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Index-Based Risk Financing and Development of Natural Disaster Insurance Programs in Developing Asian Countries

SOMMARAT CHANTARAT[1]
Crawford School of Public Policy, The Australian National University

KRIRK PANNANGPETCH
Faculty of Agriculture, Khon Kaen University, Thailand

NATTAPONG PUTTANAPONG
Faculty of Economics, Thammasat University, Thailand

PREESAN RAKWATIN
Thailand Ministry of Science and Technology, Thailand

THANASIN TANOMPONGPHANDH
School of Management, Mae Fah Luang University, Thailand

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Abstract: *This paper explores innovations in index-based risk transfer products (IBRTPs) as a means to address important insurance market imperfections that have precluded the emergence and sustainability of formal insurance markets in developing countries, where uninsured natural disaster risk remains a leading impediment of economic development. Using a combination of disaggregated nationwide weather, remote sensing and household livelihood data commonly available in developing countries, the paper provides analytical framework and empirical illustration on showing design nationwide and scalable IBRTP contracts, to analyse hedging effectiveness and welfare impacts at the micro level, and to explore cost effective risk-financing options. Thai rice production is used in our analysis with the goal to extend the methodology and implications to enhance development of national and regional disaster risk management in Asia.*

Keywords: Natural disaster insurance, index insurance, reinsurance, catastrophe bond, rice production, Thailand.

JEL classification**:** Q54, G22, G12, Q11, O53

1. Introduction

There is growing evidence that the frequency and intensity of natural disasters continue to rise over the past decades (Swiss Re 2011a). This trend is likely to continue as the impact of climate change drives greater volatility in weather-related hazards (IPCC 2007). The low-income and developing countries suffered an increase of disaster incidence at almost twice the global rates large proportion of population still rely on agriculture and live in vulnerable environments (IFRCRCS 2011). Overall, costs per disaster as a share of GDP are considerably higher in developing countries (Gaiha and Thapa 2006). Over the past decade, Asia has been the most frequently and significantly hit region occupying 80% of the major natural disasters worldwide.[2]

Less than 10% of natural disaster losses in developing countries are insured as several markets imperfections have served to impede development of markets for transferring natural disaster risks. Adverse selection and moral hazard are inherent to any form of conventional insurance products when insured have total control of and private information on the indemnified probability. Transaction costs of financial contracts necessary for controlling these information asymmetries and for verifying claimed losses are extremely high relative to the insured value especially for smallholders. Limited spatial risk-pooling potential resulted from covariate nature of natural disaster losses further impedes the development of domestic insurance market, unless local insurers can transfer the risks to international markets.

Without effective insurance market, public disaster assistance and highly subsidised public insurance programs have been the key supports for affected population in developing countries. The increasing frequency and intensity of these covariate shocks, however, could jeopardise the adequacy, timeliness and sustainability of these programs (Cummins and Mahul 2009). These public programs are largely prone to moral hazard, which could easily alleviate the program costs through induced risk taking incentives or underinvestment in risk mitigating activities among vulnerable populations. Without proper targeting, these programs could further crowd out private insurance demand impeding the development of healthy domestic insurance market.

Households in developing countries, thus, are disproportionally affected by disasters due to larger exposures but limited access to effective risk management strategies. While literatures analyse the wide array of informal social arrangements and financial strategies that households employ to manage risk, in nearly all cases these mechanisms are highly imperfect especially with respect to covariate shocks and in many cases carry very high implicit insurance premia. The resulting long-term impacts of catastrophic shocks on their economic development thus have been widely evidenced in the literatures (Barrett, *et al*. 2007 offers great review).

This paper explores the potentials of the increasingly used index-based risk transfer products (IBRTPs) in resolving the key market imperfections that impede the development and financing of sustainable natural disaster insurance programs in developing countries. Unlike conventional insurance that compensates individual losses, IBRTPs are financial instruments, e.g., insurance, insurance linked security, that make payments based on an underlying index that is transparently and objectively measured, available at low cost and not manipulable by contract parties, and more importantly highly correlated with exposures to be transferred. By design, IBRTPs thus can obviate asymmetric information and incentive problems that plague individual-loss based products, as the index and so the contractual payouts are exogenous to policyholders. Transaction costs are also much lower, since financial service providers will only need to acquire index data for pricing and calculating contractual payments. There will be no need for costly individual loss estimations. Properly securitising natural disaster risk into a well defined, transparently and objectively measured index could further open up possibilities to transfer covariate risks to international reinsurance and financial markets at competitive rates.

As natural disaster losses are covariate, it would be possible to design IBRTPs based on a suitable aggregated index. These opportunities, however, come at the cost of basis risk resulting from imperfect correlation between an insured's actual loss and the behaviour of the underlying index on which the contractual payment is based. IBRTPs will be effective only when basis risk is minimised. The contracts need to also be simple enough to hold informed demand among clients with limited literacy in developing countries, and to be scalable to larger geographical settings to ensure efficient market scale. Trade-offs among basis risk, simplicity and scalability thus constitute the key challenges in designing appropriate IBRTPs for developing countries.

Over the past decade, IBRTPs have emerged as potentially market viable approaches for managing natural disaster risk in developing countries. The growing interests among academics, and development communities have resulted in at least 36 projects in 21 countries worldwide covering risks of droughts, floods, hurricanes, typhoons and earthquakes based on objectively measured area-aggregated losses, weather and satellite imagery products.[3] Contracts have been designed to enhance risk management at various levels ranging from farmers and homeowners as target users to macro level, allowing governments and humanitarian organisations to transfer their budget exposures in provision of disaster relief programs to the international markets.

The consensus, however, has not been reached if and how IBRTPs could work in developing country settings for several reasons. First, current literatures[4] tend to either lack rigorous analysis of basis risk and welfare impacts or use aggregated data to perform such analysis. Hence, less could be learnt *ex ante* about the value of the contracts to the targeted population. Second, contract designs to date are context specific, making it very difficult to be scaled up in other heterogeneous settings. Finally, as most of the current studies are small in scale, less has been explored on the potentials for portfolio risk diversifications, transfers and financing.

This paper complements existing literatures, especially on the rigorous analysis and applications of IBRTPs in Asia. We provide analytical framework and show empirically how to use a combination of disaggregated and spatiotemporal rich sets of household and disaster data, commonly available in developing countries, to design nationwide and scalable IBRTP contracts, to analyse hedging effectiveness and welfare impacts at a disaggregated level and to explore cost effective disaster risk-financing options. Our empirical illustration explores the potentials for development of nationwide index insurance program for rice farmers in Thailand. We analyse contract design based on three forms of indices: (i) government collected provincial-averaged rice yield, (ii) estimated area yield constructed from scientific crop-climate modelling and (iii) various constructed parametric weather variables. These indices differ in risk coverage, exposure to basis risk, level of simplicity and scalability. Disaggregated welfare dynamic data obtained from the multi-year repeated cross sectional household survey are then used to estimate basis risk and to evaluate the relative hedging effectiveness of these indices given the above trade-offs.

The nationwide design coupled with spatiotemporal rich indices data further allow us to explore portfolio risk diversification and transfers through reinsurance and securitisation of insurance-linked security in the form of catastrophe bond. And through simulations based on disaggregated nationwide household dynamic data, we finally explore potential impacts of the optimally designed index insurance program under various public-private integrated risk financing arrangements. Except for the existing literatures in Mongolia (Mahul and Skees 2007) and India (Clarke, *et al.* 2012), the paper is among the very first to study IBRTPs using a countrywide analysis. Using commonly available data sets further enhance scalability of our analysis to other settings in the region.

The rest of the paper is structured as following. Section 2 provides analytical framework on the design, pricing and applications of IBRTPs. Section 3 presents the main empirical results illustrating the potentials of IBRTPs for rice farmers in Thailand. Section 4 concludes with discussions on challenges and opportunities in implementing IBRTPs and implications of our studies for the rest of Asia.

2. Managing Natural Disaster Risks using Index-Based Risk Transfer Products

Consider a setting where household's stochastic livelihood outcomes, y_{it}, are exposed to natural disasters. In our case of Thai rice farmer, y_{it} represents rice production[5] realised by household i in province l at year t.[6] Household's production can be orthogonally decomposed into the systemic component explained by a location aggregated index z_t– capturing location-aggregated risks – and the idiosyncratic variation unrelated with the index, ε_{it}, according to:

$$y_{it} = \bar{y}_i + \beta_i(z_t - \bar{z}) + \varepsilon_{it} \qquad (1)$$

where $\bar{y}_i$ and $\bar{z}$ denote expected or long-term average of the household's production and the aggregated index respectively. $\beta_i = \sigma(y_{it}, z_t)/\sigma^2(z_t)$ measures the sensitivity of household's production to the systemic risk captured by the location aggregated index.

Underlying Index

The key to designing effective IBRTP contract is to find a high quality aggregate index z_t that can explain most of the variations in y_{it} so that contractual payments based on z_t can protect households from the major systemic production shortfalls. The imperfect relationship between the index z_t and y_{it}, however, implies that β_i and ε_{it} will jointly determine basis risk associated with the contract. Low and insignificant β_i and high variations in ε_{it} could imply large basis risk.

The pre-requisites for appropriate index include (i) index being measured objectively and reliably by non-contractual party (to reduce the potential incentive problems), (ii) index being measured at low cost, in near-real time (to enhance the timeliness of indemnity payout), (iii) index has extended high-quality historical profiles of at least 20-30 years (to allow for proper actuarial analysis) and (iv) index can explain great variations in insurable loss (to minimise basis risk). Three general forms of index are currently used in the design of IBRTPs worldwide.

First is the direct measure of production $\bar{y}_t = E_t(y_{it})$ for an aggregate location. Because $\bar{y}_t$ captures all the systemic risks that cause variations in the location-averaged outcomes, IBRTPs based on $\bar{y}_t$ could offer multi-peril protection to household's production losses. The key is the spatiotemporal availability of $\bar{y}_t$ that can be measured accurately and efficiently at low cost and in timely manner by parties independent to the IBRTP contract.[7] $\bar{y}_t$ should also be representative at the micro level to minimise basis risk. The current commercialised contracts that rely on $\bar{y}_t$ are, for example, the group risk plan in North America based on county-level yield (Knight and Coble 1997), the index-based livestock insurance in Mongolia based on area-aggregated census of livestock loss (Mahul and Skees 2007) and the recently piloted area yield insurance for rice farmers in Vietnam (Swiss Re, 2011b).

Alternatively, an estimated location average production can be established from scientific earth observation, agro-meteorological or disaster models or econometric approaches such that

$$\bar{y}_t = y(w_t) + \eta_t, \tag{2}$$

Where $w_t$represents some representations of weather or natural disaster events that can explain most of the variations in $\bar{y}_t$ and are available with spatiotemporal rice historical profiles. w_t can be in some forms of accumulations or deviations from normal condition of station or gridded weather data, satellite imagery or other objectively measured magnitude and intensity of natural disasters, e.g., wind speed, scale of earthquake, etc. Depending on the chosen w_t, contract can be designed to cover single or multiple perils. From (2), an underlying index z_t that triggers contractual payments thus can be constructed either from an estimated location-averaged production, $y(w_t)$, or directly from a simple measure of w_t.

From (1) and (2), these estimated index $y(w_t)$ or $w_t$could be subjected to at least two additional sources of basis risk, relative to $\bar{y}_t$. First, η_t represents additional variations in location-averaged production that could not be explained by either $y(w_t)$ or w_t. In the case of rice production, the index might not capture some non-weather related variations of production, e.g., pest or disease outbreaks, that could affect most of the insured. How well w_t represents weather or natural disaster events experienced by the insured would further contribute to an additional source of basis risk.[8] The keys are that w_t should be measured at the most micro level, and that (2) should be established at the most micro level using disaggregated data to minimise basis risk. Carter, *et al*. (2007) show that contract triggered by econometrically estimated $y(w_t)$ has poorer hedging performance relative to the area-yield insurance for cotton farmers in Peru.

The two forms of weather index, $y(w_t)$ or w_t, could differ slightly on the potential basis risk, simplicity and so scalability. The working assumption in favour of $y(w_t)$ is that by using complex scientific or econometric modelling potentially with exogenous controls, the established $y(w_t)$ could explain household production with higher accuracyand hence with lower basis risk relative to the simple w_t. The key potential shortfall is the potential for index $y(w_t)$ to be complex for targeted clients to understand and for scaling up to larger settings. For simple w_t, on the other hand, contract design can also minimise basis risk by incorporating exogenous controls – e.g., geographical information system (GIS), agronomic data, etc. – in the construction of w_t or payout function. This would also involve trading simplicity with basis risk reduction. The transparency in the direct observation of w_t might further enhance risk transfer potential into international market (Skees 2008). The relative performance of the two forms of index has been mixed empirically, and has not been explored formally.

With $y(w_t)$, World Food Programme's Ethiopian drought insurance triggered payouts to protect farmers based on estimated livelihood losses measured by a scientific water requirement crop model (WFP 2005), and the index-based livestock insurance uses estimated livestock loss established econometrically from remote sensing Normalised Difference Vegetation Index (NDVI) to compensate Kenyan's herd losses from drought (Chantarat et al. forthcoming). Both risks have also been transferred to international market. With w_t, the rainfall and temperature index insurance contracts (designed relative to crop growth cycles) have been expanding in India since 2003 and sold to more than 700,000 smallholder farmers today with risks transferred into international markets (Gine, *et al.* 2007, Manuamorn 2007). Contracts have also been expanding in many developing counties. Using simple correlations, Clarke, *et al.* (2012), however, finds that basis risk of the Indian contracts could be very high and heterogeneous across settings. Parametric indicators of natural disasters have also been used in the design of catastrophe insurance, e.g., for earthquake in Mexico and the Caribbean (World Bank 2007).

Index Insurance

With the three general forms of underlying index, $z_t = \bar{y}_t, y(w_t), w_t$, a standard index insurance contract can be designed to compensate for production shortfall according to

$$\pi(z_t, z^*) = max\{z^* - z_t, 0\}. \quad (3)$$

This standard payoff function thus specifies contract's coverage area l and period t when the index will be measured and a strike z^* that triggers payout once the realisation of z_t falls below it.[9] An optimal contract will involve insured households scaling up or down this standard contract to meet their risk profiles and compensation needed when z_t falls below z^*.

An actuarial fair rate of this standard contract depends on strike level and can be calculated for each coverage location based on an empirical distribution of the underlying index:

$$E\pi(z_t, z^*) = \int \pi(z_t, z^*)\, f(z_t) dz_t. \quad (4)$$

$f(z_t): S_z \rightarrow \Re$ can be obtained from the historical data or can be estimated parametrically or non-parametrically using historical index data.

