WII Simulation	Obs[1)]	Mean[2)]	Std. Dev.[3)]	Utility Gain[4)]
Original Yield (No WII)	52	2736.33	1148.62	0
Simulations:				
Simulated with PPId10[5)]	52	2736.33	1137.50	244
Simulated with PPId20	52	2736.33	1142.56	196
Simulated with PAId10	52	2736.33	1141.88	213
Simulated with PAId20	52	2736.33	1141.42	227
Simulated with PDId10	52	2736.33	1141.91	184
Simulated with PDId20	52	2736.33	1125.32	409

Notes: 1) Calculated for nationally annual yields, averaging province data.

2) Premium is set at actuarial fair level, i.e. premium=coverage * possibility of triggering the indemnification.

3) SD here is less than the "SD" in Appendix III, since there are only 52 yearly observations.

4) Utility function is Ln(.), and normalized by the first row in this table.

5) "d10" stands for setting the thresholds of triggering at "<5% or >95%", i.e. the 10% possibility of getting indemnification if 0.1; "d20" stands for setting the thresholds of triggering at "<10% or >90%"

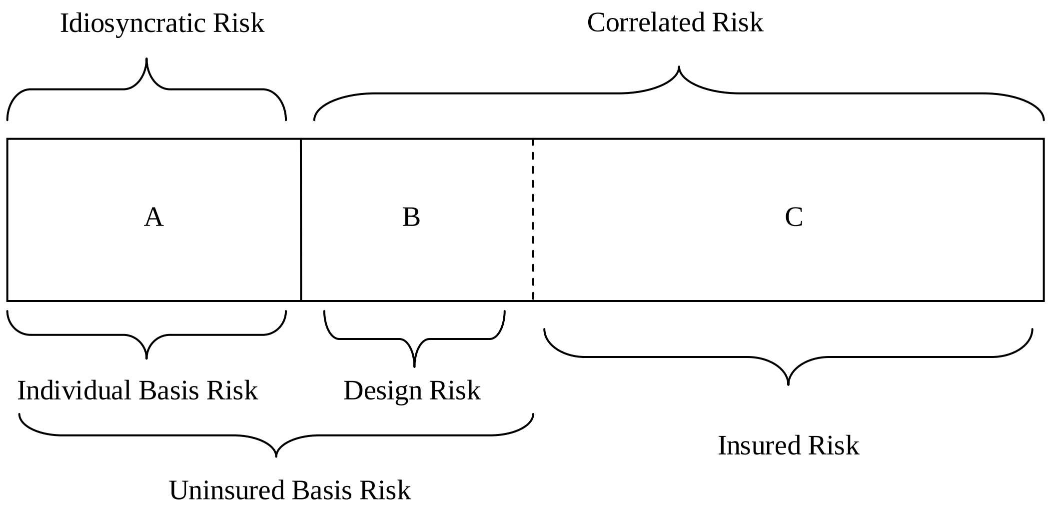


Figure 1. Classification of Risk under WII

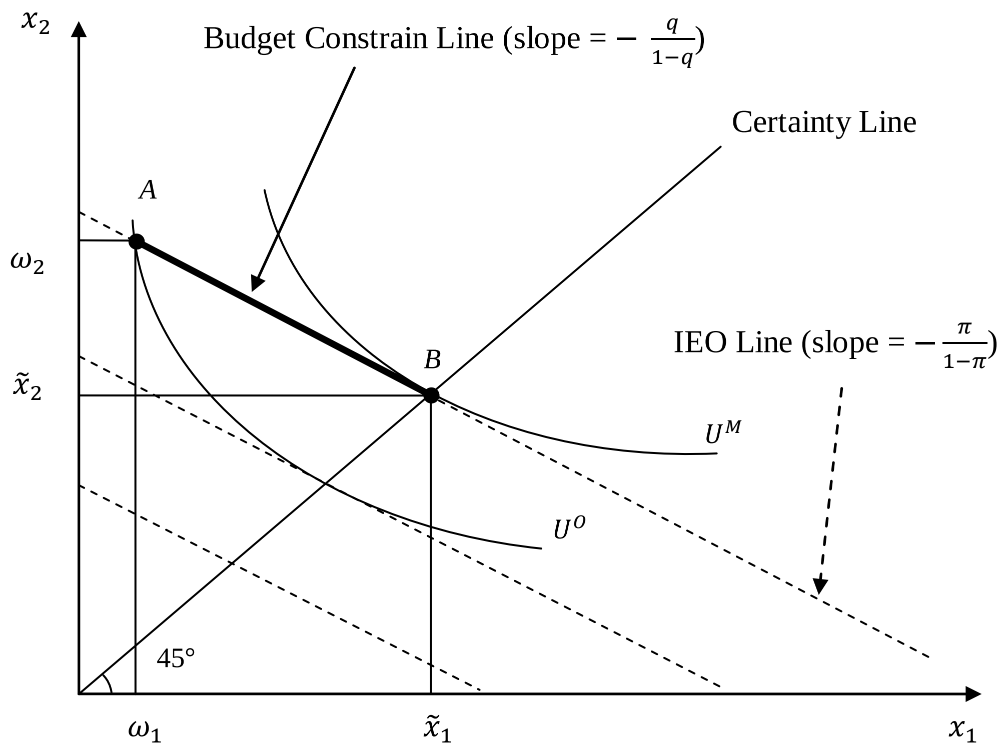


Figure 2. Utility Improvement of WII under the Ideal Situation

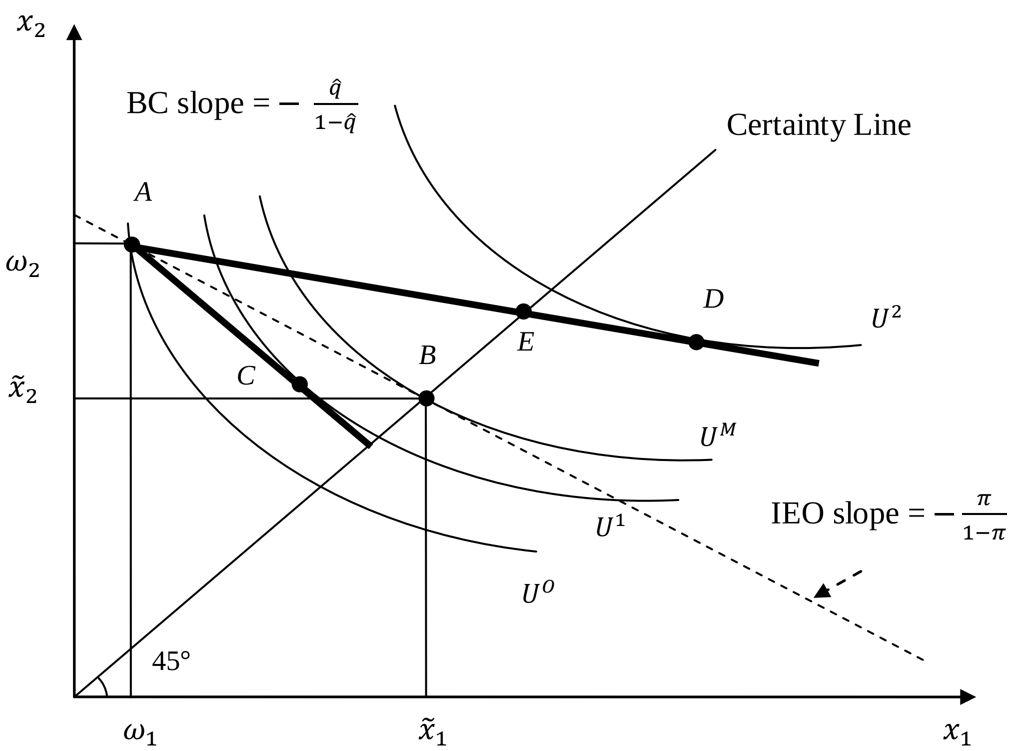


