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Basis risk and welfare effect of weather index insurance for smallholders in China

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Selected Paper prepared for presentation at the Southern Agricultural Economics Association (SAEA) Annual Meeting, Mobile, Alabama, February 4-7, 2017.

ABSTRACT

Recent years have witnessed a proliferation of weather-index insurance (WII) pilot programs in developing countries. However, the uptake of this novel insurance turns to be generally low despite that most WII programs are heavily subsidized by central and local government. Although basis risk is widely referred to as the most serious drawbacks to the effectiveness of index-based insurance, the impact of basis risk on the potential benefits of adopting weather index insurance is rarely documented. This paper designs a weather index contract for cotton in Shandong province and examines impact of two components of basis risk, covariate risk and idiosyncratic risk, separately. The findings of this paper underscores the importance of minimizing covariate risk in designing weather index insurance contracts and sheds lights on the different impacts of basis risk components on potential benefits of WII.

Introduction

An extensive body of literature has discussed the failure of conventional insurance to provide smallholders affordable risk protection instrument due to informational asymmetry and moral hazard (Skees and Reed 1986, Quiggin, Karagiannis and Stanton 1994, Coble et al. 1997, Just, Calvin and Quiggin 1999, Skees et al. 2009, Skees 2011). Index-based insurance, which anchors indemnity payments to an objective indictor correlated with insured value, largely mitigates those problems and has been seen as a prospective alternative for small farms to manage risk. In particular, weather index insurance (WII) has become one of the most popular types of index-based insurance in developing countries, given that the correlation between weather-related perils such as droughts, floods and freezes and crop losses is widely and profoundly recognized by smallholders (Luo et al. 1994, Vedenov and Barnett 2004, Karlan et al. 2007). Although recent years have witnessed a proliferation of WII pilot programs in developing countries, unfortunately, the uptake of this novel insurance turns to be generally low despite that most WII programs are heavily subsidized by central and local government (Miranda and Farrin 2012, Cole et al. 2013). At the same time, a vast of rural poor in developing countries is still exposed to weather-related perils and is in need of access to affordable and efficient micro-insurance service. Explanations to this dilemma such as financial literacy, cash constraint and knowledge of risk have been discussed. However, basis risk, also known as the Achilles Heel of weather index insurance, has not been sufficiently researched yet. Basis risk refers to the imperfect correlation between the predicted losses based on weather index and farmers' actual losses. Essentially, from the perspective of policymakers or government, promoting WII as risk management intervention is trading off between basis risk and the problems of adverse selection and moral hazard. While it was recognized as early as when the innovative product emerges, until recently, basis risk has started to be discerned, quantified and evaluated from the perspective of farmers (Bryan 2010, Mude et al. 2012, Norton et al. 2012, Karlan et al. 2014, Jensen et al. 2015, Elabed and Carter. 2016). In general, basis risk is widely understood as one of causes of low uptake. However, some studies have discussed that in some extreme case, prospective buyers might increase demand with basis risk (Jensen, Mude and Barrett. 2014). Detailed description on the mechanism on how basis risk affects farmers' demand for WII remains to be insufficient. Basis risk is composed of covariate risk and idiosyncratic risk. Covariate risk, also known as design risk, is associated with the imperfect match between the index-predicted loss and realized losses experienced among all policy holders within an area. Idiosyncratic risk is defined as individual or farm-level variation around the index-predicted mean. Only a few studies have pointed out that the two types of risk might impact the demand of WII in different magnitude. (Jensen, Mude and Barrett. 2014, Jensen, Barrett and Mude. 2016)

The limited access to historical yield data is considered to be one of the major obstacles to analyze the welfare impact of basis risk. In another word, the index insurance has to be designed at aggregated level of yield, usually county-level yield, and however the overall basis risk is determined from farm level yield. While the limit of farm-level yield data reinforces the advantage of index-based insurance contracts for which the requirement of symmetric information is abated, it arguably augments the challenge to measure idiosyncratic risk and assess household-level welfare. We can further decompose covariate risk is derived from spatial mismatch problem and prediction error. Spatial mismatch arises when the coverage of weather data is not perfectly overlaid with the range dimension of observed crop yield. In reality, it is rarely seen that every county has its own weather station. Accordingly, the weather conditions of counties located distant from the weather station are less accurately measured. The most common technique to relieve spatial mismatch is spatial interpolation, i.e. estimate the values of “missing” weather data with observed ones. In general, there are two types of interpolation techniques: deterministic and geostatistical. Currently, geostatistical interpolation methods or Kriging are widely used in such a context. Kriging estimates out-of-sample weather factors via regression against observed weather factors of surrounding points, with errors weighted by spatial covariance. It is shown to provide an unbiased and efficient estimate for weather factors (Tabios, Guillermo and Salas. 1985, Juha, et al 2013, Kim, Seok-Cheol, et al. 2015). Prediction errors refer to the difference between actual shared losses among policy holders who use the same index and weather-index predicted losses. Albeit impossible to eliminate it, covariate risk can be reduced by improving the quality of the index. On the other hand, idiosyncratic risk falls outside the scope of insurance contract designer (Jensen et al.2014). As a result of the absence of historical farm-level yield data, measuring idiosyncratic risk precisely appears to be building castle up in the air. Few studies have explicitly discussed the magnitude of idiosyncratic risk. A few exceptions include Mude et al.(2012), Jensen et al.(2014) and Jensen et al.(2015) emphasize the decomposition of basis risk into covariate risk and idiosyncratic risk and highlight the adversely effect of idiosyncratic risk on the welfare effect of index insurance based on the longitudinal household dataset and ex post efficiency evaluation on index-based livestock insurance (IBLI) in northern Kenya. However, due to idiosyncratic risk, the potential benefit effects of a unit of WII vary across heterogeneous policyholders. Moreover, working along with the risk aversion and the variation of insured yield, basis risk has complicated effects on the individual demand for WII. The existing literature has not yet fully explored these questions to date.