Optimal Contract and Hedging Effectiveness

An optimal insurance design defines a combination of a standard contract and a coverage scale that maximises the insured's welfare. For simplicity, we consider a risk-averse household with preference over consumption represented by class of mean variance utility function with $\theta > 0$ representing an Arrow-Pratt coefficient of absolute risk aversion.[10] With stochastic net income from production y_{it} under assumed deterministic price, insured household's income available for consumption can thus be written as

$$c_{it} = y_{it} + \alpha_i\big(\pi(z_t, z^*) - \delta E\pi(z_t, z^*)\big) \quad (5)$$

where α_i is a coverage choice that scales liability of the standard contract to meet household's risk profile.[11] $\delta > 1$ is a market premium loading factor. Subjected to (3), (4) and (5), an optimal coverage scale for $\pi(z_t, z^*)$ can thus be derived as

$$\max_{\alpha_i^*(\theta, z^*, \delta)} E(c_{it}) - \frac{\theta}{2}\sigma^2(c_{it}) \quad (6)$$

This simple mean variance utility representation allows us to derive an optimal insurance design $\{\pi(z_t, z^*), \alpha_i^*(\theta, z^*, \delta)\}$ for insured household in each coverage location with

$$\alpha_i^*(\theta, z^*, \delta) = \left|\rho_{y_{it}, \pi(z_t, z^*)}\right| \frac{\sigma(y_{it})}{\sigma\big(\pi(z_t, z^*)\big)} - \frac{(\delta - 1)E\pi(z_t, z^*)}{\theta\sigma^2\big(\pi(z_t, z^*)\big)}\,. \quad (7)$$

Household's optimal insurance coverage is thus increasing in the magnitude of the correlation between their production and the contractual payment, variations in their production and risk aversion. The optimal coverage is also decreasing in the premium loading. If the contract is actuarial fair, this optimal coverage scale will be equivalent to a typical financial hedge ratio.

By comparing expected utility of consumption with (c_{it}^{π}) and without contract ($c_{it}^{no\pi}$), we can quantify the magnitude of household's welfare gain from an optimal insurance contract as

$$EU(c_{it}^{\pi}) - EU(c_{it}^{no\pi}) = \frac{\theta}{2}[\sigma^2(c_{it}^{no\pi}) - \sigma^2(c_{it}^{\pi})] - [E(c_{it}^{no\pi}) - E(c_{it}^{\pi})]. \tag{8}$$

This implies that for a risk-averse household, welfare gain from insurance contract will be proportional to the variance reduction relative to the mean reduction in the insured consumption stream. Welfare gain thus increases in risk aversion and decreases in premium loading. The gain decreases with basis risk ($\beta_i, \varepsilon_{it}, \eta_t$) through its effects on variance reduction.

With $U'(\cdot) > 0,$ the welfare measure in (8) can be translated into comparison of certainty equivalence, $\bar{c}_{it}$, with and without insurance. $\bar{c}_{it}$ of stochastic production income streams is defined as the value of consumption that, if received with certainty, would yield the same level of welfare as the expected utility of the stochastic consumption stream. Hence, $U(\bar{c}_{it}) = EU(c_{it})$. The welfare improvement impact, $EU(c_{it}^{\pi}) - EU(c_{it}^{no\pi}) > 0,$ can thus be translated into $\bar{c}_{it}^{\pi} - \bar{c}_{it}^{no\pi} > 0,$ which reflects risk-reduction value of insurance and so the insured's willingness to pay in excess of the current price in order to obtain the insurance. This utility-based welfare measure thus allows us to formally compare hedging effectiveness across contract designs, households and locations with heterogeneous settings.[12]

Portfolio Pricing and Risk Diversification

With catastrophic natures of natural disaster risks, pricing a stand-alone contract in (4) – relying on marginal distribution of an index in one coverage location – will likely result in high market premium rate especially due to catastrophe load. Capacity to pool these covariate risks across larger geographical or temporal coverage, or with tradable securities (with potentially less correlated returns) might enhance cost effective pricing as part of a well-diversified portfolio.

In specific, the market premium rate of a standard index insurance contract priced as part of a portfolio P can be disaggregated into

$$\delta E\pi(z_t, z^*) = \left(E\pi(z_t, z^*) + c(\mathrm{P}_m)\right) \cdot k \qquad (9)$$

Where administrative load k reflects some constant factor to cover all the transaction costs and an increasing function $c(\mathrm{P}_m)$ representing a catastrophe load to cover the total cost associated with securing the risk capital and obtaining reinsurance coverage to finance the catastrophic risk represented by probable maximum loss (PML), P_m. Typically, PML can be established using Value at Risk (VaR) of the insurer's portfolio payouts net premium received at some ruin probability $1 - m,\ m \in (0,1)$. Specifically, consider an insurer's diversified portfolio consisting of index insurance contracts covering geographical locations (each with portfolio weight $\rho = \sum_i \alpha_i^*$) in the region.

$$\mathrm{P}_m(\mathrm{P}) = \mathrm{VaR}_m(P) = -\inf\{p \in \Re\colon F_P(p) > m\},\ \ \mathrm{P} = \sum \rho\left(\pi(z_t, z^*) - E\pi(z_t, z^*)\right) \qquad (10)$$

Where P represent the portfolio's stochastic net payout position with cumulative density F_P. Thus, for any better diversified portfolio P^a with respect to P^b, $\mathrm{P}_m(\mathrm{P}^a) < \mathrm{P}_m(\mathrm{P}^b)$ implying $c(\mathrm{P}^a) < c(\mathrm{P}^b)$. And so by (9), the risk reduction benefit of insurer's portfolio diversification will result in lower market insurance premium through reduction of required catastrophe load.

For portfolio pricing,[13] an empirical multivariate distribution of the underlying indices in the portfolio: $f(z_{1t}, z_{2t}, \ldots, z_{Nt})\colon S_z \to \Re$, needs to be established from observed historical data or estimated empirically by fitting a standard parametric distribution (e.g., multivariate normal distribution) or by using a non-parametric approaches taking into account the correlation structure of the indices(e.g. copulas).

Various national and regional catastrophe insurance pools have been created to enhance spatial diversifications of natural disaster insurance programs, e.g., earthquake insurance program for homeowners in Turkish (Gurenko, *et al*. 2006), the area-yield based livestock insurance program in Mongolia (Mahul and Skees 2007) and various private and public weather index insurance programs in India (Clarke, *et al*. 2012). At the regional level, the Caribbean Catastrophe Risk Insurance Facility has been established as an insurance captive special purpose vehicle to provide 15participating countries with catastrophe index insurance for hurricanes and earthquakes. The facility acts as risk aggregator allowing countries to pool their country-specific risks into a better-diversified portfolio. This resulted in a reduction in premium cost of up to 40% of the USD 17 million premiums in 2007 (World Bank 2007). Similar regional risk pooling arrangement has been initiated for the Pacific islands (Cummins and Mahul 2009).

Index-based Reinsurance

Achieving cost effective pricing of a well-diversified insurance program relies on ability of risk aggregator to minimise cost of financing portfolio risk, especially the catastrophic layer, $c(\mathrm{P}_m)$. Typically, insurer first spreads the covariate risk inter-temporally by building up reserve over time at the cost of foregone investment return on capital.[14] The reserve, however, can be exhausted and would not be sufficient when catastrophic events strike. Reinsurance is the most common mechanism of transferring covariate risk from primary insurers to international markets.

Index-based reinsurance contracts have been increasingly used, as they could resolve market imperfections and thus result in lower reinsurance rates (Skees, *et al*. 2008). The common form is a stop-loss contract, which provides reinsurance payout when the insurer's portfolio payout exceeds some percentage of the fair premium received. For an insurer holding index insurance portfolio P, a $n\%$ stop-loss reinsurance payoff function with$n \geq 100\%$ can be written as

$$\pi(\mathrm{P}_t, n) = \max\left\{\sum \rho\, \pi(z_t, z^*) - n \sum \rho\, E\pi(z_t, z^*), 0\right\}. \qquad (11)$$

As in (9), market reinsurance rates will include administrative load as well as catastrophe load.

Cummins and Mahul (2009) found that catastrophe reinsurance capacity is available for developing countries as long as their risk portfolio is properly structured and priced. Reinsurance prices also tend to be lower in developing countries than in some developed countries because of the added diversification benefit to the reinsurers and investors.[15] However, reinsurance pricing is also very volatile with premiums rising dramatically following major loss events.[16] Reinsurance thus might not be suitable for the highly catastrophic risk especially of extreme impacts but very rare frequency, as substantial catastrophe loads will be added to take into account extreme maximum probable losses and rare historical statistics to allow for proper actuarial analysis (Cummins and Mahul 2009, Froot 1999).

Securitisation of Index Insurance Linked Security

While there will always be an important role for reinsurance in transferring disaster risks, catastrophe bond (cat bonds)[17] are evolving into a cost-effective means of transferring highly catastrophic risks (Skees, *et al*. 2008, Cummins and Mahul 2009). Cat bonds involve the creation of a high-yield security that is tied to a pre-specified catastrophic event, and is financed by premiums flowing from a linked (re) insurance contract. If the event does not occur, the investor receives a rate of return that is generally a few hundred basis points higher than the LIBOR. If the event does occur, the investor loses the interest and some pre-defined portion (up to 100%) of the principal, so that funds are then used for insurance indemnity payments. The use of cat bonds linked with index (re) insurance has been growing and becoming more attractive to investors.

Consider a multi-year cat bond linked with a reinsurance contract. The price of cat bond issued with face value F, annual coupon payment c and time to maturity of T years, at which the bondholder agrees to forfeit a fraction of the principal payment F by the total reinsurance indemnity $\sum_{t \epsilon T} \pi(\mathrm{P}_t, \gamma)$ up to a cap $\overline{\Pi} < F$ can be written as

$$B\left(\sum_{t \epsilon T} \pi(\mathrm{P}_t, n), \overline{\Pi},\, T\right) = e^{-rT} E\left[F - min\left(\sum_{t \epsilon T} \pi(\mathrm{P}_t, n), \overline{\Pi}\right)\right] + \frac{c}{r}(1 - e^{-rT}). \qquad (12)$$

Like a typical bond, cat bonds are valued by taking the discounted expectation of the coupon and principal payments under the underlying multivariate distribution of the indices in the reinsurance portfolio $f(z_{1t}, z_{2t}, \dots, z_{Nt})$ and the required rate of return on investment r.

The main advantage of securitising cat bond is the potential to avoid default or credit risk with respect to catastrophe reinsurance, as the catastrophic losses imposes a significant insolvency for reinsurers. In contrast, cat bonds permit diffusion of highly catastrophic risk among many investors in the capital market, the volume of which is many times that of the entire reinsurance industry.[18] Cat bond pricing has now been comparable to reinsurance and similarly rated corporate bonds, due to added market diversification, and as market and investors have gained experience with these securities.[19] Since the average cat bond term is 3 years, the prices of the contract are stable for multiple years. Cat bond prices are also found to be lower in developing countries as investors seek to diversify their portfolios with different exposures and geographical areas (Guy Carpenter 2008, Swiss Re 2007 and Cummins and Mahul 2009).

Since 2006, the Mexican government has issued cat bonds to provide financing for the most catastrophic layer of the government-owned nationwide disaster insurance fund, FONDEN. At issue, the cat bonds were competitively offered at 235 basis points above LIBOR. If earthquakes of at least 8.0 Richter occur in a defined zone, investors will lose their entire principal, and so up to USD 160 million is then transferred to the government for disaster relief (FONDEN, 2006).

Public-Private Integrated Natural Disaster Risk Financing

Viability of market for natural disaster insurance relies on cost effective risk financing. Risk layering offers novel approach in disaggregating insurable risk, so that the least expensive instrument can be chosen for each specific layer (Hofman and Brukoff, 2006) in an integrated risk financing. In developing countries, disaster risk financing involves combinations of national insurance pool, reinsurance and various forms of public support (financed by government budget or securitisation). An insurance indemnity pool can be created to allow local insurers to diversify their risks and contribute capital to the reserve pool, from where indemnity payments for higher frequency but lower impact losses can be drawn. Reinsurance could potentially be acquired for the relatively lower frequency but higher impact layer, when indemnity payments exceed the pool. And public supports prove to be important especially for the low frequency but catastrophic layer, where reinsurance costs could be prohibitive and private demand could be low (due to cognitive failure or the crowding out effect of the public disaster relief [20]).

Experiences in developing countries have shown that public supports in financing the tailed risk could have critical role in the development of market viable natural disaster insurance program. Existing programs include governments acting as reinsurers (where it is cost prohibitive or impossible to access international reinsurance market), providing financial support directly to local insurers for obtaining international reinsurance or other risk transfer instruments, or providing catastrophic insurance coverage for the tailed risk directly to targeted clients to complement the market product. They can then used IBRTPs designed and targeted at the tailed risk as cost effective risk transfer instruments to protect their budget exposures.

In the on-going nationwide index-based livestock insurance in Mongolia, a complementary combination of commercialised insurance product for the smaller losses and public disaster insurance for the catastrophic losses are available nationwide. Government also provides 105% stop-loss reinsurance for the national indemnity pool using their budget and contingent loans (Mahul and Skees 2007). The Mexican state-owned reinsurance company, Agroasemex, has been offering unlimited stop-loss reinsurance for more than 240 self-insured fund, Fondos, which provide insurance against disaster affected agricultural production losses to households in 50% of the country's total insured agricultural area (Ibarra and Mahul 2004). Since 1999, the Turkish government has implemented compulsory earthquake insurance by establishing the Turkish catastrophe insurance pool and transfer extreme risk to reinsurance market (Gurenko, *et al*. 2006).

3. Index-based Disaster Insurance Program for Rice Farmers in Thailand

Rice is the country and region's most important food and cash crop. In Thailand, rice production occupies the majority of arable land with the largest proportion of farmers (18% of the population) relying their livelihoods on. Improving and stabilising rice productivity is thus one of the core prerequisites for the country's economic development. Thai rice production, however, has been increasingly threatened by natural disasters, especially droughts and floods.