Figure 3. Insurers Incorrectly Predict the Disaster Possibility

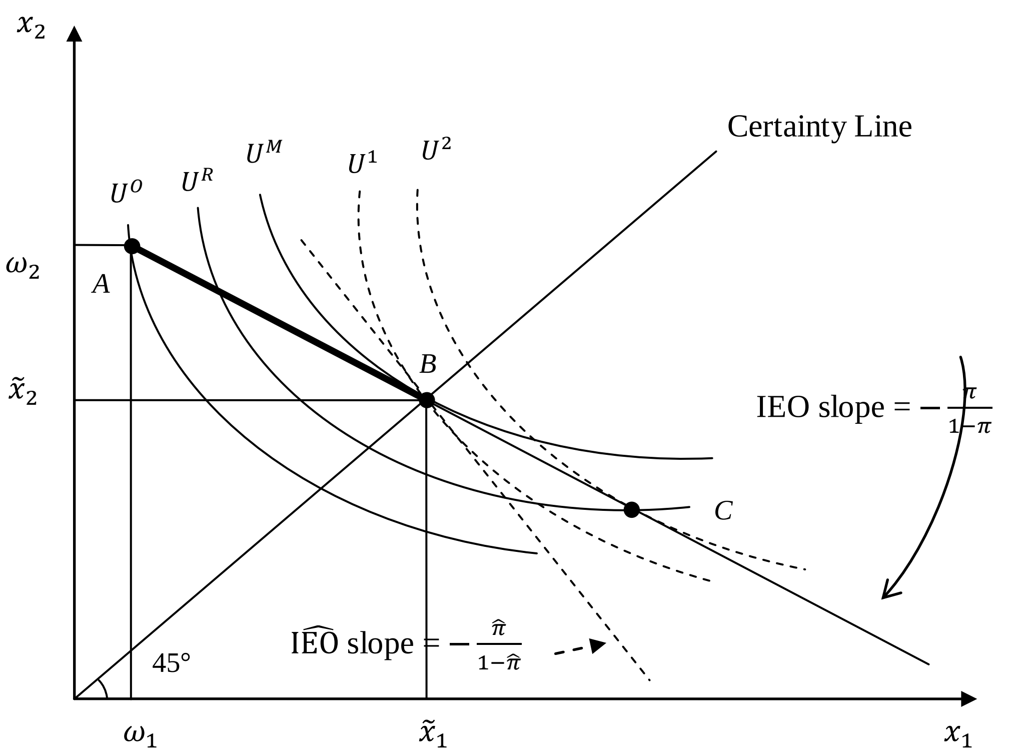


Figure 4. Overestimating Future Risks by Farmers

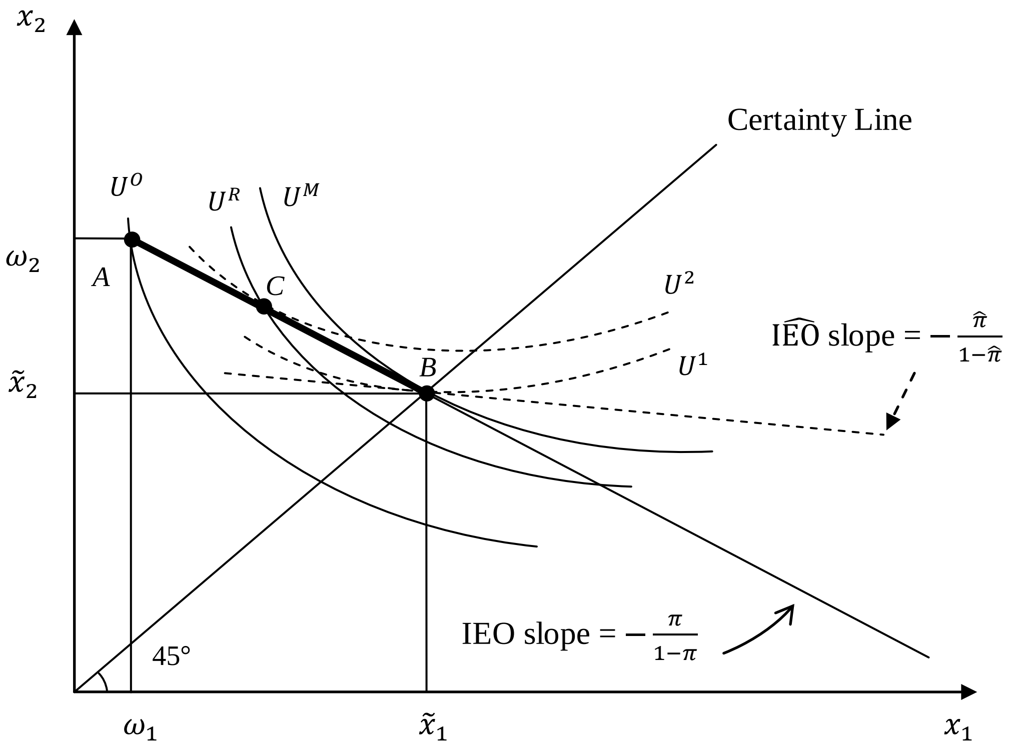


Figure 5. Underestimating Future Risks by Farmers

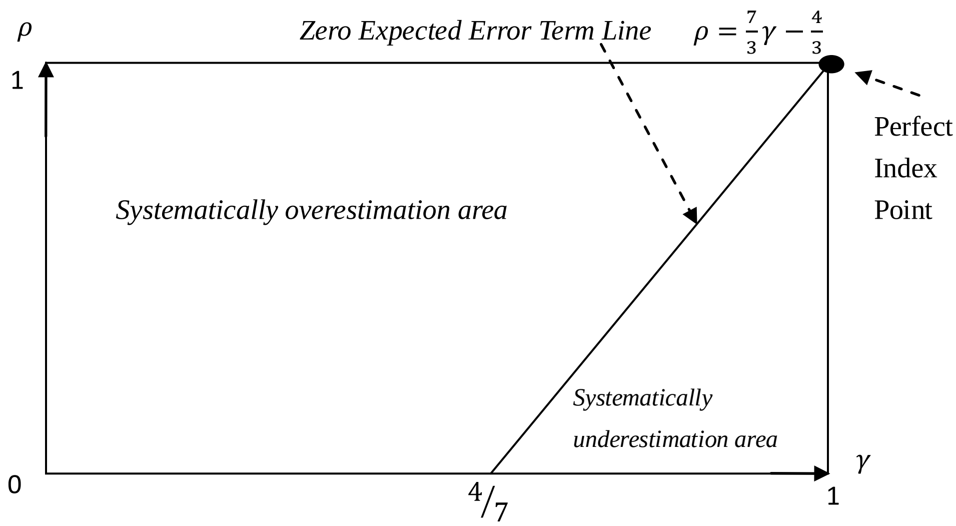
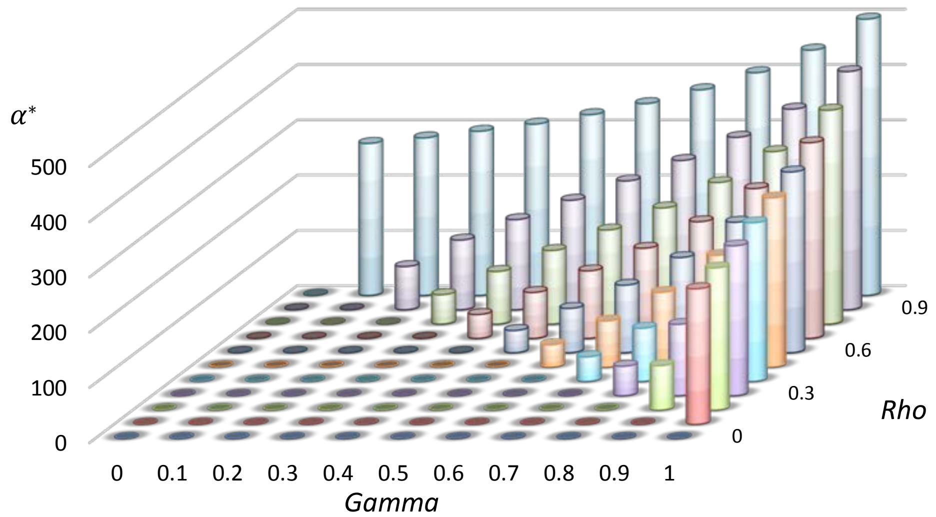
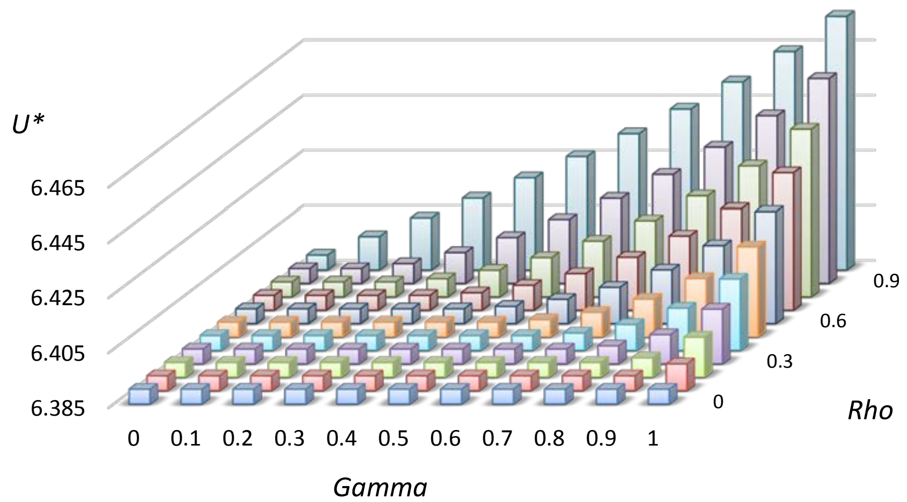


Figure 6. General Quality of the Index (Given $\pi = 0.3$)