This paper adds to the existing literature on the impact of basis risk on smallholders in developing countries by examining impact of covariate risk and idiosyncratic risk separately. We design a weather index for cotton in Shandong province, China, price the insurance contract based on a framework developed by Vedenov and Barnett (2005). An artifact stochastic risk is then added to the realized yield at aggregate-level to simulate heterogeneous household risk exposures. Potential willingness-to-pay (WTP) is elicited via the model proposed by Elabed and Carter (2015). Specifically, we construct the weather index by building panel model including multiple weather factors during the growth season of cotton, rather than focusing on univariate weather factor such as rainfall or temperature, to minimize the basis risk of this insurance contract. Then, scenarios with different levels of heterogeneous risk and how farmers' WTP will response are presented. The findings of this paper underscores the importance of minimizing covariate risk in designing weather index insurance contracts and sheds lights on the different impacts of basis risk components on potential benefits of WII.

The remainder of the paper is structured as follows. In the following session, we discuss the technologies for the construction of weather index and describe the weather-yield model, followed by the pricing of the WII contract. The impacts of covariate risk and idiosyncratic risk on the demand for the contract are presented in the next section. The implications and conclusions of our findings are discussed in the final section.

Weather Index Design

Spatial Interpolation

Constructing a relationship between crop yield and weather variables is not ever a simple task but it is first rank importance for the efficiency of WII. In this study, county level data is used to build index. Essentially, WII insures one or more weather-related perils which can be observed from a set weather data. In an ideal world, the geographic area at which yield data measures should be perfectly matched the area at which observed weather data is measures. However, in most case, index designers would face the problem of "missing" weather data because there are no weather stations at many locations of interested. A simple possible solution to this question is to use the weather data from neighbor weather station. However, substantial information such as the distance has been missed and spatial adverse selection might arises due to unevenly distributed basis risk across regions. In this study, we use spatial interpolation to "fill the holes". Specifically, we applied Ordinary kriging, which has been proved to provide unbiased estimate the variability of the weather variables of interest, such as rainfall and temperature (Tabios and Salas 1985, Cob 1996, Cao et al 2015) to estimate the weather conditions for counties with no weather station.

Ordinary kriging assumes the weather factors at site S as follows:

$$Y(S) = \mu + \varepsilon(S),$$

where $Y(S)$ is a weather factor, for example rainfall, of county s, μ is a constant and zero-mean $\varepsilon(s)$ is random disturbance defined as follows:

$$\varepsilon(S) = \sum_{i=1}^{n} \omega_i(s_i) * [Y(s_i) - \mu], \text{with} \sum_{i=1}^{n} \omega_i(s_i) = 1$$

where i indexes the nearby county and the weight of county i, $\omega_i(s_i)$ is called ordinary kriging weight. $\mathrm{Y}(s_i)$ is the weather factor at neighbor county i. Then, the local mean $\widehat{\mathrm{Y}}(\mathrm{s})$ is estimated locally as weighted averages of nearby locations, as follows:

$$\hat{Y}(S) = \sum_{i=1}^{n} \omega_i(s_i) * Y(s_i),$$

In this study, yearly yield data at county level is provided by Ministry of Agriculture, P. R. China, and monthly meteorological data is obtained from China Meteorological Data Sharing Service System. The dataset spans from 1980 to 2012. 5 weather stations which maintain high quality data are selected from 34 weather stations. 14 major cotton producing counties nearby the weather stations are chosen as the sample areas. The map of Shandong Province and counties of interest are shown in Figure 1:

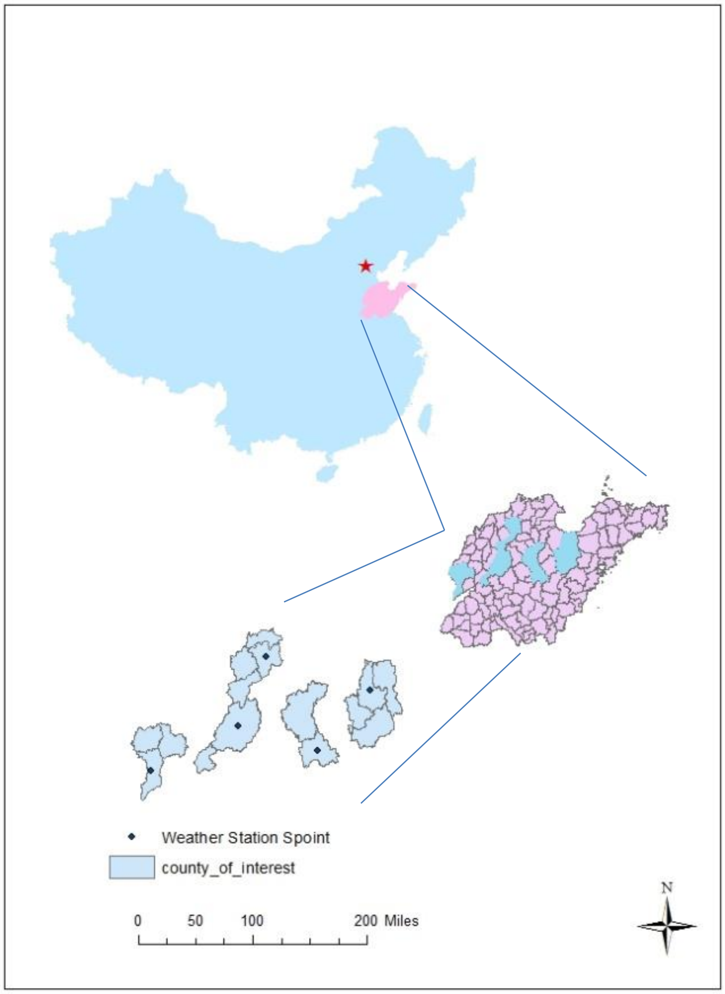

Figure 1. Map of sample counties and weather stations

Index Design

Insurers should leverage all possibly accessible information to construct weather index and minimize the design risk that the insured are exposed to, as noted by Jensen et al. "…lest they inadvertently peddle lottery tickets under insurance label". Considerable skepticism has arisen regarding the index based on a simple weather factor such as rainfall or temperature even for the area where that factor plays a dominant role in crop growing. The goal of weather index designing is to predict yield with weather data as precisely as possible to maximize potential benefits of WII. In this study, underlying weather variables affecting yield within the growing season of the cotton are included in the weather-yield model. To date, it remains open to discuss on determining the variables and optimal functional form among numerous candidates to model the relationship between weather conditions and crop yields. For purposes of this analysis, we apply dynamic fixed effect model to accommodate the existence of time effect and the time-invariant county-specific effect such as elevation, flatness and soil type. First lag of dependent variable is also included in the model to allow autocorrelation process in cotton yield deterministic in order to absorb long-term county-specific changes. The index model is fitted as follows:

$$y_{it} = \alpha_i + y_{it-1} + X_{it}^T\beta + i.\text{year} + \varepsilon_{it}$$

where y_{it} is logarithm of cotton yield of county i in year t, and y_{it-1} is first lagged dependent variable. α_i represents county-specific effect. X_{it} represents constant and the meteorological variables that strongly affect cotton growth and harvest, such as rainfall (monthly average rainfall in cm) and temperature (monthly average daily temperature in celsius). $i.year$, year dummies, absorb regular and stochastic time effects such as long-term trend and sudden adoption of agronomic technology and ε_{iy} represents stochastic disturbance, the variance of which reflects the magnitude of prediction errors. In the sample providence, the growing season of cotton in sample counties spans from April to October, thus rainfall and temperature of these months are considered as weather factors to predict cotton yield. We include quadratic forms to simulate the effects of weather inputs that either inadequate or excessive are detrimental to the harvest of cotton. The fitted model is presented in Table 1 (Appendix) and time series plots of realized yield and index-predicted yield is presented in Figure 2. The insignificant variables were not dropped given that statistically insignificant predictors might contribute to predict cotton yield and the insignificance could result from high correlation among weather inputs. One point is worth to notice that, in all cases, index design has to face the trade-off between the precision of predictions and econometric parsimony. More complicated functional form of index would achieve high goodness-of-fit, and meanwhile importance has to be placed on accessibility to the public.