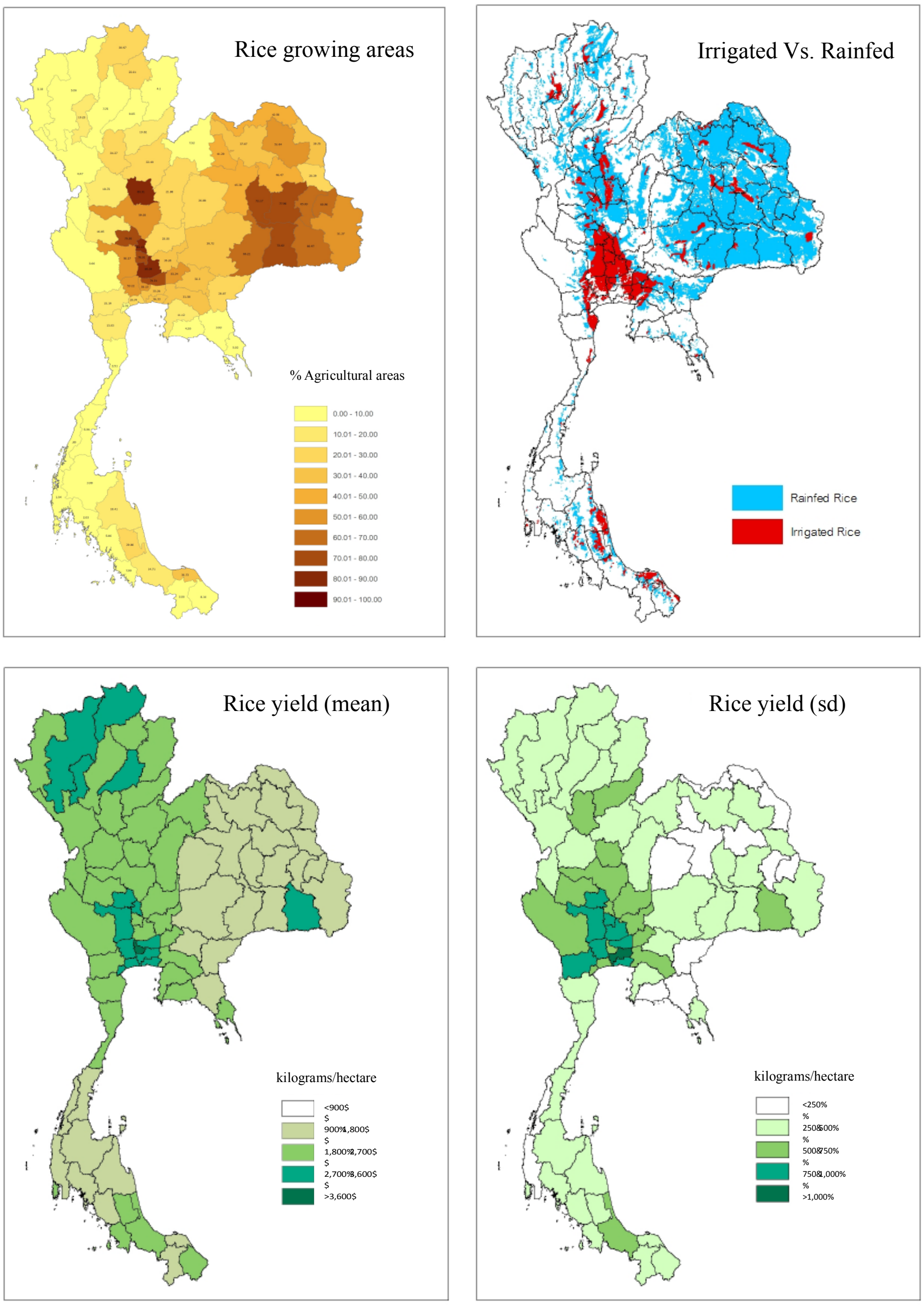
Thai farmers typically take out input loans and expect to pay back with income raised through the harvested crop. Production shocks thus usually bring about increasing level of accumulated debt, as farmers could face difficulties in repaying their loans and in smoothing their consumption. These translate directly to high default risk facing rural lenders, especially the Bank of Agriculture and Agricultural Cooperatives (BAAC) holding the majority of agricultural loan portfolios in the country. While instruments that allow rice farmers to hedge other key risks are largely available – e.g., public rice mortgage program for hedging price risk – sustainable insurance that could insure farmers' production risks without distorting their incentives to improve productivity are still largely absent.

Rice Production, Exposures to Natural Disasters and the Current Programs

There are about 9.1 million hectares of rice growing areas in Thailand in 2010.[21] Figure 1 presents variations in rice paddy areas and production systems across the country's 76 provinces.[22] The key growing provinces, where rice paddy occupies at least 50% of the total arable areas, are clustered mainly in the central plain especially around Chao Phraya River basin and the lowland Northeast. Small numbers of rice growing provinces are also scattered around the upland North and the South.

Production regions vary in cropping patterns due to heterogeneous irrigation systems, ecology, soil and weather patterns. Irrigations are available in less than 25% of the total growing areas. These occupy most of the central provinces and some areas in the North and the South, allowing farmers to cultivate two crops a year. Yields thus tend to be higher in these regions. The majority of rainfed production occupies almost the entire key growing areas in the lowland Northeast, relies extensively on rainfall and so harvests lower yields. The main crop cycles typically start with the onset of annual rain, which usually comes during mid May-November and varies slightly across regions. The second crop can then be grown throughout the rest of the year depending on water availability. As the key growing areas around Chao Phraya River basin are flood prone, crop cycles deviate slightly in order to avoid extended flood periods.

Figure 1: Growing Areas and Variations in Rice Production in Thailand

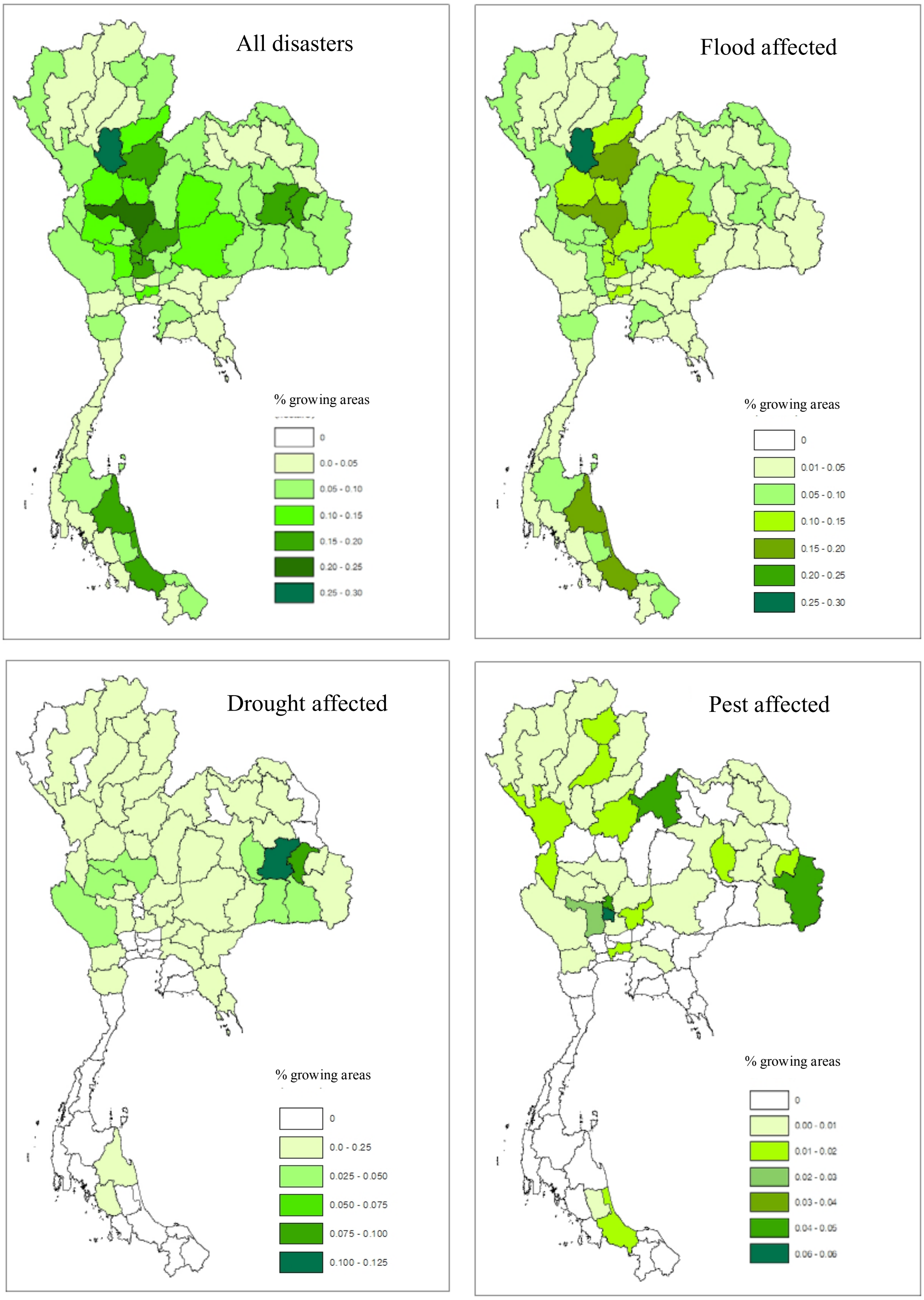


Note: Data are obtained from GISTDA, Ministry of Science and Technology for the two top graphs and from Ministry of Agriculture and Cooperatives for the two bottom ones.

Rice cropping cycle spans about 120 days from seeding to harvesting (Siamwalla and Na Ranong, 1980). Long dry spells and extended flood periods appear as the two key shocks affecting productions with increasing frequency. Sensitivity to these key disasters varies across different stages of crop growth. Figure A1 presents growth stages of rice crop and stage-specific vulnerability. According to World Bank (2006)'s collective scientific findings,[23] the first 105-day period from seeding to grain filing critically requires enough water (25-30 mm of rainfall per 10-day period), and thus is vulnerable to long dry spells that could result from late or discontinued rain. Farmers are also already well adapted to small dry spells by adjusting their planting periods or re-planting when loss occurs early in the cycle. As cycle progresses to maturity and harvesting (during the 105-120 day period that typically fall into the peak of seasonal rain), plants become vulnerable to extended flood that could come about at least when 4-day cumulative rainfall exceeds 250 mm. These drought and flood conditions established by World Bank (2006), however, depend critically on drainage and other geographical variables.

Catastrophic crop losses from dry spells typically occur in the rainfed areas during the onset of rain in July-August, whereas, losses from extended floods occur in the peak of rain during September-October. Exposures differ across regions. The north-eastern rainfed production are especially vulnerable to long dry spell, while most of the irrigated production in the central plain are subject to long periods of deep flooding annually. Productions in the South are vulnerable to floods caused by thunderstorms (Siamwalla and Na Ranong, 1980). Pest also serves as one of the key covariate risks for rice production. Figure 2 presents government records of incidences and spatial variations of actual rice crop losses from these three main shocks in 2005-2011. Flood losses occur with the highest frequency and significance relative to others.

Figure 2: Rice Growing Areas Affected by Key Disasters (2005-2011)



Note: Data are obtained from Thailand Ministry of Agriculture and Cooperatives.

Over the past decade, the Thai government has been providing disaster relief program for farmers when disaster strikes. The program compensates about 30% of total input costs for farmers, who live in the government declared disaster provinces and are verified by local authorities to experience total farm losses. Government spends about 3,350 million baht[24] on average per year for rice farmers affected by droughts, floods and pests. And the program cost could increase up to 40% in some extreme years. Despite these tremendous spending, results from randomised farmer survey imply that the compensations are largely inadequate and subjected to serious delay especially from loss verification process (Thailand Fiscal Policy Office, 2010). There are also increasing evidence of moral hazard associated with the program, especially as farmers start growing the third crop off suitable season.

The nationwide rice insurance program–a top-up program for disaster relief –was piloted in 2011. The program was underwritten by a consortium of local insurers and reinsured by Swiss Re. At 50% subsidised premium rate of 375 baht/hectare nationwide, the program covered main rice season, and compensated farmers up to 6,944 baht/hectare (about30% of farmers' input costs) should they experience total farm losses from droughts, floods, strong winds, frosts and fires during the cropping cycle. To be eligible for compensation, farmers' paddy fields need to be in the government's declared disaster provinces, and the losses need to be verified by local authorities. About 1.5% of growing areas were insured in 2011. The flood resulted in a loss ratio of as high as 500% for the first year. Reinsurance prices thus inevitably increased more than double making it not market viable for the following years. This program continued in 2012 at the same (highly subsidised) rate but with government now taking the role as an insurer.[25]

The current program thus resumes various inefficiencies and market problems, commonly evidenced in the traditional crop insurance to jeopardise the program's sustainability (Hazell, *et al.* 1986). First, like other conventional insurance, the program would be subjected to moral hazard, e.g., when it induces additional risky off-season rice cropping, etc. Second, high direct subsidisations distorted market prices and thus could reduce sustainability of the market in the longer run. This could further exacerbate incentive problems. Third, this voluntary program is offered at one single premium rate for farmers with different risk profiles. It could potentially signify adverse selection and moral hazard.[26] Fourth, because the government's declaration of disaster areas can be subjective in nature, asymmetric information at the government level could further arise. The highly subjective local verification of losses could potentially induce rent seeking at various levels, further affecting the commercial sustainability of this program. The highly subjective and non-transparent nature of loss measures would no doubt lead to increasing risk pricing in the international market. Finally, the program resumed inefficiencies in time and cost of loss verification in the relief program.

We explore the use of IBRTPs in developing an alternative and potentially more sustainable index-based rice insurance program that could effectively protect rice farmer's production income or input loan from these key covariate production shocks. The goal is also to explore how disaggregated household data and spatiotemporal disaster data sets commonly available in developing countries could be used to design nationwide, scalable contracts that could further permit rigorous analysis of micro-level welfare impacts and cost effective pricing through diversifications and transfers.

Data

Five disaggregated nationwide data sets are used in this study. The first four sets are used to construct objectively measured indices for index insurance design, and the last set represents variations in households' incomes from rice production, and thus is used to establish optimal contract design, basis risk and hedging effectiveness associated with various designed contracts.