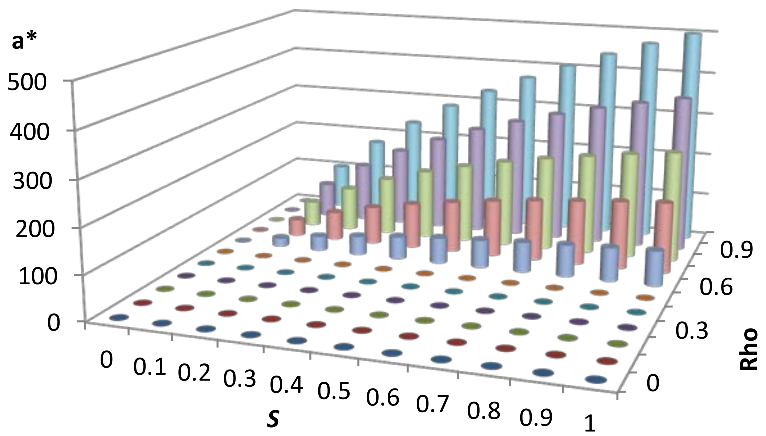


Panel A: Optimal Solutions of the Coverage

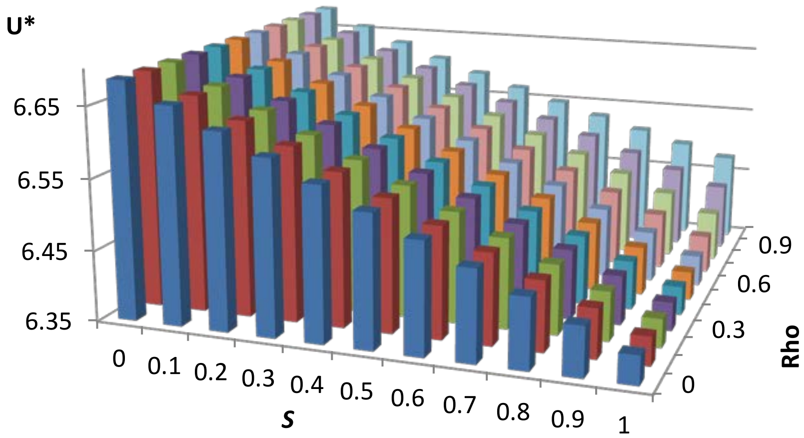


Panel B: Maiximized Utility Levels

Figure 7. Farmers' Pessimistic Choice When Indices are Imperfect

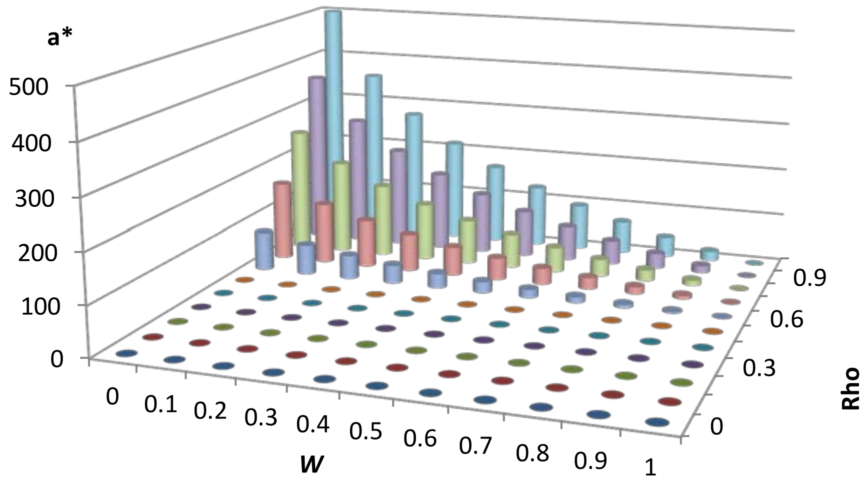


Panel A: Optimal Solutions of the Coverage

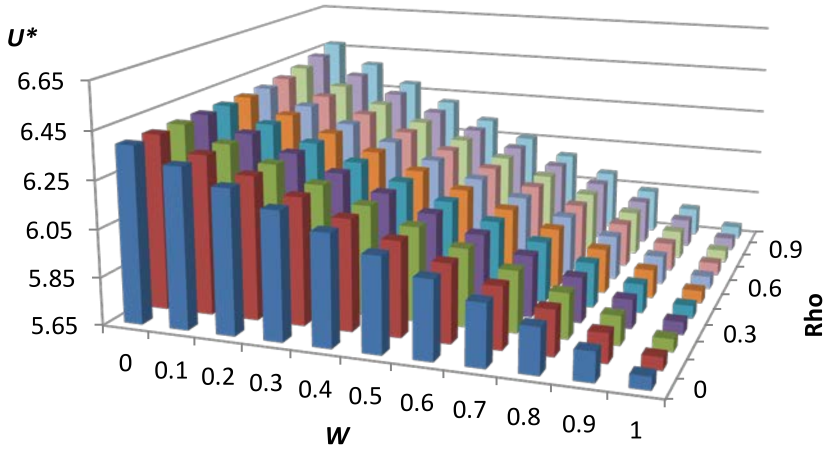


Panel B: Maiximized Utility Levels

Figure 8. Strong Farmers' Pessimistic Choice When Indices are Imperfect

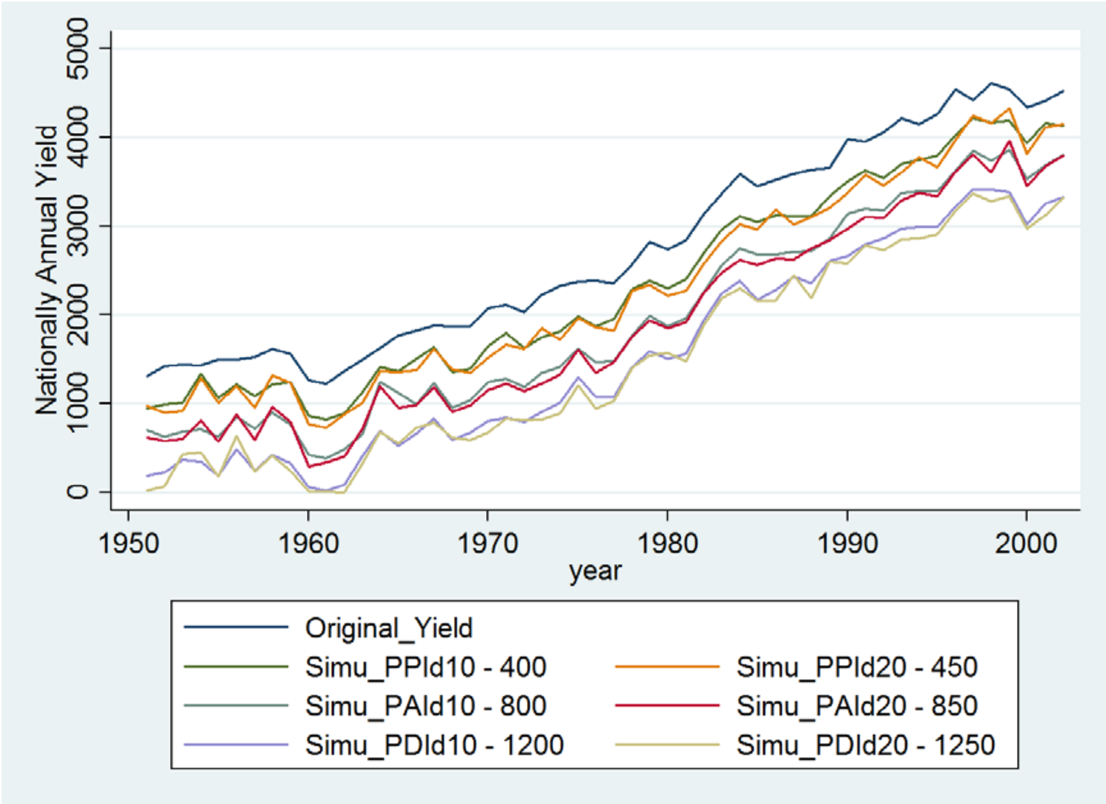


Panel A: Optimal Solutions of the Coverage



Panel B: Maiximized Utility Levels

Figure 9. Weak Farmers' Pessimistic Choice When Indices are Imperfect



Note: "-400" stands for subtracting 400 units from simulated results for distinguishing the 2nd simulation from others. Other numbers in the legend have similar means.

Figure 10. Smoothing Outcomes Using WII in the Last Half Century in China

Appendix I Calculation of Possibility Distribution under Homogeneity Assumption

Used Assumptions:

$Perception\ Assumption\ holds\ for\ farmers, but\ not\ for\ insurers;$

$Quality\ Assumption\ does\ not\ hold\colon\ P(T|D) = \rho;\ P(\bar{T}|\bar{D}) = \gamma;$

$Homogeneity\ Assumption\ hold\colon P(L|D) = 1, and\ P(D) = \pi, so\ P(L) = \pi.$

Therefore: $P(T|D) = P(T|L) = \rho;\ P(\bar{T}|\bar{D}) = P(\bar{T}|\bar{L}) = \gamma$

Calculations:

$P(Bad) = P(LT) = P(T|L)P(L) = \rho\pi$

$P(Over - good) = P(\bar{L}T) = P(T|\bar{L})P(\bar{L}) = [1 - P(\bar{T}|\bar{L})]P(\bar{L}) = (1-\gamma)(1-\pi)$