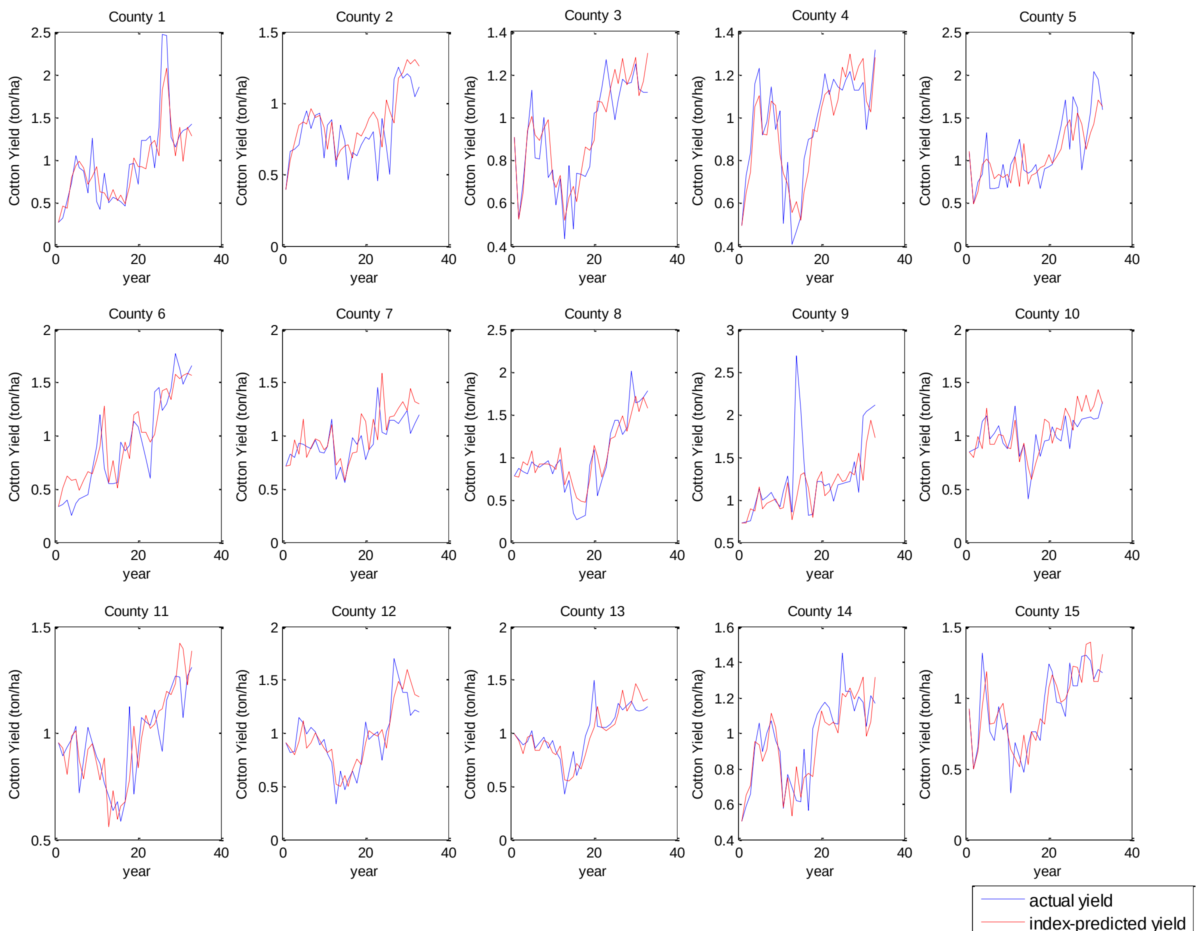

Figure 3. Time series of realized yield and index-predicted yield

Contract Design

The indemnity payment of WII for year t is determined by the difference between the realization of the index i.e. the detrended predicted yield I_{it} and contract target minus the deductible. The contract target is set as long-term average yield and deductible ratio 20%, as the current practice of crop insurance contract does in the sample providence, therefore, the maximum indemnity is 80%*target of the contract. The contract pays indemnity as follows:

$$\mathrm{indem}_{\mathrm{it}} = \max\{0.8 * \ {I_i}^T - I_{it} \ , 0\}$$

where ${I_i}^T$ is the target.

An insurer is assumed to underwrite the weather-related risk of cotton yield for the 15 counties with an elementary contract for each county and its total indemnity of the insurer for each year is computed as follows:

$$indem_t = \sum_{i=1}^{15} indem_{it}$$

The actuarially fair premium of the i^{th} contract is computed as the expectation of indemnity payments.

$$\mathrm{premium}_i = \mathrm{E}(\mathrm{indem}_{it}) = \int_0^{0.8*{I_i}^T} f_{I_i}(x) * indem_{it}(x)dx,$$

where $f_{I_i}(x)$ is non-parametric probability density of I_i in which the kernel function is normal density function. The realized yield with no insurance and predicted yield with WII are presented in Figure 3 (Appendix).

The impact of basis risk on the WTP

Covariate Risk

Covariate risk accounts for the loss that weather index cannot capture at aggregated level. It absorbs the basis risk shared by policyholders who buy the same index contract. These losses might be caused by or non-weather related shocks that affect a fair large area such as crop disease, pests or might arise due to imperfect model design. Here aggregated level is at county level. Idiosyncratic risk measures the risk exposure associated with household heterogeneity. We treat idiosyncratic risk as stochastic deviation from the county-average yield. The yield for a smallholder from county i is then simulated as follows:

$$y_{it} = \mathrm{Y}_{it} + \varepsilon_{it},$$

where Y_{it} represents yield of county i and y_{it} represents household-level yield. $\varepsilon_{\mathrm{it}}$ is stochastic disturbance following normal distribution k times of standard deviation of county-level yield. In reality, the stochastic disturbance is not necessarily zero mean, and its variance might have correlation with variance of county-level yield with high stochasticity. In this study, we set the mean equal to zero and non-zero in different scenarios and the standard deviation of county yield times an expansion factor k. k is randomly drawn from 1.1 to 4 to reflect different magnitude of idiosyncratic risk.

The "revenue" of the farm with the protection of weather index insurance is computed as follows:

$$\pi_{idx_{it}} = y_{it} + \mathrm{indem}_{it} - \mathrm{premium}_i$$

We assume individual is constant relative risk averse, therefore, the utility function of individual is as follows:

$$u(\pi) = \begin{cases} \dfrac{\pi^{1-\theta}}{1-\theta}, & if\ \theta \in [0,1) \\ log(\pi), & if\ \theta = 1 \end{cases}$$

Under the assumption of Expectation Utility Theory, the WTP is defined as the maximum amount of money a smallholder is willingness to pay and indifferent between WII and no insurance protection. Thus, WTP is elicited to equal the utility of revenue under no insurance weather index insurance:

$$\mathbb{E}_{f_{\pi_{\mathrm{idx|y}}}}[u(\pi_{\mathrm{idx|y}})] = \mathbb{E}_{f_{\pi_{\mathrm{noins}}}}[u(\pi_{\mathrm{noins}} + \mathrm{TWP})]$$

Since θ is unknown, we impute θ from 0.1 to 0.9 to represent different levels of risk aversion across smallholders. Figure 4 presents the relationship between WTP and CRRA for each county. Y-axis is WTP divided by actuarially fair premium to show the ratio of WTP to actuarially fair premium. First, the ratio of WTP to fair premium fall below 1, but this does not indicate the market of WII is surely to fail because as we know the WTP of an insurance contract largely depends on the variation of the insured value and the variation yield is lower than individual yield. However, the result of relatively low WTP does provide explanation that WII programs highly subsidized by the government experienced low uptake rate without consideration of external obstacles such as lack of access or trust. Second, as we expected, WTP has an upward slope with the CRRA. However, by comparing WTP across the sample counties which have different degrees of covariate risk, we can see that the demand is not necessarily ascending with the decrease in the level of covariate risk. The counties with high WTP (Count 1, 6 and 8) have the highest variation in yield and lowest degree of covariate risk. This finding shows that the demand for WTP depends on the combination of the variability of yield, covariate risk and risk preference. In particular, the regions with high degree of overall downside risk are most likely to have strong demand for WII with low covariate risk.