First, measures of area-yield indices are drawn from the provincial rice yield data collected annually by the Office of Agricultural Extension at Thailand Ministry of Agriculture and Cooperatives (MoAC). The data are available for all the provinces nationwide from 1981-2010 and were collated from a combination of an annual survey of randomised villages in each province and official records by local agricultural extension offices. They are thus representative at the provincial level. Yield data reflect total yield from all crops harvested each year. To remove time trend potentially resulting from technical change, improvements in varieties, irrigations and other management practices, we de-trend the data using a robust Iterative Reweighted Least Squares Huber M-Estimator[27] to first estimate the time trend. The resulting estimated trended yield is thus obtained as $y_t^{tr} = \hat{a} + \hat{b}t.$ And so the de-trended yield series for each province is thus estimated as $y_t^{detr} = y_t + (T - t)\hat{b}.$

Second, objectively measures of weather indices are drawn from 20×20 kmgridded daily rainfall data obtained from the simulated regional climate model ECHAM4-PRECISE constructed by Southeast Asia System for Analysis, Research and Training (START) as part of their regional climate change projections. These simulated climate data were verified and rescaled to match well with the comparable data from observed weather stations (Chinvanno, 2011). These simulated weather data are available from 1980-2011.[28]

Third, estimated rice yield data were then constructed using an integrated crop-climate model developed by Pannangpetch (2009). High resolution GIS maps of soil types (1999), rice growing areas constructed by LANDSAT 5TM (2001) and ECHAM4-PRECISE weather were first overlaid in order to cluster geographical areas into distinct simulation mapping unit (SMU)[29] representing the smallest homogenous areas, where crop response to weather conditions could be uniform. DSSAT crop model was then used to estimate longitudinal estimated rice yields driven by ECHAM4-PRECISE weather controlling for exogenous time-invariant SMU-specific GIS characteristics and crop management. These estimated yields reflect total yields from one (two) crops harvested in the rainfed (irrigated) SMUs. As the simulated yield variations are driven solely by variations in weather, these data can serve as objectively measured index for IBRTPs.

Fourth, the remote sensing Normalised Difference Vegetation Index (NDVI)[30] data are extracted from Tera MODIS satellite platform every 16 days from 2000-2011 throughout the country at a 500-meter resolution. NDVI data provide indicators of the amount and vigour of vegetation, based on the observed level of photosynthetic activity (Tucker, 2005). The data have been increasingly used for monitoring land use patterns, crop productions and disaster losses worldwide. We use NDVI data in detecting variations in crop cycles across regions. This knowledge is critical in the construction of appropriate weather indices that ally well with different stages of crop growth. Some GIS information characterising production systems that could condition the sensitivity of rice production to shocks and records of annual crop cycles are also obtained from MoAC for cross checking with NDVI data.

Fifth, household-level incomes from rice production data are obtained from multi-year repeated cross-sectional Thai Socio-Economic Survey (SES) surveyed nationwide every 2-3 years from 1998, 2000, 2002, 2004, and 2006 to 2009Thailand's National Statistical Office. Each round, a total of 34,000-36,000 households were randomly sampled from the sampled villages in all provinces (10-25 sampled households per village; 30-50 sampled villages per province). Because no household is sampled more than once during these surveys, our analysis thus can be based on repeated household cross sectional data.[31] Subset of households from the 6 rounds, who reported their socioeconomic status as farm operator and rice farming as the main household enterprise, are used in this study. The subsample size in each round ranges from 2,500-3,100 households with households per province varying from 5 in the non-rice provinces to 150 in the key rice growing provinces. Because there is no direct measure of rice production, we use household's annual[32] income from crop production per hectare as a representation of y_{it}. This annual income measure thus includes income from more than one cropping seasons in irrigated areas. Other household and area characteristics are also extracted from SES data.

All of the GIS variables are first constructed at pixel level before downscaling to provincial level, so that these can all be merged with household-level data. Table1 provides summary statistics of the key variables extracted from these five data sets. Overall, mean de-trended provincial averaged rice yield stands at 2,622 kilograms per hectare with high standard deviation capturing the variations across households and years. Household's averaged income from rice production is at 40,246 baht per hectare per year. This results from cultivating 1-3 crops (with 1.64 crops on average) a year. Total input costs are averaged as high as 49% of income[33] implying that households earn about 20,525 baht as farm profit per hectare per year. Mean rice-growing areas per household is about 1.92 hectares. About 89% of households take out input loan each season. And critically, their accumulated agricultural debt stands at an average of 141% of annual income in any given year. Apart from the lowland majority, 6% of total rice growing areas are upland, 12% is flood prone and 19% locates near river basin.

Table 1: Summary Statistics of Key Variables

Variables	N	Mean	S.D.	Minimum	Maximum
Rice production and rainfall					
Rice growing areas, 1981-2010 - Country (million hectare)	30	9.2	0.2	8.7	9.5
- Province (% total area)	2,240	53%	24%	2%	92%
Annual cumulative rainfall (cm), 1980-2011	2,432	425	124	179	889
Provincial yield (kg/hectare/year), detrended 1981-2010	2,240	2,622	868	710	5,398
Rice farming households					
Household crop production income (baht/hectare/year)	18,216	40,246	31,541	0	98,137
Rice cropping land size (hectare)	18,216	1.92	3.56	0.16	47.00
Number of times cultivated rice per year	18,216	1.64	1.13	1.00	3.00
Number of members working on farm	18,216	2.75	1.24	1.00	6.00
Input and operating cost per cropping season (proportion of income)	18,216	0.49	0.31	0.37	0.89
Household takes out loans for input cost each season = 1	18,216	0.89	0.23	0.00	1.00
Total outstanding agriculture loans (proportion of annual income)	18,216	1.41	6.94	0.00	256.25
Annual Interest rate on 12-month agricultural loan	18,216	0.06	0.03	0.02	0.15
Household size	18,216	3	1	1	6
Head age	18,216	50	14	17	94
Head female = 1	18,216	0.17	0.38	0.00	1.00
Head highest education - primary = 1	18,216	0.85	0.38	0.00	1.00
Head highest education - secondary = 1	18,216	0.05	0.20	0.00	1.00
Head highest education - university = 1	18,216	0.00	0.00	0.00	0.00
Head highest education - vocational = 1	18,216	0.00	0.06	0.00	1.00
Own house = 1	18,216	0.96	0.18	0.00	1.00
Own agricultural land = 1	18,216	0.81	0.42	0.00	1.00
Provincial production characteristics					
Households' farm located in the irrigated areas = 1	77	0.22	0.43	0.00	1.00
Upland areas (% total rice paddy)	77	6%	27%	0%	100%
Flood plain areas (% total rice paddy)	77	12%	47%	0%	100%
River basin areas (% total rice paddy)	77	19%	41%	0%	100%
Indices (% of provincial long-term mean)					
Provincial yield index, 1981-2010	2,240	100%	14%	41%	146%
Estimated yield index, 1980-2011	2,432	100%	24%	57%	146%
Cumulative rainfall index, 1980-2011	2,432	100%	27%	29%	154%
Moving dry spell index, 1980-2011	2,432	100%	35%	38%	165%
Moving excessive rain spell index, 1980-2011	2,432	100%	31%	41%	179%

Index Insurance Designs for Thai Rice Farmers

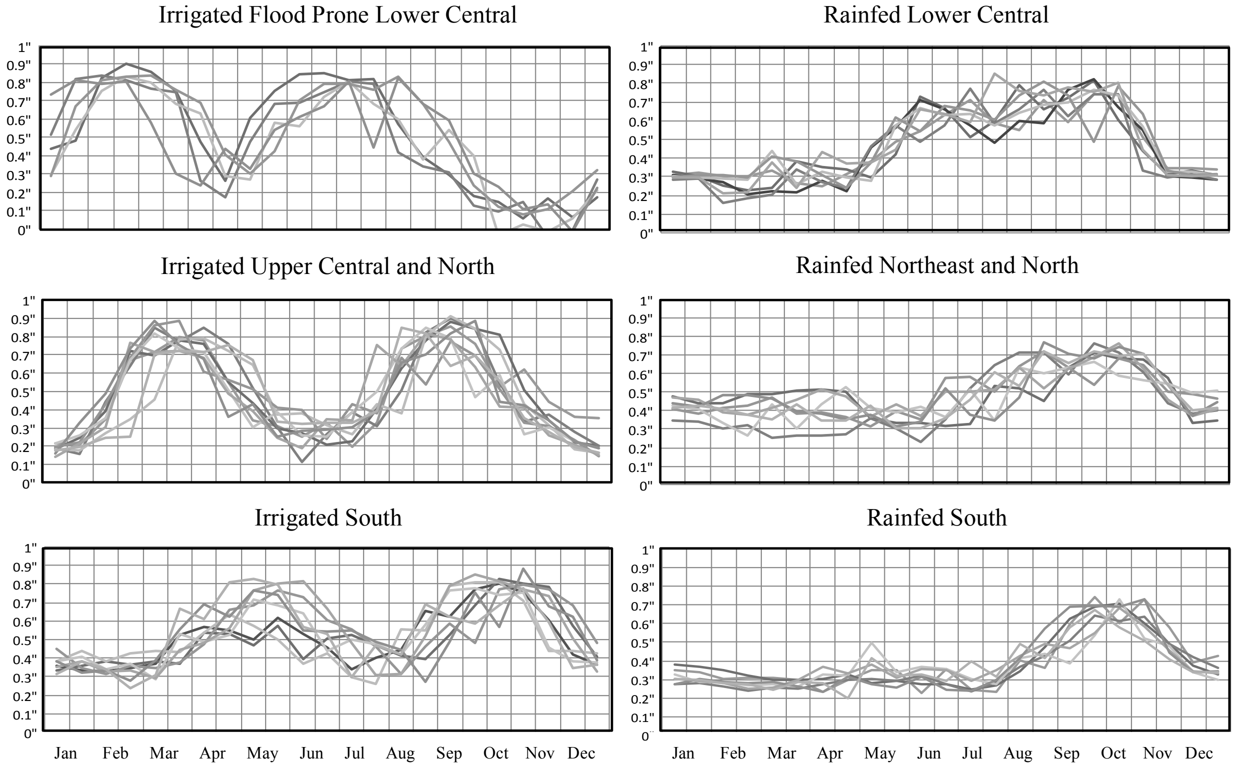
Various spatiotemporal data sets allow us to explore various standard index insurance contracts for Thai rice farmers based on the following constructed indices.

First, direct measures of area yields $\bar{y}_t$ can be constructed from annual provincial yield data. As it offers protection against any covariate risks affecting provincial yield, not just from weather, it could perform well in the case of Thai rice, where pest constitutes one of the key covariate threats. Second, estimated provincial yields $y(w_t)$ can be constructed from the SMU-specific modelled yields. To the extent that the complex crop-climate predictive model performs well in predicting weather-driven yield shocks, this index could provide good hedging effectiveness for farmers. Third, we explore various parametric weather indicesw_t. But because the sensitivity of plants to weather shocks varies across stages of crop growth, knowledge of cropping cycles and how they vary spatially and temporally are thus critical.

Cropping Cycles and Weather Indices

Smoothing [34] the provincial NDVI data in a one-year window results in uni- or bi-modal patterns. Each of these NDVI modes corresponds well with one full 120-day crop cycle. These smoothed provincial NDVI patterns can then be clustered into six distinct zones with homogenous crop cycles presented in Figure 3. Normal starts of the main and second crops in the irrigated areas vary across flood prone lower Central (mid May, December), upper Central and North (July, January) and South (August, March). Normal starts of the main crop in the rainfed areas follow those of the irrigated zones with those of Northern Province sallying well with those of the North. The variations of crop cycles observed objectively from the patterns of NDVI also align well with the MoAC-collected records of cropping patterns in some key provinces.

Figure 3: Contract Zones with Distinct Crop Cycles observed from NDVI



These six distinct zone-specific crop cycles then form a basis for constructing provincial weather indices. For each crop cycle, we extend World Bank (2006)'s crop scientific findings and so explore two provincial dry spell indices covering weather conditions in the first 105 days and a flood index covering those in the 106-120 days of the cycle. These indices are constructed for both main and second crops in the two-crop zones opening a possibility that farmers can obtain insurance protection for both crops. All weather indices are constructed first at pixel level and then averaged toward provincial indices.

First, a simple cumulative rainfall index can be constructed from daily rainfall $R_d$as

$$CR_t = \sum_{d=1}^{105} R_d. \tag{13}$$

The level of CR below some critical strikes thus could reflect the extent of dry spell that could in turn damage rice production. The key advantage of this is its simplicity. Hence this index has been used in various piloted projects including one in the north-eastern province in Thailand.[35] This simple index, however, might not reflect the extent of dry spell well, as it fails to take into account how rainfall is distributed within 105-day period. In particular, high CR could result from couple large daily rains and a long dry spell (that would otherwise damage crop).

Alternatively, a moving dry spell index, which measures the extent that 10-day cumulative rainfall falls below the crop water requirement (30mm for 10-day period) in each and every 10-day dry spell in the 105 cropping days, can be constructed as

$$MD_t = \sum_{\tau=1}^{96} \max\left(30 - \sum_{d=\tau}^{\tau+9} R_d, 0\right). \tag{14}$$

MD above some critical strikes thus could better reflect the extent of dry spell that really matters to rice production. This index has widely been identified to better quantify the extent of dry spells. But because of its relatively more complexity, this index has not been used widely.[36]

Continuous excessive rainfall is the key cause of extended flooding periods in the paddy fields. World Bank (2006) found that the 4-day cumulative rainfall above 250 mm can trigger high probability of extended flood causing losses to harvesting rice crops. We thus quantify flood index using a moving excessive rain spell index to measure the extent that 4-day cumulative rainfall excess 250 mm as

$$ME_t = \sum_{\tau=106}^{117} \max\left(\sum_{d=\tau}^{\tau+3} R_d - 250, 0\right). \tag{15}$$

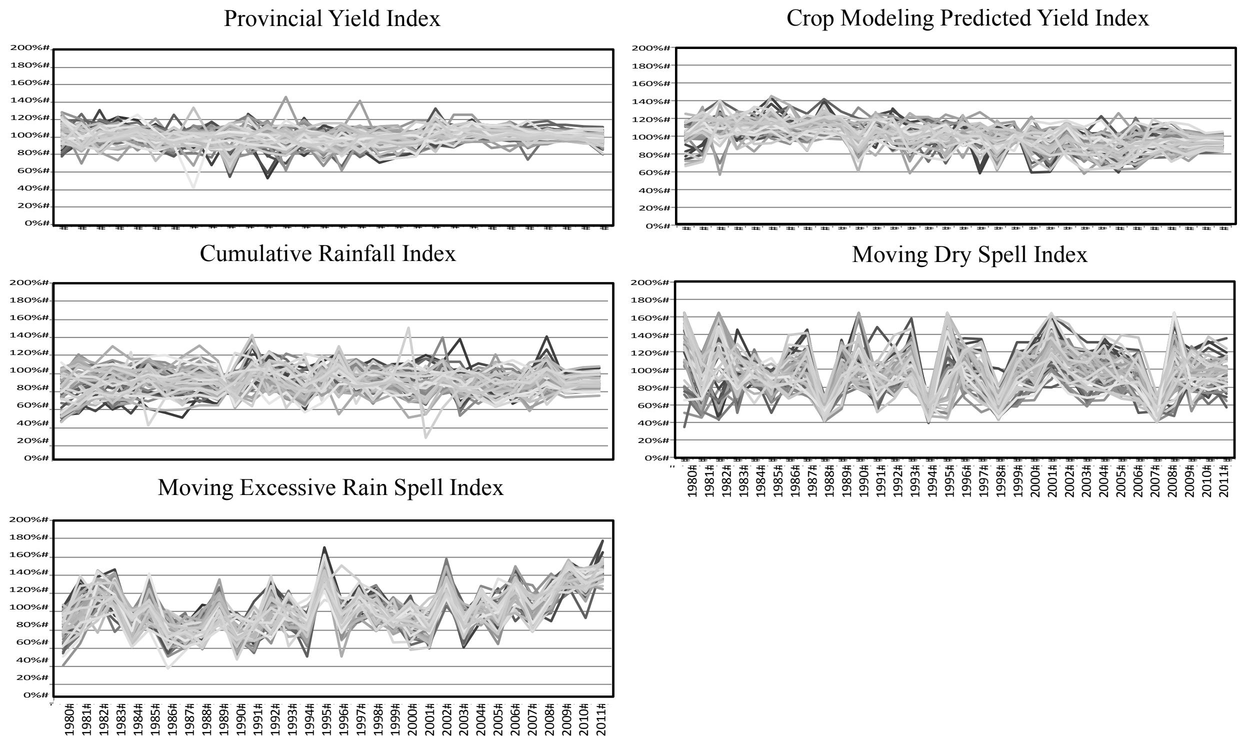
I above some critical strike thus could indicate flood event. But the extent that ME could determine extended flooding period and crop losses should also vary across production systems, which in turn determine soil type, drainage system, crop variety, etc.