$P(Over - bad) = P(L\bar{T}) = P(\bar{T}|L)P(L) = (1-\rho)\pi$

$P(Good) = P(\bar{L}\bar{T}) = P(\bar{T}|\bar{L})P(\bar{L}) = \gamma(1-\pi)$

Appendix II. Calculation of Possibility Distribution for Heterogeneous Farmers

Used Assumptions:

Perception Assumption holds for farmers, but not for insurers;

Quality Assumption does not hold: $P(T|D) = \rho$; $P(\bar{T}|\bar{D}) = \gamma$; *Let* $\rho \equiv \gamma$;

Homogeneity Assumption does not hold: $P(L|D) \neq 1, P(D) = \pi$, *and*

Strong Farmer: $\begin{cases} P(L^S|D) = S \\ P(L^S|\bar{D}) = 0 \end{cases}, S \in [0,1]$; *Weak Farmer:* $\begin{cases} P(L^W|D) = 1 \\ P(L^W|\bar{D}) = W \end{cases}, W \in [0,1]$.

Conditional Independent Assumption: $(L^M, L^S, L^W) \perp T|D$

Calculations:

For Strong Farmer

$\boldsymbol{P(Bad)} = P(L^S T) = P(L^S T|D)P(D) + P(L^S T|\bar{D})P(\bar{D}) = P(L^S|D)P(T|D)P(D) + P(L^S|\bar{D})P(T|\bar{D})P(\bar{D}) = \boldsymbol{S\rho\pi}$

$\boldsymbol{P(Over-good)} = P(\bar{L}^S T) = P(\bar{L}^S T|D)P(D) + P(\bar{L}^S T|\bar{D})P(\bar{D}) = P(\bar{L}^S|D)P(T|D)P(D) + P(\bar{L}^S|\bar{D})P(T|\bar{D})P(\bar{D}) = \boldsymbol{(1-S)\rho\pi + (1-\rho)(1-\pi)}$

$\boldsymbol{P(Over-bad)} = P(L^S \bar{T}) = P(L^S \bar{T}|D)P(D) + P(L^S \bar{T}|\bar{D})P(\bar{D}) = P(L^S|D)P(\bar{T}|D)P(D) + P(L^S|\bar{D})P(\bar{T}|\bar{D})P(\bar{D}) = \boldsymbol{S(1-\rho)\pi}$

$\boldsymbol{P(Good)} = P(\overline{L^S}\bar{T}) = P(\overline{L^S}\bar{T}|D)P(D) + P(\overline{L^S}\bar{T}|\bar{D})P(\bar{D}) = P(\overline{L^S}|D)P(\bar{T}|D)P(D) + P(\overline{L^S}|\bar{D})P(\bar{T}|\bar{D})P(\bar{D}) = \boldsymbol{(1-S)(1-\rho)\pi + \rho(1-\pi)}$

For Weak Farmer

$\boldsymbol{P(Bad)} = P(L^W T) = P(L^W T|D)P(D) + P(L^W T|\bar{D})P(\bar{D}) = P(L^W|D)P(T|D)P(D) + P(L^W|\bar{D})P(T|\bar{D})P(\bar{D}) = \boldsymbol{\rho\pi + W(1-\rho)(1-\pi)}$

$$\boldsymbol{P(Over-good)} = P(\overline{L^W}T) = P(\overline{L^W}T|D)P(D) + P(\overline{L^W}T|\bar{D})P(\bar{D})$$
$$= P(\overline{L^W}|D)P(T|D)P(D) + P(\overline{L^W}|\bar{D})P(T|\bar{D})P(\bar{D})$$
$$= \boldsymbol{(1-W)(1-\rho)(1-\pi)}$$

$\boldsymbol{P(Over-bad)} = P(L^W \bar{T}) = P(L^W \bar{T}|D)P(D) + P(L^W \bar{T}|\bar{D})P(\bar{D}) = P(L^W|D)P(\bar{T}|D)P(D) + P(L^W|\bar{D})P(\bar{T}|\bar{D})P(\bar{D}) = \boldsymbol{(1-\rho)\pi + W\rho(1-\pi)}$

$\boldsymbol{P(Good)} = P(\overline{L^W}\bar{T}) = P(\overline{L^W}\bar{T}|D)P(D) + P(\overline{L^W}\bar{T}|\bar{D})P(\bar{D}) = P(\overline{L^W}|D)P(\bar{T}|D)P(D) + P(\overline{L^W}|\bar{D})P(\bar{T}|\bar{D})P(\bar{D}) = \boldsymbol{(1-W)\rho(1-\pi)}$