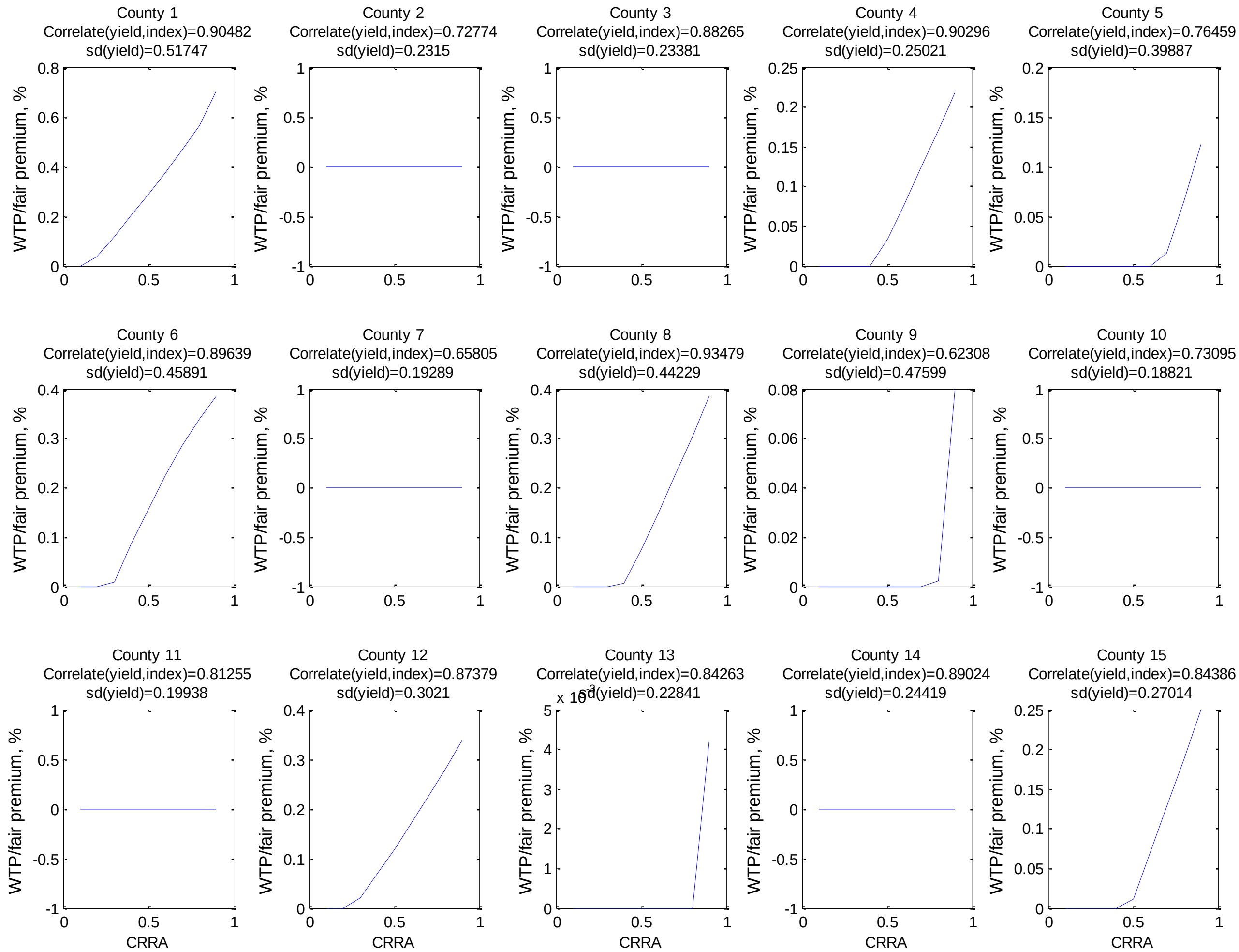

Figure 4. WTP and CRRA at county level

Idiosyncratic Risk

Although in this study we see idiosyncratic risk as a stochastic disturbance, much idiosyncratic loss does not occur randomly. It might involve heterogeneous household characteristics and small local condition. It is possible that the degree of idiosyncratic risk is correlated with the level of risk aversion, size of production and so force, which implies adverse selection. Jensen, Barrett and Mude (2014) find that little idiosyncratic risk is associated with household characteristics.

We analyze the impact of idiosyncratic risk on WTP in three scenarios. In first scenario, we assume idiosyncratic risk is mean zero in order to focus on the impact of the increase in yield variation. A standard deviation randomly drawn from 2 to 5 times of the standard deviation of aggregated yield is added to the county yield distribution. In scenario II, we allow the mean of the stochastic deviation varies across 80% to 120% of county yield. It is more close to the practice. In scenario III, two simulations are presented to show the WTP of high-yield smallholders and low-yield smallholders separately for targeting purposes. The two groups have the same variation of yield with that in scenario II. However, the yield mean in high-yield group is randomly drawn from a pool (1, 1.5)*county-average and the yield mean in low group is drawn from (0.5, 1)*county-average. In order to illustrate the overall picture of these three scenarios, we take means of WTP the 15 counties and plot the relationship between WTP and CAAR (Figure 5).