The three weather indices so far are constructed based on the assumption that insured cropping cycles in each year and province follow the six smoothed zone-specific patterns. Because famers tend to adjust their production annually in order to adapt to small inter-year variations in rainfall patterns, using fixed crop cycles as a basis for index construction might result in mis-representations of crop losses from drought and flood events. Alternatively, indices can be constructed based on a dynamic crop cycle. Because successful seeding critically requires at least 25 mm of rainfall (World Bank 2006), the first day from the fixed zone-specific starting date when a 1-day, 2-day or 3-day cumulative rainfall exceeding 25 mm can be used to trigger the start of an insured cropping cycle, during when the underlying weather indices will be constructed. Appropriateness of dynamic crop cycle relies on the choice of cycle triggering threshold. We experiment among the three choices above and choose the optimal threshold that yields the highest explanation power of the constructed indices in predicting actual losses.

In order to effectively compare contracts designed with various indices, we standardise these indices into relative percentage forms with respect to their provincial-specific expected value.[37] Specifically, provincial indices can be constructed from $\mathbb{Z}_t = \bar{y}_t, y(w_t), CR_t, MD_t, ME_t$, as $z_t = \mathbb{Z}_t / E_l(\mathbb{Z}_t)$. And so per-hectare payout of a standardised index insurance contract that protects household's insurable resulting from $\mathbb{Z}_t = \bar{y}_t,\ y(w_t),\ CR_t$ falling below their expected values can be rewritten from (3) as $\pi(z_t, z^*) = max\{z^* - \mathbb{Z}_t / E_l(\mathbb{Z}_t), 0\} \times\ \bar{y}$. An insurable $\bar{y}$ represents provincial averaged production income or input cost per hectare to be insured. And the first term on the right-hand side reflects payout rate (in percentage of insurable) with respect to strike level z^* defined in percentage of $E_l(\mathbb{Z}_t)$. The reverse of the payout function above thus contractual payout for a contract that protects household when $\mathbb{Z}_t = MD_t,\ ME_t$ exceed their expected values.

Table 1 provides statistics of these standardised indices. Figure 4 plots the five indices and their spatial distributions across all rice growing provinces.[38] Overall, provincial averaged, estimated yield indices and CR exhibit lower temporal variations relative to weather indices. Their spatial variations, however, are larger than the last two weather indices. MD seems to well capture the key covariate drought events in the country especially in 2008, 2001, 1995 and 1990. ME captures the key flood years well especially the catastrophic floods in 1995 and 2010-11.

Figure 4: Temporal and Spatial Distributions of the Key Indices



Basis Risks and Hedging Effectiveness

How well might these indices explain variations in household's annual crop income per hectare? Household data are merged with these indices at the provincial level in order to estimate (1). Without household panel, we instead use 6-year repeated cross sectional data to estimate, for each index, the following equation[39]

$$lny_{ilt} = X_{ilt}\gamma + D_l\mu + \eta_t + \lambda z_{lt} + \kappa D_l z_{lt} + \varepsilon_{ilt}. \qquad (16)$$

The first three terms capture household's long-term expected income with X_{ilt} absorbing characteristics of households entered in each survey round, D_l absorbing provincial time invariant characteristics especially with respect to rice production systems (e.g., upland, flooded plain, closure to river basin) and η_t absorbing time effect that captures trend in income common across all households. The last three terms reflect stochastic shocks to household income. We also interact D_l with the index in order to capture variations in sensitivity of income to weather shocks across different production systems. The systemic shock thus can be represented by $\beta = \lambda + D_l\kappa$ reflecting the sensitivity of household income to provincial index z_{lt}. The portion of household income unexplained by the index ε_{ilt} thus represents basis risk associated with the index. This equation is estimated separately for irrigated and rainfed regions using simple linear least squared with standard deviations clustered at provincial level.[40]

Table 2 first presents estimation results. Different regressions explore how different indices can explain variations in farm income of the rice growing households controlling for household and provincial characteristics and time effects that determine household's long-term mean income. The first column shows that these controls explain about 40% and 48% of the income variations for households in the irrigated and rainfed areas respectively, implying a maximum of 60% and 52% of income variations that households are still unable to manage using existing mechanisms. Moving from left to right, we can explore how much of these remaining income variations could be explained using different indices. Except CR, all the indices significantly explain income variations though with different significant level. At 1% significant level, the provincial yield index explains an extra 13% and 11% of income variations in the irrigated and rainfed areas. The estimated yield perform relatively worse, explaining an extra 7% and 9%.

Table 2: Estimation of Farm Income of Rice Growing Households

	No Index	**Yield index**		**Weather index - Fixed Cycles**				**Weather index - Dynamic Cycles**			
		Yt	Y(wt)	CR	MD	ME	MD+ME	CR	MD	ME	MD+ME
Irrigated Areas											
Index 1		4.67***	3.63*	2.43	-3.39*	-4.17**	-2.11*	2.54*	-3.22*	-4.02**	-2.87*
		(1.19)	(2.79)	(2.85)	(2.17)	(2.35)	(1.51)	(2.23)	(2.29)	(2.54)	(1.88)
Index 2							-4.01**				-3.89**
							(2.23)				(2.26)
HH, area and time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.38	0.51	0.45	0.44	0.46	0.48	0.52	0.46	0.45	0.46	0.49
Observations	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009	4,009
Rainfed Areas											
Index 1		3.91***	2.81*	2.98*	-6.17**	-4.29**	-5.89**	3.12**	-6.19**	-4.32**	-5.91**
		(1.22)	(2.07)	(2.19)	(3.54)	(2.89)	(2.98)	(2.01)	(3.27)	(2.59)	(3.24)
Index 2							-3.92**				-4.23**
							(2.51)				(2.69)
HH, area and time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.45	0.56	0.54	0.53	0.58	0.55	0.67	0.54	0.59	0.55	0.67
Observations	14,206	14,206	14,206	14,206	14,206	14,206	14,206	14,206	14,206	14,206	14,206

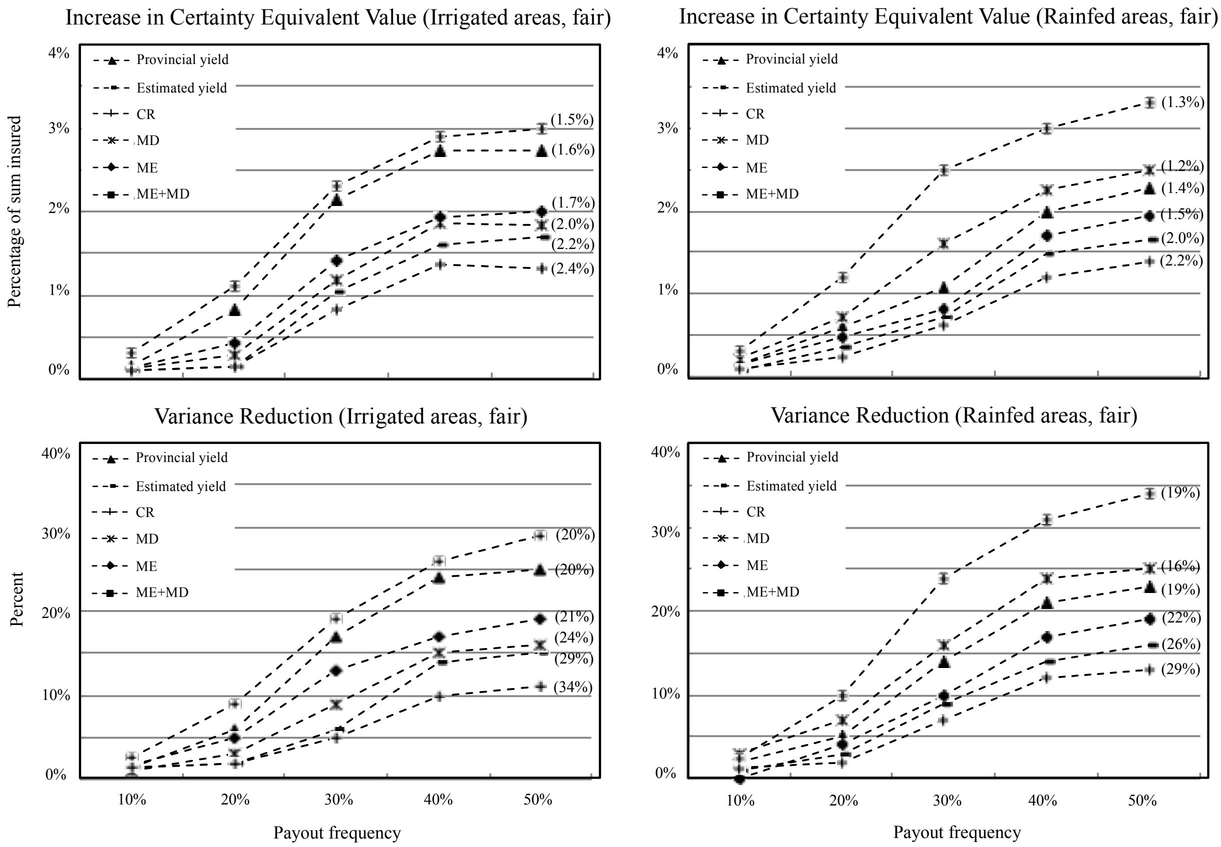
Note: Coefficients represent net effect of provincial index $\beta = \lambda + D_K$. Standard errors in parentheses. * significant at 10%, ** at 5% and *** at 1% respectively. Household controls include household size, head age, gender and education, whether household owns land, land size, whether household owns house, number of member working on farm. Provincial control includes upland, flood plain and river basin areas. Time effects are captured by year dummies. Standard errors are clustered at provincial level. The best results for dynamic cycles use the first day in the fixed cycle when the 2-day cumulative rainfall reaches 25 mm as trigger starting point.

Among weather indices constructed based on the fixed 6-zone crop cycles, CR performs the worst among all albeit its relative advantage in simplicity. While explaining only 8% of income in the irrigated areas, MD significantly explain up to 13% of the income variations in the rainfed areas, where cropping rely extensively on rainfall. ME explains only about 10% of income variations in both areas. This raises question if it could serve as appropriate index for insuring flood losses in these areas. Combining MD and ME, we found that the two-peril index combination outperform others and explain 14% and up to 19% of income variations in irrigated and rainfed areas respectively. Despite the added complexity, using dynamic crop cycles in determining index coverage does not add substantial improvement (if at all) to the explanation powers of the constructed weather indices.[41] Overall, the two-peril index combination MD+ME based on fixed zone-specific crop cycle thus strikes us as the potential basis risk-minimising underlying index for Thai rice contract.

How might hedging effectiveness of the optimal contracts based on these indices vary given the observed variations in household-level basis risks? The 6-year household data are limited in temporal variations, and so might under-representthe incidence of extreme events. Using the established relationship and distributions of household-level basis risk estimated in (16), we thus expand our data temporally and spatially by simulating 32-year income dynamics of representative households based on 32-year index data. In specific, for each year t from 1980-2011, 1,000 idiosyncratic shocks are randomly drawn for each province l from the province-specific empirical distributions $f(\varepsilon_{ilt})$ estimated using bootstrapping. Using the 32-year index data, provincial averaged household characteristics and provincial characteristics along with the estimated coefficients in (16), we then simulate 32-year income dynamics of 1,000 households in each province l from 1980-2011. Households' optimal coverage scales for various contracts and strike levels can then be estimated according to (7).[42] These then allow us to compute household-specific certainty equivalent values of consumption with and without various insurance contracts.

Figure 5 presents our results from 32-year income dynamics of 76,000 simulated households with assumed risk aversion $\theta = 3$ and actuarially fair contract prices. The two top panels compare averaged utility-based hedging effectiveness in term of increasing certainty equivalent values gained from obtaining insurance contract relative to no contract.[43] The bottom two compare effectiveness based on simple variance reduction. Contracts are compared at the same level of payout frequency thus controlling for the same level of risk coverage and cost despite varying underlying risk distributions across indices and provinces.[44] Overall, both measures of hedging effectiveness of these actuarial fair priced contracts increase at a decreasing rate as payout frequency increases. Hedging effectiveness is very minimal for contracts with low payout frequency, e.g., of less than once every five years. This is due to the nature of systemic shocks on rice production, which tend to be less extreme but occur quite often. Variations of hedging effectiveness across households are high and vary across indices.

Figure 5: Comparison of Hedging Effectiveness across Optimal Contracts



Note: Plots are averaged across 76,000 simulated households with CARA = 3. Average standard deviations around the estimated series in parentheses.