Appendix III.A Summary Statistics

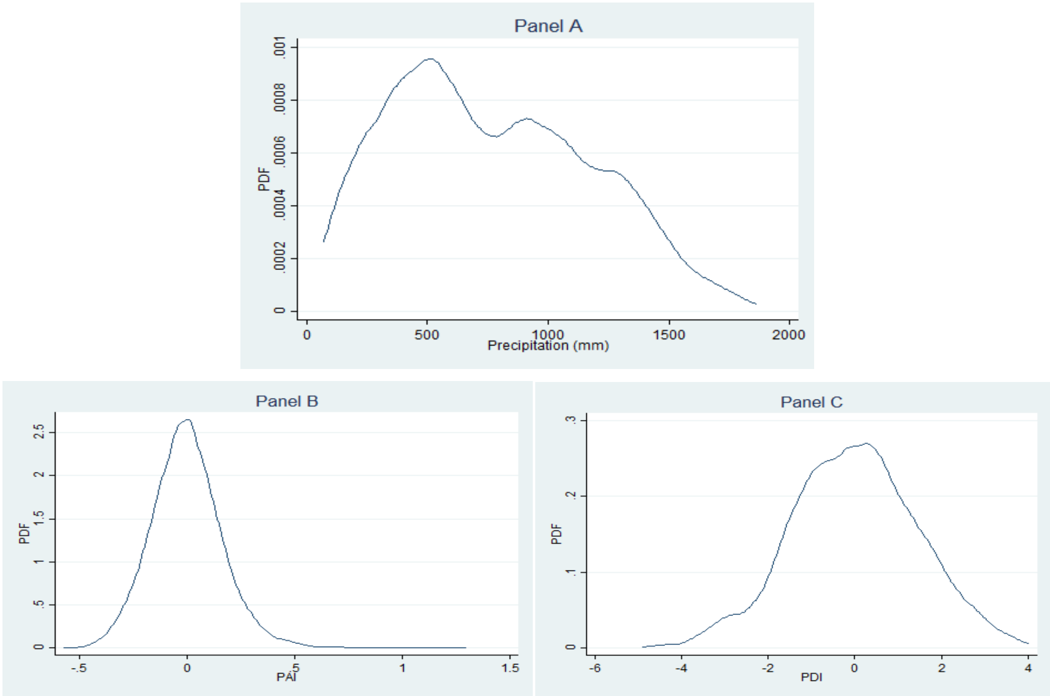
Region	Annual yield (Kg/Ha.)		Annual temperature[2] (Centigrade)		Annual precipitation (mm)	
	Mean	SD	Mean	SD	Mean	SD
Total[1]	2736	1414	12.5	5.1	765	411
Anhui	2610	1279	15.0	0.5	981	165
Beijing	3307	1654	11.8	0.7	509	175
Fujian	3240	1074	18.4	0.5	1311	174
Gansu	1674	671	7.1	0.6	248	34
Guangdong	3289	1327	21.6	0.4	1444	213
Guangxi	2656	1024	21.0	0.4	1360	161
Guizhou	2495	662	15.1	0.4	969	94
Hebei	2189	1074	10.1	1.1	444	96
Heilongjiang	2050	898	1.9	0.8	438	60
Henan	2345	1288	14.2	0.5	617	110
Hubei	3229	1394	15.7	0.5	979	150
Hunan	3566	1384	16.6	0.4	1209	141
Jiangsu	3523	1703	14.8	0.6	864	143
Jiangxi	3118	1236	17.5	0.3	1390	207
Jilin	2963	1860	4.3	0.8	543	69
Liaoning	3010	1514	8.2	0.7	580	104
Neimenggu	1491	860	3.9	0.8	251	39
Ningxia	1756	907	8.0	0.6	229	55
Shaanxi	1822	743	11.3	0.5	538	89
Shandong	2753	1562	12.3	0.5	574	114
Shanghai	4461	1369	16.0	0.7	966	179
Shanxi	1876	778	8.6	0.7	417	81
Sichuan	3109	1108	11.8	0.7	772	70
Xinjiang	2398	1492	7.5	0.6	106	19
Yunnan	2359	648	16.3	0.5	921	81
Zhejiang	3854	1180	16.2	0.7	1232	183

Note: 1) N=1352, # of Provinces=26, # of years=52 (1951-2002)

2) Inside each year, temperature varies largely from Jan. to Dec., but "Annual (average) temperature" varies little among years.

Source: Chinese National Meteorological Bureau and Chinese National Statistics Bureau.

Appendix IV. Distribution of Precipitation, PAI and PDI



Appendix V. Provincial Agricultural Production Trends in 1949-2012 in China