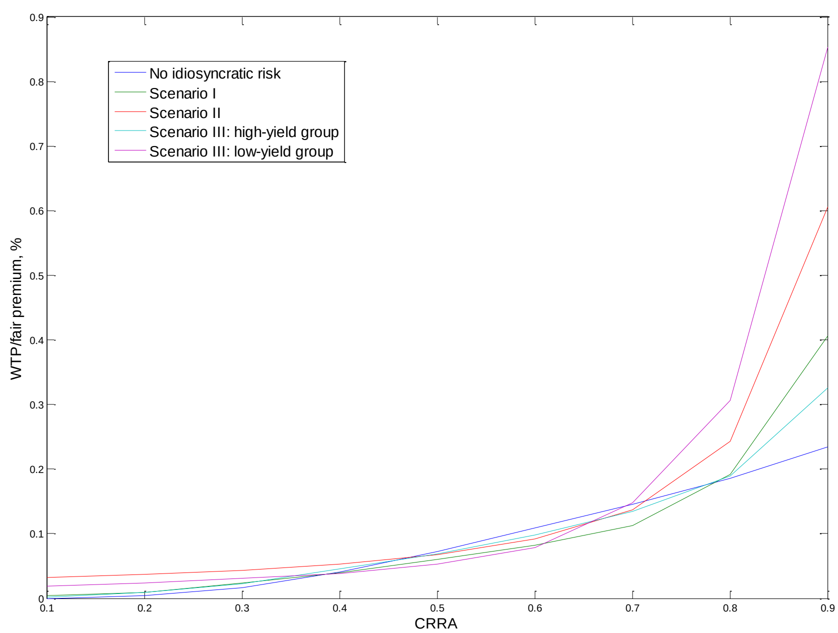

Figure 5. WTP and CRRA at household level

The WTP does significantly not response to idiosyncratic risk in Scenario I and II. This finding echoes the precedent research of Jensen, Mude and Barrett (2014), in which they find households do not response to the increase in idiosyncratic risk (they refer as misinterpretation). This implies that the increase in variability of crop yield could raise smallholders' motivation to seek to protection from insurance even the insurance contract is not able to cover all of the potential loss. In Scenario III, different groups with the same degree of yield variation show distinct demand for WII. High-yield group are inclined to purchase WII while low-yield show much lower WTP. However, even for high-yield group, the WTP is still lower than fair premium.

Conclusion

Because index insurance is largely free of moral hazard problems and exhibits lower administrative cost than conventional insurance, index insurance appears to be a potential instrument to manage risk for smallholders in developing rural areas. However, basis risk, the inherent weakness of index insurance, and the WTP for index insurance with basis risk seem to be less explored via empirical analysis and field experiment. This paper underscores the impact of basis risk on potential demand for in three aspects. First, the degree of covariate risk is likely to be large, primarily due to imperfect correlation between weather conditions and crop loss. The presence of such covariate risk makes the WTP for weather index insurance generally fall below the actuarially fair premium. In other words, farmers are probably not willing to purchase weather index insurance at market rate. Coupling with the degree of covariate risk, the variability of crop yield plays a critical role in determining the potential benefits of index insurance to smallholders. The counties where the high variability of crop yield is high tend to be more willing to purchase index insurance than counties where the crop yield does not vary very much across years. Ex ante examination with farm-level longitude data is necessary for index construction to minimize design risk. Second, the impact of idiosyncratic risk on the demand for weather index insurance can be decomposed into two conflicting aspects. First, it increases the magnitude of basis risk and reduces the benefits of the insurance contracts to the insured. At the same time, higher idiosyncratic risk implies higher variation of crop yield and therefore moderates the negative effects of the increase in basis risk. Moreover, it is often that the overall demand for WTP is inert to response with increase in idiosyncratic risk. This is mildly encouraging for the development of index insurance since idiosyncratic risk is out of the insurer's control. However, we should be cautious with this conclusion, because pervasive information imperfection will impede the realization of this hypothesis. Third, by examining the WTP of heterogeneous smallholders, the group whose yields are consistently higher than the yield at aggregated level tent to be willing to purchase WII at a higher price and the group whose yields fall below the aggregated mean have slightly less demand. This implies that the levels of the first order moment of yield have impact on the demand for WII.

References

Aalto, Juha, et al. "Spatial interpolation of monthly climate data for Finland: comparing the performance of kriging and generalized additive models." Theoretical and Applied Climatology 112.1-2 (2013): 99-111.

Barnett, Barry J, and Olivier Mahul.. "Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries". American Journal of Agricultural Economics 89.5 (2007): 1241-1247.

Barnett, Barry J, Christopher B Barrett, and Jerry R Skees. "Poverty Traps and Index-Based Risk Transfer Products". World Development 36.10 (2008.):1766-1785.

Boucher, Stephen R, Michael R Carter, and Catherine Guirkinger. "Risk Rationing and Wealth Effects in Credit Markets: Theory and Implications for Agricultural Development". American Journal of Agricultural Economics 90.2 (2008):409-423.

Breustedt, Gunnar, Raushan Bokusheva, and Olaf Heidelbach, “Evaluating the Potential of Index Insurance Schemes to Reduce Crop Yield Risk in an Arid Region,” Journal of Agricultural Economics, 59 (2008), 312-328.

Bryan, Gharad. “Ambiguity and insurance.” Unpublished manuscript (2010).

Chantarat, Sommarat, Andrew G. Mude, and Christopher B. Barrett 2009. “Willingness to pay for index based livestock insurance: Results from a field experiment in northern Kenya.” Nairobi.[Short title: Chantarat et al.(2009)]

Clarke, Daniel J, “A theory of rational demand for index insurance,” Department of Economics, University of Oxford, 2011.

Coble, Keith H., Robert Dismukes, and Sara Thomas. “Policy implications of crop yield and revenue variability at differing levels of disaggregation.” annual meeting of the American Agricultural Economics Association, Portland. 2007.

Dercon, Stefan, Ruth Vargas Hill, Daniel Clarke, Ingo Outes-Leon, and Alemayehu Seyoum Taffesse, “Offering rainfall insurance to informal insurance groups: evidence from a field experiment in Ethiopia,” Journal of Development Economics, 106 (2014), 132-143.