The optimal contracts with MD+ME index exhibit the highest hedging effectivenessin both measures. The provincial yield index, which was originally perceived to provide larger coverage for non-weather location systemic shock, performs almost as good as MD+ME in the irrigated zones but worse in the rainfed zones. The simplest contracts based on CR perform the worst in all cases. On average, the optimal MD+ME contractscovering 1-in-3year losses could result in 2.3% and 2.5% increase in households' average certainty equivalent valuesin irrigated and rainfed areas respectively. This could imply that the rates that households are willing to pay for the contracts on top of the fair rates. and up to 20%

and 25% reduction in consumption variance in irrigated and rainfed areas respectively. This could imply The MD+ME contract also appears with the lowest variations in contract performance across households. These results are also robust with respect to other underlying risk aversion and premium loading assumptions.

Optimal Contract Designs

The two-peril MD+ME contract is thus chosen as appropriate basis risk minimising contracts for Thai rice production in this study. For each cropping season, MD index is constructed for the first 105 days and ME index for the 105-120 days of the cycle. The fixed period of insurable crop cycle for each province is drawn fromthe zone-specific patterns. A seasonal contract payout per insured hectare is thus a combination of payouts from the two indices optimally scaled with $\alpha^*_{MD}$and α^*_{ME} estimated using the risk profiles of 76,000 simulated households. The top panel of Table 3 reports mean provincial scales, actuarial fair premium rates[45] and probable maximum lossesby zones and strike levelsfor seasonal contracts available for the main crop.

Table 3: Optimal Seasonal Contracts and Actuarial Fair Rates

	Strike = 110% (Avg. payout freq. = 50%)				**Strike = 120%** (Avg. payout freq. = 30%)				**Strike = 130%** (Avg. payout freq. = 20%)			
Zone	α*(MD)	α*(ME)	Fair rate	PML	α*(MD)	α*(ME)	Fair rate	PML	α*(MD)	α*(ME)	Fair rate	PML
	Contracts available for main crop only											
Irrigated Lower Central	0.7	0.8	16%	68%	0.8	0.9	9%	56%	0.8	0.9	5%	38%
Irrigated Upper Central-North	0.6	0.8	16%	65%	0.7	0.8	8%	52%	0.7	0.8	4%	35%
Irrigated South	0.8	0.9	14%	59%	0.8	1.0	7%	49%	0.8	1.0	3%	32%
Rainfed Lower Central	1.1	0.9	15%	57%	1.1	0.9	7%	46%	1.1	0.9	3%	27%
Rainfed Northeast-North	1.1	0.9	12%	48%	1.1	0.9	6%	37%	1.1	0.9	2%	23%
Rainfed South	1.0	1.0	12%	46%	1.0	1.0	6%	32%	1.0	1.0	2%	19%
Nationwide	**0.9**	**0.9**	**14%**	**59%**	**1.0**	**1.0**	**7%**	**47%**	**1.0**	**1.0**	**3%**	**29%**
	Contracts available for both main and second crops											
Irrigated Lower Central	0.7	0.8	15%	64%	0.8	0.9	8%	53%	0.8	0.9	4%	33%
Irrigated Upper Central-North	0.6	0.8	14%	61%	0.7	0.8	7%	49%	0.7	0.8	3%	31%
Irrigated South	0.8	0.9	13%	57%	0.8	1.0	6%	48%	0.8	1.0	2%	28%
Rainfed Lower Central	1.1	0.9	14%	57%	1.1	0.9	7%	46%	1.1	0.9	3%	27%
Rainfed Northeast-North	1.1	0.9	12%	48%	1.1	0.9	6%	37%	1.1	0.9	2%	23%
Rainfed South	1.0	1.0	12%	46%	1.0	1.0	6%	32%	1.0	1.0	2%	19%
Nationwide	**0.9**	**0.9**	**12%**	**55%**	**1.0**	**1.0**	**6%**	**43%**	**1.0**	**1.0**	**2%**	**27%**

Note: Payout frequencies are for both perils from MD+ME. Optimal scales are estimated at fair rates using annual data. Hence, they are similar for both contracts. Optimal scales, fair rates are averaged across provincial rates. PMLs are maximum provincial values. Prices are based on 1980-2011 historical burn rates. Price estimates from Monte Carlo simulations are comparable so omitted. The nationwide scales is averaged provincial scales weighted by shares of growing areas.

Overall, the optimal coverage scales for the rainfed zones are larger than those of irrigated zones due to their larger income sensitivities to these indices, especially the MD index. Actuarial fair rates are, however, larger at all strike levels for the irrigated zones, especially the irrigated flood prone lower central zone,due to largerindex variations. Mean provincial fair premium rates vary from 12-16% for 1-in-2 year coverage to 6-9% for 1-in-3 year coverage to 2-5% for 1-in-5 year coverage. The variations of mean provincial premium rates across zones also imply spatial variations of the exposures to floods and droughts. The extent of catastrophic risks of the provincial contracts can be shown by estimated MPLs at $VaR_{99\%}$. The PMLs range from as high as 68% of total sum insured for 1-in-2 year coverage to 56% for 1-in-3 year coverage.

Portfolio Pricing and Potentials for Risk Diversifications

Making the seasonal contracts available for both main and second crops in the irrigated areas could further allow for temporal risk pooling across seasons within a year. The bottom panel of Table 3 reflects these results. While the optimal coverage choices remain the same (as they are established from an annual model (16)), the fair rates and PMLs reduce slightly for the seasonal contracts available for both crops in the three 2-crop zones. A nationwide portfolio of provincial contracts is then constructed with provincial weights established from combining provincial optimal scales and provincial share of rice growing area. The bottom row in each panel of Table 3 reflects the spatial risk pooling benefits. Catastrophic layers of the insurable risk of the nationwide portfolio reduce for all strikes relative to those of the individual provincial contracts.

These resulting spatial and temporal risk-pooling benefits can be explained in Table 4. In the top panel, the estimated pairwise correlations of the zone portfolios could be as low as -0.12 between the rainfed northeastern and irrigated southern regions. In the middle panel, the estimated pairwise correlations of the main crop portfolio and the second crop portfolio could also be as low as -0.07 in the irrigated southern region. As in (9), pricing provincial contracts as part of a diversifying portfolio could thus result in lower rates through lower catastrophic loads.

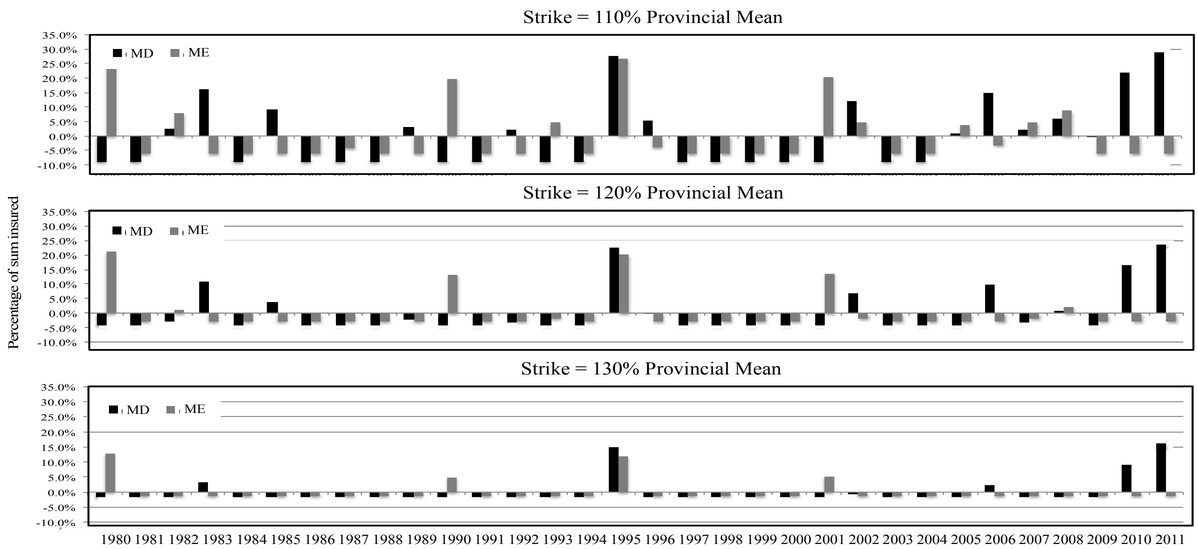
Table 4: Diversification Potentials of Nationwide Index Insurance Portfolio

	Geographical Diversifications					
Contract Zones	1	2	3	4	5	6
1. Irrigated Lower Central	1.00					
2. Irrigated Upper Central-North	0.56	1.00				
3. Irrigated South	0.42	0.18	1.00			
4. Rainfed Lower Central	0.78	0.57	0.21	1.00		
5. Rainfed Northeast-North	0.48	0.44	-0.12	0.86	1.00	
6. Rainfed South	0.62	0.21	0.74	0.72	0.41	1.00
	Temporal Diversifications					
Seasonal crop coverage	1	2	3	4	5	6
Second crop	0.23	0.11	-0.07			
	Diversifications with Tradables					
Tradables	Coeff.	Std.Err.	Adj. R2	N		
Thai Stock Exchange Index (SET)	4.60	3.60	0.07	32		
NASDAQ	47.90	58.80	0.04	32		
Corporate bond AAA	-503.50	486.86	0.02	32		
Food price index	138.87	52.26	0.16	32		
Rice future	512.10	250.76	0.01	16		
CDD, Florida, U.S.	-14.7*	5.40	0.22	28		
CDD, Calgary, Canada	-11.6***	2.90	0.31	28		
CDD, Madrid, Spain	-9.6**	1.73	0.14	28		
HDD, Melbourne, Australia	-17.3**	5.90	0.24	24		

Note: Relationships are estimated from portfolio ne payout at 110% strike. All high frequency tradable returns are converted to annual unit by averaging returns within year. Commodity price indices, futures, weather and other CaTindices are obtained from Chicago Merchantile Exchange (CME).

Figure 6 plots the net payout (payout net fair premium rates as percentage of total sum insured) of the nationwide portfolio of index insurance contracts available for both crops at various strike levels. How might the annual portfolio payouts co-move with annual returns of various tradables in capital, commodity, future and weather markets? Table 4 reports these results. We found no significant pair-wise relationship between the portfolio of Thai rice insurance and the key market indices, e.g., Thai Stock Index (SET), NASDAQ, and securities in commodity or future markets. Our key results are the significant and negative relationships between the portfolio and various actively traded weather indices from around the world. While these results are based on low frequency (aggregated annually) data, they could signal potential diversifying values of Thai rice insurance portfolio in the portfolio of global weather risks.

Figure 6: Nationwide Index Insurance Portfolio's Net Payouts



Risk Financing and Transfer

Figure 6 shows that the net payout position of risk aggregators, e.g., local insurers, appears with great exposures especially during the key catastrophic years. For example, the occurrence of both catastrophic drought and flood in 1995 result in net payoutsof as high as 43% of total sum insured for contracts with 1-in-3 year coverage (120% strike). This signals the importance of international market risk transfers in ensuring the sustainability of the program.

Table 5 reports actuarial fair premium rates and the associated PMLsof various stop-loss reinsurance contracts. Because the underlying risks are not as catastrophic as that of earthquakes, etc., with reasonable PMLs of about 49% sum insured, we assume an optimistic case, where the potential market rates for these reinsurance contracts are established with an additional catastrophic load at 3% of the estimated PMLs. This could reflect the potential costs of capital for reinsurer in holding necessary reserve or obtaining other risk financing instruments. At these potential market rates, we then illustrate some designs of a zero-coupon cat bond with principle payments linked with 100% stop-loss reinsurance contracts for the nationwide portfolios.

Table 5: Actuarial Fair Stop-Loss Reinsurance

	Stop Loss Level (% of Pure Premium)					
	100%		105%		110%	
Strike	Mean	PML	Mean	PML	Mean	PML
110%	6%	49%	5%	43%	5%	41%
120%	3%	39%	4%	35%	3%	31%
130%	1%	25%	2%	23%	2%	20%

Note: Nationwide seasonal contracts available for both main and second crops. Prices are based on historical burn rates estimated from 1980-2011 distributions

Table 6 reports cat bond prices for various specifications of requiredrate of returns for investor, a cap (% of principle) that limit investor's principle loss if reinsurance contract triggers payouts and strike levels ofnationwide insurance portfolio for the linked 100% stop-loss reinsurance contracts. Cat bond with 100% cap is thus riskier comparing to that with 50% cap since an investor would be exposed to losing all of his/her principle should the catastrophic events triggered reinsurance payout. The required rates of return are set at 4%, 6% and 10% translating into risk premiums between 2.93-8.93% at the current LIBOR rate of about 1.07% [46] Comparing with other existing cat bonds (with relatively more catastrophic underlying risks) and the Mexican cat bond with as low as 2.35% premium above LIBOR, it seems this chosen range of risk premiums is sufficiently representative of spreads required by investors in the market (Froot 1999). We note that the total return realised by investors when the bond is not triggered is always higher than the required return used in computing bond prices. The difference between the two presents the added premium associated with the catastrophic risk.[47] The bond prices thus decrease (hence the bond yields increase) with riskiness of the underlying reinsurance contract, the cap value and the required rates of return.

These results are, however, only for illustration of how Thailand's nationwide rice insurance portfolio might be securitised and transferred to international capital market. The actual potential of cat bond will also rely on the costs associated with securitising the contract relative to other means. The key feature that deviates this cat bond from others is its coverage of less extreme shocks relative to other earthquake- or hurricane-linked products in the market.

Table 6: CAT Bond Linked with Stop-Loss Reinsurance

Required Returm	Capped (%) Principle Losses	100% Stop-Loss Reinsurance on Nationwide Portfolio 110%	120%	130%
4%	100%	0.8412	0.8729	0.8898
	50%	0.8823	0.8942	0.9064
6%	100%	0.8276	0.8511	0.8688
	50%	0.8667	0.8818	0.8997
10%	100%	0.8096	0.8212	0.8389
	50%	0.8532	0.8734	0.8935

Note: Bond prices are calculated assuming market rates of stop-loss reinsurance = fair rates + 3% PML

How Might this Nationwide RiceIndex Insurance Program Work?

Our results so far imply that (i) the basis risk minimising contract with two-peril MD+ME index could provide up to 35% reduction in the insured's consumption variance, (ii) households are willing to pay between 2-4% of total sum insured on top of the fair rates for contracts with 1-in-2 year to 1-in-3 year payout frequency, (iii) it could be cost effective to price provincial seasonal contracts as part of a pooled nationwide portfolio and (iv) opportunities could exist in transferring portfolio risks to international markets through some forms of illustrated reinsurance and securitisation. We now illustrate the potential market rates, how the designed program and public support can be integrated in the risk financing in order to enhance market viability, and more importantly, how the programcould benefit farmers, agricultural lenders and government.

Table 7 reports potential market rates for the provincial contracts priced as part of the nationwide portfolio under various market arrangements. With a working assumption that the additive catastrophic load for a contract equals to the market rate for 100% stop-loss reinsurance coverage for that contract, our pricing results in an additional 50% mark up from the fair rates.[48] Ascatastrophic loads drive high mark-up rates, insurable risk can then be layered so that complementary public financing of tailed risk beyond some cappedindemnity payouts from insurers could result in reduction of market rates. As shown in Table 7, when insurer's payouts are capped at 30% of total sum insured, market rates for the 1-in-2 year and 1-in-3 year contracts reduce dramatically to their fair rates (and even below their fair rates for a cap of20%).[49]

Table 7: Potential Market Pricings and Arrangements for Nationwide Index Insurance

		Market Arrangements							
		Potential Market Rates		With Public Financing of Tailed Risk beyond Capped Payout at 20%		30%		40%	
Strike	Payout freq.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
110%	50%	17.8%	(4.6%)	11.9%	(3.1%)	14.3%	(3.3%)	16.9%	(3.7%)
120%	30%	8.8%	(3.7%)	**4.2%**	**(2.3%)**	**6.4%**	**(3.1%)**	8.8%	(3.7%)
130%	20%	**3.1%**	**(2.1%)**	3.1%	(2.1%)	3.1%	(2.1%)	**3.1%**	**(2.1%)**
		Increase in certainty equivalent value, $CE^{insured}$ - $CE^{uninsured}$(% sum insured per season)							
Low risk aversion (θ=1)		0.1%		3.6%		1.4%		0.1%	
Med. risk aversion (θ=3)		0.2%		4.2%		2.0%		0.2%	
High risk aversion (θ=5)		0.4%		4.9%		2.7%		0.4%	
		Simulated impacts of insurance on households, agricultural loans and government (θ=3)							
Net income for consumption		24,275		33,052		31,278		24,275	
(No I = 25,314 baht/year)		(28,978)		(24,464)		(26,464)		(28,978)	
5-yr loan outstanding		39%		0%		9%		39%	
(No I = 90% 1-yr income)		(57%)		(0%)		(17%)		(57%)	
Input loan default rate		21%		0%		8%		21%	
(No I = 47% per year)		(12%)		(0%)		(4%)		(12%)	
Government spending		0		843		297		0	
(No I = 0 million baht)		(0)		(3,249)		(1,580)		(0)	

Note: The potential market rates = fair rates + market rates for 100% stop-loss reinsurance. Reinsurance market rates = fair rates + 3% PML. Payouts are capped as % of total sum insured. Those in bold are welfare maximising contract strike for each market arrangement. CE and impacts of insurance are for the welfare maximising coverage. Results vary across provinces. Mean reported with standard deviations in parentheses.

Based on 32-year income dynamics of 76,000 simulated households, welfare maximising contract strike levelunder each market arrangement is then marked in bold in Table 7. The associated increases in certainty equivalent consumption are also reported for farmers with low, medium and high levels of risk aversion. The 1-in-5 year contract appears optimal under fully market-based index insurance program. But with low risk coverage, its utility-based hedging effectiveness is low but still positive, implying that on average households are willing to buy this contract at the market rate and contribute up to 0.4% of total sum insured on top of the current rate. With government financing indemnity payouts beyond 20-30% caps, the welfare maximising strike shifts to 1-in-3 year contract. These market arrangements also result in larger hedging effectiveness through lower insurance prices and larger resulting optimal risk coverage.

Which market arrangement is appropriate for this nationwide index insurance program? We explore this further by simulating the potentialimpacts on farmers, agricultural loan portfolios and government of these market arrangements for the nationwide index insurance program, as well as theexisting program. To do so, several assumptions are made. First, we assume that all 76,000 simulated farmers areclienteles of BAAC. Each year, they take out a loan to finance total input cost and to obtain insurance coverage for income from all cultivated rice crops (one or two). Total production income is then used to pay back the loan. From SES data, total input cost is assumed to be49% of averaged provincial crop production income, which also vary across provinces. Household is assumed to pay back their loan as much as is feasible – the maximum repayment is reached when net income available for consumption drop to zero.

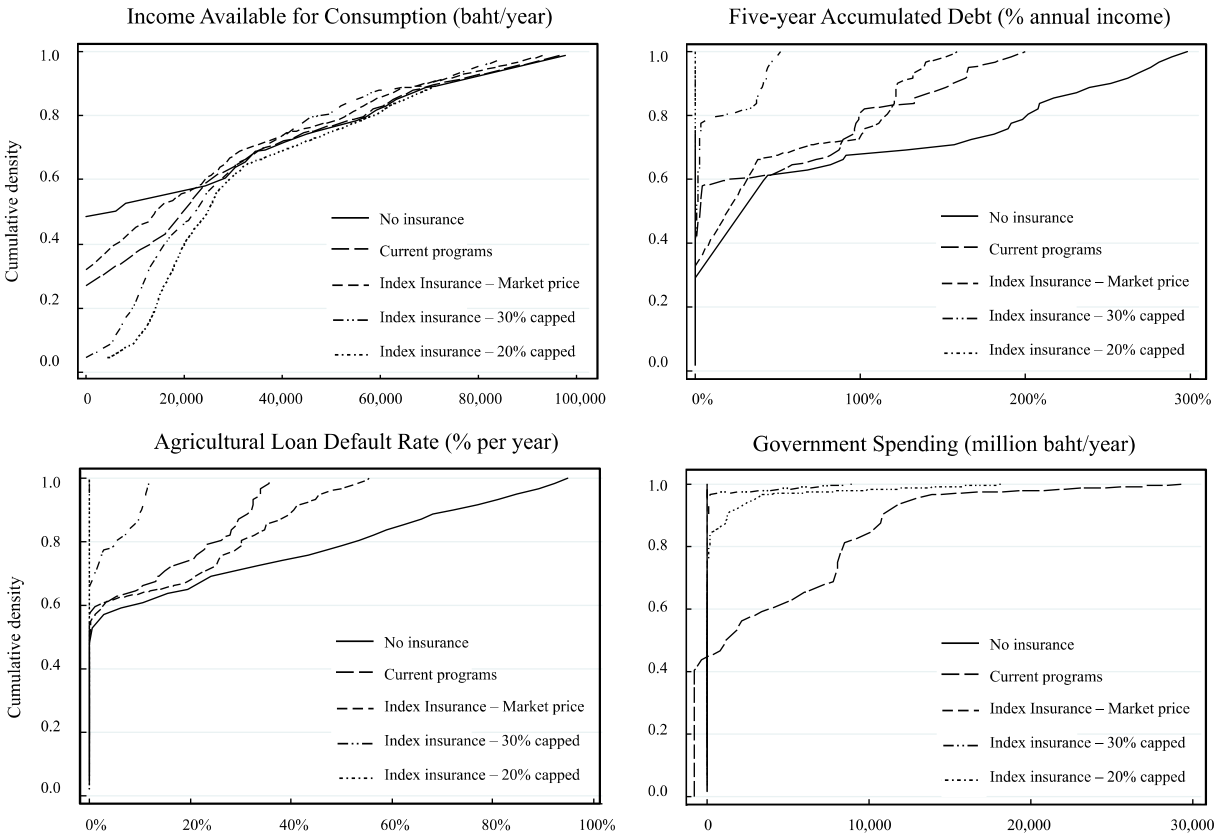
With these assumptions, household's production income available for consumption per hectare per year thus reflects totalincome after receiving insurance payout and netting out all the accumulated loans outstanding up to that year:

$$c_{it} = \max\,(0, y_{it} + \alpha^{*}\pi(z_t, z^{*}) - \sum_{\tau=1}^{t}(1+r)^{t-\tau+1}L_{\tau}) \tag{17}$$

where insurance payout reflects summation of the two potential payouts for each index$\pi(z_t, z^*) = max\{\mathbb{Z}_t/E_l(\mathbb{Z}_t) - z^*, 0\} \times \bar{y}$with$\mathbb{Z}_t = MD_t, ME_t$ and $\bar{y}$ is the provincial averaged production income per hectare. The optimal coverage scale$\alpha^* = (\alpha^*_{MD}, \alpha^*_{ME})$. The nominal interest rate$r$ is at 6.75% per year. Total loan taken per hectare$L_t = 49\%\bar{y} + \delta E\pi(z_t, z^*)$. From SES data, we assume that household cultivates 1.92 hectare of rice paddy each year.

Based on 32-year dynamic data of 76,000 simulated households, Figure 7 plots cumulative densities of income available for household consumption, five-year accumulated debt position realised at any given year, BAAC'sannual loan default rates and annual government spending [50] under various schemes. The bottom panel of Table 7 also reports means and SDs of these impacts. With no disaster insurance market andgovernment support, there is about 50% probabilities that income available for consumption of Thai rice farming households could collapse to zero. Household's five-year accumulated debt realised in any given year is almost always positive with an average of 90% of annual production income. This outstanding debt could be as high as 300% of averaged annual income in any given year. And BAAC's loan default rate is estimated at 47% per year on average. The existing program with a combination of government's disaster relief and subsidised insurance[51] results in favourable distributional impacts that almost always first order stochastically dominate those of the baseline. The key drawback, however, is the tremendous government budget exposure, which stands at an average of 8,890 million baht per year, and could reach 29,930 million baht in some key years.

Figure 7: Simulated Impacts of Various Nationwide Index Insurance Arrangements



Note: Cumulative densities based on 32-year dynamic data of 76,000 simulated households in 76 provinces nationwide

The market driven index insurance program without government support could also result in dramatically improvement in distributional impacts relative to the baseline case ofno market and government support. The probabilities of zero income available for consumption, the averaged long-term debt accumulation and BAAC'sloan default rates reduce by half and also with great reduction in variations. These distributional impacts are, however, relatively smaller on average but not necessarily first order stochastically dominated by those of the existing program. This is because, on the one hand, farmers pay higher market prices for market-based index insurance product that covers smaller sets of disasters relative to the existing product. On the other hand, compensations from index insurance (based on provincial averaged income)tend to be larger than those of the existing program (based on 30% of input cost) when the contract is triggered. With comparable impacts but no cost to the government, this purely market driven index insurance product could be appealing as one of the risk management tools for Thai rice farmers.

These distributional impacts further improve substantially for the index insurance program withintegrated public financing of tailed riskbeyond insurer's payout caps. At 30% (20%) payout cap, the resulting lower insurance prices and larger optimal risk coverage lead to more than 80% (almost 100%) reduction in probabilities of zero income available for consumption, long-term accumulated debt and BAAC's loan default ratesrelative to the baseline. The required public financing of these tailed risks are also substantially smaller in means and variations comparing to those required in the existing program. A case for public financing of tailed risk for Thailand's nationwide index insurance program thus could be strong. First, these public-private market arrangements are no doubt superior in both potential impacts on households and BAAC loan and on government's budget exposure relative to the existing program. And second, their distributional impacts are substantially larger than those under purely market-driven program.

4. Conclusions and Implications for the Rest of Asia

This paper laid out why index based risk transfer products could be attractive as a means to address important insurance market imperfections that have precluded the emergence and sustainability of formal insurance marketsin developing countries. It then provides analytical framework for designing and evaluating optimal index insurance contracts using disaggregated data, and for analysing the potentials for these insurable risk to be diversified, transferred and financed in order to enhance sustainability of the program. It then illustrates how disaggregated and spatiotemporal rich sets of household and disaster data, commonly available in developing countries, could be used to design and analyse nationwide, scalable disaster index insurance program for rice farmers in Thailand.

Relative to the direct measures of provincial yield andthe estimated yield based on climate-crop modelling, we found that objectively measured weather data could be carefully constructed as basis risk minimising indices for index insurance contract. Objectively measured remote sensing data also proved to be useful in controlling for heterogeneous cropping patterns across larger geographical areas nationwide. The transparency of these weather indices and control measures along with their spatiotemporal availability could hold further advantages in scaling up contract designs to wider settings.

Using household level data in estimating basis risk and so in simulating contracts' hedging effectiveness, we found the resulting contract performance, optimal contract scales and pricings to vary largely across provinces and households. Contract designed at the provincial level – the most micro level given our representative data – was thus considered. Overall, the optimal provincial contract based on basis risk minimising combination of moving dry spell and moving excessive rain spell indices could result in up to 25% reduction in the variations of household's income available for consumption. Simple cumulative rainfall, widely used in marketable contracts worldwide, however, appeared with the lowest performance. This raised concerns on the extent of basis risk associated with currently available contracts.

We found evidence of temporal and spatial diversification benefits, as we scaled insurance portfolio to cover all provinces nationwide and to cover the second crop grown among farmers in the irrigated areas each year. Thus return to scale in term of cost effective portfolio pricing can thus be achieved as part of nationwide, multi-seasonal coverage insurance program. Spatiotemporal availability of weather data further allowed us to show using simple correlation exercise that nationwide index insurance portfolio of Thai rice could be diversifiable with other weather indices worldwide in the global portfolios. This could imply, on the one hand, that local risk aggregators could diversify their portfolio risk with appropriate hedging portfolio of global weather indices. On the other hand, tradable security linked with Thai nationwide insurance portfolio, e.g., cat bond, could be appealing in the international market as diversifiable security in various diversifying global portfolios.

The transparency of these weather indices and control measures in fact could further promote the possibility of cost effective risk transfers in the international market. We thus designed the corresponding reinsurance contracts and cat bonds, and illustrated their potentials and how these might be useful as risk transfer instruments. The key distinction of our cat bonds from others is the coverage of relatively higher frequency but lower impact losses from floods and droughts, comparing to other earthquake- or hurricane-linked products. Skees, *et al*. (2008) also discussed the potentials of micro-cat bond in transferring covariate but less extreme risks out of developing countries.