Elabed, Ghada, and Michael R. Carter. “Basis risk and Compound-risk Aversion: Evidence from a WTP Experiment in Mali.” University of California at Davis (2014).

Hellmuth, Molly, Daniel Osgood, Ulrich Hess, Anne Moorhead, and Haresh Bhojwani. “Index Insurance and Climate risk: Prospects for Development and Disaster Management”: Climate and Society No. 2. (2009). International Research Institute for Climate and Society (IRI), Columbia University, New York, USA.

Hess, Ulrich, Jerry Skees, Andrea Stoppa, Berry Barnett, and John Nash. “Managing Agricultural Production Risk: Innovations in Developing Countries”. Agriculture and Rural Development (ARD) Department Report 32727-GLB. 2005

Holdaway, Margaret R. “Spatial modeling and interpolation of monthly temperature using kriging.” Climate Research 6.3 (1996): 215-225.

Jensen, N., C. Barrett, and A. Mude. “Index-based insurance: Lottery ticket or insurance?” (2015).

Jensen, Nathaniel Duane, Andrew Mude, and Christopher B. Barrett. “How basis risk and spatiotemporal adverse selection influence demand for index insurance: Evidence from northern Kenya.” Available at SSRN 2475187 (2014).

Jensen, Nathaniel Duane, Christopher B. Barrett, and Andrew Mude. “Basis risk and the welfare gains from index insurance: Evidence from northern Kenya.” Available at SSRN 2505764 (2014).

Jensen, Nathaniel D., Christopher B. Barrett, and Andrew G. Mude. "Index Insurance Quality and Basis Risk: Evidence from Northern Kenya." American Journal of Agricultural Economics (2016): aaw046.

Just, R. E., L. Calvin, and J. Quiggin. “Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives.” Amer. J. Agr. Econ. 81(1999)

Kim, Seok-Cheol, et al. “Comparison Of Spatial Interpolation Methods For Estimation Of Air Temperature.” 20th World Congress of Soil Science. 2014.

Leblois, Antoine, Philippe Quirion, and Benjamin Sultan, 101 (2014), 67-80 “Price vs. weather shock hedging for cash crops: Ex ante evaluation for cotton producers in Cameroon,” Ecological Economics,.

Miranda, Mario J., and Katie Farrin. “Index insurance for developing countries.” Applied Economic Perspectives and Policy 34.3 (2012): 391-427.

Norton, Michael T., Calum Turvey, and Daniel Osgood, “Quantifying spatial basis risk for weather index insurance,” The Journal of Risk Finance, 14 (2012), 20-34.

Quiggin, J., G. Karagiannis, and J. Stanton. “Crop Insurance and Crop Production: An Empirical Study of Moral Hazard and Adverse Selection.” In Economics of Agricultural Crop Insurance, eds., D. L. Hueth and W. H. Furtan, pp. 253-272. Norwell, MA: Kluwer Academic Publish

Skees, J. R., and B. J. Barnett. “Conceptual and Practical Considerations for Sharing Catastrophic Systemic Risks.” Rev. Agr. Econ. 21(1999):424-441.

Skees, J. R., J. R. Black, and B. J. Barnett. “Designing and Rating an Area Yield Crop Insurance Contract.” Amer. J. Agr. Econ. 79(1997):430-43

Skees, J.R., and M.R. Reed. “Rate-Making and Farm Level Crop Insurance: Implications for Adverse Selection.” Amer. J. Agr. Eeon. 68(August 1986):653-59.

Skees, Jerry R, and Benjamin Collier. 2008. The Potential of Weather Index Insurance for Spurring a Green Revolution in Africa. Global Ag Risk Inc

Skees, Jerry R, Jason Hartell, JQ Hao, A Sarris, and D Hallam. 2006. Weather and Index-Based Insurance for Developing Countries: Experience and Possibilities. In Agricultural Commodity Markets and Trade: New Approaches to Analyzing Market Structure and Instability, edited by A. Sarris and D. Hallam. Northampton, MA: Edward Elgar.

Skees, Jerry. “Innovations in Index Insurance for the Poor in Low-Income Countries.” Financial Inclusion, Innovation, and Investments: Biotechnology and Capital Markets Working for the Poor (2011): 73.

Smith, Vincent H., and Alan E. Baquet. “The demand for multiple peril crop insurance: evidence from Montana wheat farms.” American journal of agricultural economics 78.1 (1996): 189-201.

Tabios, Guillermo Q., and Jose D. Salas. “A comparative analysis of techniques for spatial interpolation of precipitation1.” (1985): 365-380.

Appendix:

Table 1. Weather-yield model

VARIABLES	Log(yield)
Lag.Log(yield)	0.519**
	(0.071)
Apr. Rainfall	0.012
	(0.033)
Apr. Rainfall-square	0.000
	(0.004)
May Rainfall	-0.018
	(0.011)
May Rainfall-square	0.001
	(0.001)
Jun. Rainfall	0.019
	(0.020)
Jun. Rainfall-square	-0.000
	(0.001)
Jul. Rainfall	0.010
	(0.006)
Jul. Average Temperature-square	-0.000
	(0.000)
Aug. Rainfall	0.003
	(0.005)
Aug. Rainfall-square	-0.000
	(0.000)
Sep. Rainfall	0.012+
	(0.006)
Oct. Rainfall	-0.016
	(0.015)
Apr. Average Temperature	-1.348
	(2.126)
Apr. Average Temperature-square	0.666
	(0.688)
May Average Temperature	7.846+
	(3.807)
May Average Temperature-square	-2.157*
	(0.843)
Jun Average Temperature	-9.502+
	(5.247)
Jun. Average Temperature-square	1.864+
	(1.006)
Jul Average Temperature	-3.576
	(5.947)
Jul. Average Temperature-square	0.767
	(1.085)
Aug Average Temperature	7.007
	(9.901)
Aug. Average Temperature Square	-1.391
	(1.959)
year2	-0.312
	(0.207)
year3	-0.004
	(0.264)
year4	-0.069
	(0.244)
year5	-0.178
	(0.270)
year6	-0.366
	(0.368)
year7	-0.152
	(0.197)
year8	-0.292
	(0.222)
year9	-0.091
	(0.266)
year10	-0.338
	(0.243)
year11	-0.397
	(0.326)
year12	-0.350
	(0.257)
year13	-0.728*
	(0.301)
year14	-0.230
	(0.380)
year15	-0.633*
	(0.251)
year16	-0.324
	(0.300)
year17	-0.261
	(0.260)
year18	-0.236
	(0.247)
year19	-0.229
	(0.318)
year20	-0.140
	(0.285)
year21	-0.156
	(0.297)
year22	0.034
	(0.148)
year23	-0.204
	(0.198)
year24	-0.068
	(0.320)

year25	-0.323
	(0.266)
year26	-0.453+
	(0.229)
year27	0.053
	(0.208)
year28	0.084
	(0.205)
year29	-0.081
	(0.233)
year30	0.037
	(0.226)
year32	-0.096
	(0.230)
year33	0.010
	(0.194)
Constant	4.185
	(14.363)
Observations	477
Number of code	15
R-squared	0.678

Robust standard errors in parentheses
** p<0.01, * p<0.05, + p<0.1

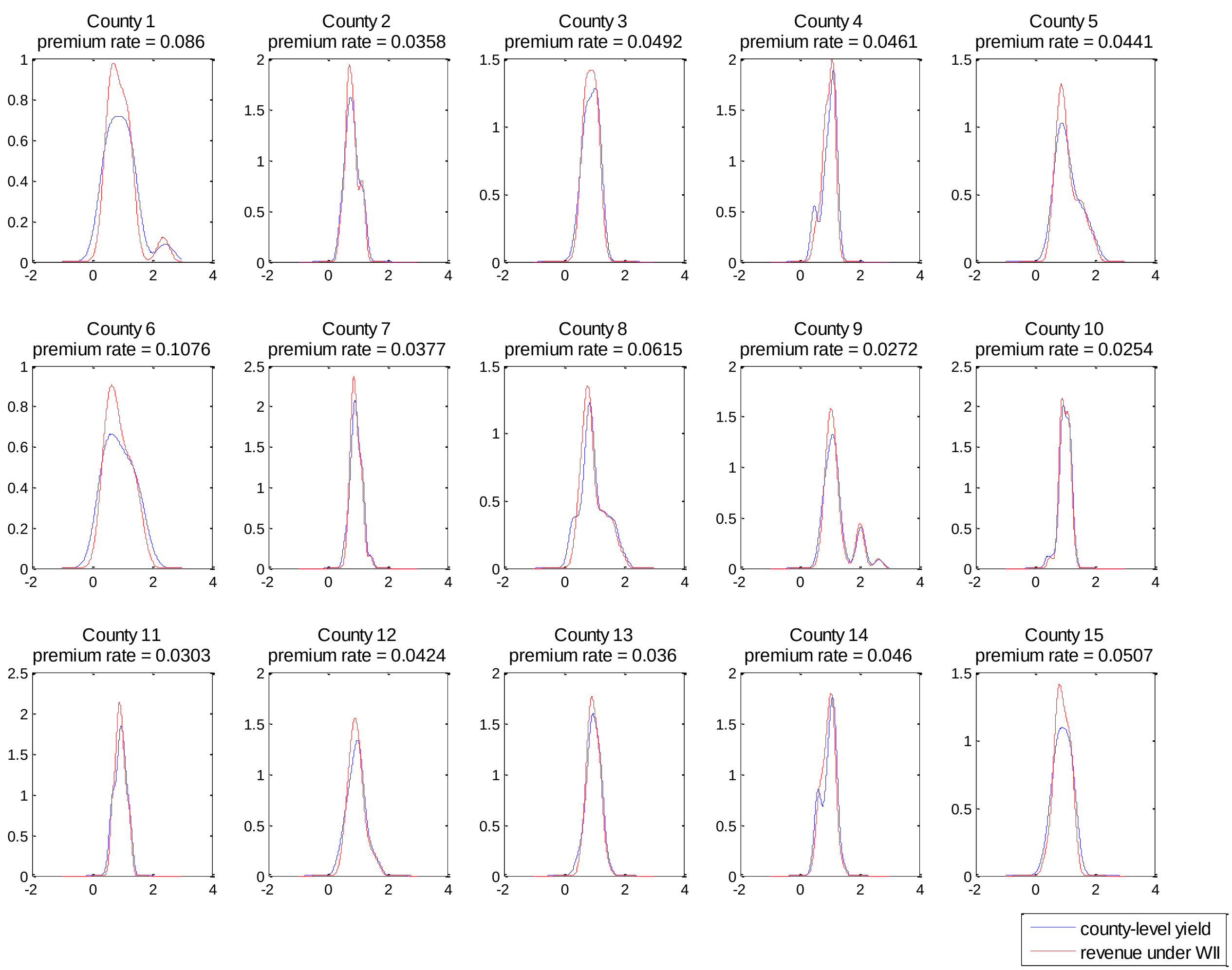

Figure 3. Mon-parametric PDFs for county-level yield and revenues with WII