Bringing all the results together, we asked what might appropriate market arrangement be to ensure sustainable implementation of this nationwide insurance program? Using disaggregated spatiotemporal rich data, we simulated the potential impacts on household welfare, agricultural loan portfolio and government of this nationwide program under various market arrangements relative to the current program. The purely market driven program was found to result in more than 50% reductions in probabilities that household consumption collapsing to zero, in means and variations of five-year accumulated debt and BAAC's annual loan default rates. As these impacts are comparable to those of the current program, albeit no budget exposure to the government, the market-driven program thus already proved as one of the effective disaster risk management tools for the setting. Properly layering insurable nationwide risk, we further found public financing of tailed risk beyond the 20-30% capped to insurer's payout rates to result in substantial reduction in market premium rates. These in turn resulted in up to twice the impacts of the purely market-driven program, though with substantial smaller budget exposures to the government relative to the current government program. There could thus be a strong case for public financing of tailed risk in enhancing development values and market viability of Thailand's nationwide index insurance program.

How might this nationwide insurance program be implemented? An insurance indemnity pool of the nationwide index insurance contract could be created to allow local insurers to diversify their risks and contribute capital to the reserve pool, from where indemnity payments can be drawn. Reinsurance could potentially be acquired when indemnity payments exceed the pool but for the risk up to some appropriate capped level. Government could then finance the low frequency but catastrophic tailed risk through various options, e.g., offering complementary disaster insurance coverage for this tailed risk, providing the insurers direct coverage or financing of the transfers of this tailed risk. Government could also maintain some necessary reserve and use some forms of IBRTPs to hedge their exposures in the international market.

The design and market arrangement of this nationwide index insurance for Thai rice farmers thus deviate largely from the current program. First, unlike direct premium subsidisation, public financing of the tailed risk does not distort market prices. The capped commercialized contracts are still sold at their market rates and the rates differ across provinces with different risk profiles. This prevents the potential adverse selection problem, likely to occur under the current scheme with one price for all. Second, the public financing of the tailed risk provides complementary, rather than substituting, coverage. This thus would not crowd out private demand for insurance, especially for the risk layer that should appropriately be absorbed by the households and market. Third, the government's budget exposure to financing of the tailed risk could be insured through some forms of IBRTPs. This, in turn, could enhance sustainability of the program. And more importantly, the key advantages of these index insurance design relative to the current loss-based insurance program are (i) relatively lower transaction cost, especially in loss verifications, (ii) relatively lower adverse selection and moral hazard, (iii) the contract still preserves insured household's incentive to take good care of their farms and so to adjust their cropping patterns to avoid risk since the indemnity is regardless of their actions and (iv) contract could potentially make timely payout as verification of these indices are in near real time.

Various limitations of the current study are worth noting with the goal to stimulate future required research ideas. First, our analyses are based on simulated rainfall data, not the actual data observed at various stations. Despite its relative advantage in the relatively richer spatial distribution, simulated data need to be verified with actual weather experienced at the micro level. Efforts are also underway in many developing countries, including Thailand, in constructing appropriate gridded data from observed station data in order to improve spatial distribution of the station data. Second, the current analysis mapped the relatively higher spatial resolution weather data with household data at provincial level, due to the lack of sub-district locators in the SES data. Efforts should be made in matching weather or disaster variables at the most micro level possible. Third, various spatiotemporal available remote sensing products, could have high potential in improving the measures and performance of the underlying indices. Efforts are underway in using these products to detect inter and intra year variations of rice growing areas, stage of crop growth, paddy losses and the extent of natural disasters (see Rakwatin, *et al*. 2012, for example). And fourth, the observed increases in frequency and intensity of natural disasters imply the need for incorporating simulated impacts of climate change in the modelling and pricing of insurable risks. The ECHAM4-PRECISE simulated climate data used in this analysis could allow us to do so. Alternatively, various available hazard modellings that allow for risk simulations under various extreme scenarios could also be used.

The analytical framework as well as the empirical methodology proposed in this paper should be replicable in other settings and in other developing Asian countries, where exposures to covariate natural disaster risks remain uninsured. The data sets used in this paper should well be available in other Asian countries. The extended time series of spatiotemporal rich weather data as well as remotely sensed data are available worldwide at high quality and low cost.[52] And the high quality, national representative household dynamic welfare data similar to Thai SES data should well be available in the key Asian countries. Some examples include repeated cross-sectional household data from Indonesia National Socioeconomic Survey (SUSENAS), available every year from 1990-2010, from Vietnam Household Living Standards Survey (VHLSS), available every 2 years from 2002 to 2010.

This paper offers an optimistic view of the potentially optimal designs, market viability and impacts of IBRTPs designed at a large nationwide scale. These results could deviate largely from actual implementation in the real world. At least, four key implementation challenges are worth noting. First, it could be difficult to establish informed effective demand among clientele with relatively low financial literacy in developing countries. Second, the presence of large basis risk could still be possible in some coverage areas. Third, cost of marketing and delivery mechanisms of the contract could still be high in developing countries. And fourth, the targeted clientele could have financial constraints in paying insurance premium.

These key challenges thus place significant implications on how index insurance program should be implemented in developing country settings. Should the insurance contracts be offered as a stand alone or linked with other financial products? Linking with other existing financial products might resolve high implementation costs and relax some financial constraints among targeted clientele. Should the program be established at the micro, meso or macro levels? Extended investment in education, training and extension tools are thus critical if contracts are sold directly to households. At the meso level, rural banks like BAAC could obtain insurance contract to insure their loan portfolio, so that they can then lend insured loans to households. Groups and cooperatives can obtain coverage for their group saving or credit schemes. One testable assumption is that group-sharing network could potentially smooth out individual basis risk associated with index insurance contracts. Necessary randomised impact evaluation research has been launched around the world in attempt to address these questions. Extended discussion of key implementation challenges of IBRTPs in developing countries to data are summarised in Miranda, *et al*. (2012) and IFAD and WFP (2010). Overall, the challenges are significant, but the considerable prospective gains associated with IBRTPs for enhancing development of sustainable disaster insurance programs in developing countries would seem to justify considerable new effort in this area.

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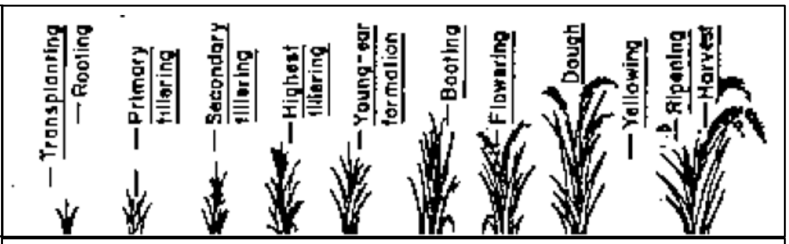
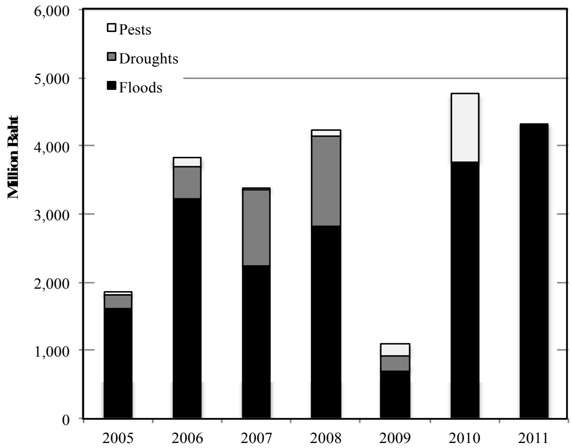
APPENDIX

Figure A1: Growth Stages of Rice Plants and Key Variables

Rice growth stage (Yukawa (1989) and Murphy (1998))									
Days after seeding	20	28	35	45	58	75	86	105	120
Height (cm)	5	25	35-55	35-55	60-65	80-95	80-95	80-95	80-95
Crop water requirement	25.4	39.6	35.9	35.2	43.1	47.4	42.8	0	0
Critical rainfall level (mm/10-day)	25	30	30	30	40	35	0	0	0

Note: Data are obtained from World Bank (2006)

Figure A2: Government Budget Spent on Disaster Reliefs for Rice Farmers (2005-2011)



Note: Data are obtained from Thailand Ministry of Agriculture

Table A1: Summary of Existing Pilot Projects of IBRTPs in Asia

Country/Product	Type	Targeted users	Risk	Index	No. latest beneficiaries	Risk financing	Progress
Bangladesh **Weather index insurance**	Micro level, standalone, group-based contracts, linked with loans	Farmers, farmer's groups	Drought and flood	Simple weather parameters	-	-	Under development
India **Public and private weather index insurance**	Micro level, standalone, linked with loans, seed sales, contract farming	Farmers (small, medium, large)	Various weather-related shocks (excess and deficit rainfall, humidity and frost)	Station rainfall, temperatures, weather-linked crop diseases, fog, humidity, satellite weather index	> 700,000 across the country	Public agricultural insurer (AIC), ICICI Lombard, IFCCO-Tokio, Swiss Re, Tokio Marie, Endurance Re, SIRIUS Re	First piloted in 2003, expand largely Mostly unsubsidized except some small numbers of states
Mongolia **Index-based livestock insurance**	Micro level, private-public partnership in risk financing	Nomadic herders	Severe weather, especially winter storm	District census of aggregate livestock mortality rate	4100 in 4 provinces	Insurance pool of local insurers with government providing stop-loss reinsurance, WB contingent loan for catastrophe loss through risk layering	First piloted in 2006; expand gradually
Thailand **Drought insurance for maize and rice**	Micro level, distributed by Bank of agricultural & agricultural coop.	Maize and rice farmers	Droughts	Cumulative rainfall during growing season	817 in 11 provinces	Consortium of nine local insurers Sompo Japan	Product for maize first piloted in 2007, government supports to expand. For rice first piloted in 2011

Cont. Table A1

Country/Product	Type	Targeted users	Risk	Index	No. latest beneficiaries	Risk financing	Progress
Vietnam **Area-yield index insurance for rice**	Micro level, cover loans to rice farmers	Rice farmers	Covariate shocks that affect area yield	Area yield indexbased on data from the Vietnam's Bureau of Statistics	10 provinces	Agribank Insurance Joint Stock Company (ABIC) as insurer, reinsurer using Swiss Re and Vietnan National Reinsurance Corpopration (Vina Re)	Sold since 2011
The Philippines **Area-yield index insurance for rice**	Micro level, supported by the German GTZ	Rice farmers	Covariate shocks that affect area yield	Area yield index triggers relative to 15-year average yield	17 irrigated municipalities	Local insurer	Piloted in 2012
Vietnam **Flood insurance for**	Meso level protecting bank from loan defaults	Vietnam Bank of Agri.and Rural	Early flooding of rice fields during rice harvest	River level measured at the upper Mekong river during early rice	-	-	First designed in 2008 but has not been

ENDNOTES

[1] Chantarat is the corresponding author and can be contacted at Arndt-Corden Department of Economics, Crawford School of Public Policy at the Australian National University, Australia (sommarat.chantarat@anu.edu.au). The rest of the authors can be contacted at Faculty of Agriculture at Khon Kaen University, Faculty of Economics at Thammasat University, Geo-Informatics and Space Technology Development Agency (GISTDA) at Thailand Ministry of Science and Technology and School of Management at Mae Fah Luang University respectively. We thank Fiscal Policy Office at the Ministry of Finance, Office of Agricultural Extension and Agricultural Economics at the Ministry of Agriculture and Cooperatives, GISTDA and Thailand National Statistical Office for sharing necessary data. Ratchawit Sirisommai has provided much appreciated research assistance. We also thank Hiroyuki Nakata, Nipon Poapongsakorn, Yasuyuki Sawada and participants at the ERIA workshop on Economic and Welfare Impacts of Disasters in East Asia for helpful comments. Any errors are the authors' sole responsibility.

[2] The major disasters of the decade leading to large number killed in Asia include the 2004 Indian Ocean tsunami (226,408 deaths), the 2008 Cyclone Nargis in Myanmar (138,375), the 2008 Sichuan earthquake in China (87,476), the 2005 Kashmir earthquake (74,648) and the 2001 major earthquakes in Gujarat, India (20,017). The recent major disasters leading to widespread affected populations in Asia include the 2010 floods in China (134 million people), the 2009 droughts in China (60 million people), the 2010 Indus river basin flood in Pakistan (more than 20 million people) and the 2011 river flood in Thailand (13.6 million people).The three costliest natural disasters in 2011 are all in Asia: earthquake and tsunami in Japan (USD 281 billion), river flood in Thailand (USD 45.7billion) and earthquake in New Zealand (USD 20 billion).

[3] Table A1 summarises the existing IBRTP projects piloted in Asia to date. Growing numbers of literature has also depicted opportunities and challenges of implementing IBRTPs. See IFAD and WFP (2010), Barnett, *et al*. (2008), for example, for review. See Chantarat, *et al*. (forthcoming, 2011, 2008, 2007), Clarke, *et al*. (2012) and Mahul and Skees (2007) for examples related to IBRTP designs in the developing world, and Mahul (2000) for examples related to agriculture in high-income countries.

[4] With the exception of some on-going new projects, see for example, Chantarat, *et al*. (forthcoming) and various piloted projects funded by USAID-I4 Index Insurance Innovation Initiative at http://i4.ucdavis.edu/projects/. These ongoing pilot projects undertake rigorous contract design and ex-ante evaluation using high-quality household welfare data in addition to their proposed ex-post evaluation through multi-year household-level impact assessment.

[5] In other cases, this measure might be household's income, asset or consumption. Note that consumption reflects its various income streams as well as net flows of informal social insurance and perhaps other stochastic payments.

[6] For simplicity, we drop location subscript $l$throughout the chapter.

[7] High-quality data of $\bar{y}_t$, however, might not be readily available in most of the developing countries.

[8] For example, station weather with relatively lower spatial distribution might be subjected to higher basis risk especially in areas with large microclimate. The increasingly available gridded weather data combining satellite and station weather data using GIS and distance weighting techniques are increasingly used as alternative indices.

[9] This standard payoff function is equivalent to a put option on underlying index. Deviation from this standard payoff function includes a call option that triggers payout when index realisation is above strike level.

[10] In specific, we consider CARA utility function $U(c_{ilt}) = -e^{-\theta c_{ilt}}$ so that $EU(c_{ilt}) = E\left(-e^{-\theta c_{ilt}}\right) = E(c_{ilt}) - \frac{\theta}{2}\sigma^2(c_{ilt})$under normally distributed consumption (Ljungqvist and Sargent, 2004).

[11] This scaling factor has been used widely in the literatures, e.g., Skees, *et al*. (1997).

[12] Parallel hedging effectiveness measures have been used in Cummins, *et al*. (2004).

[13] Another advantage of portfolio pricing that can incorporate larger spatiotemporal distribution of data series into statistical analysis is the potential efficiency gain from the reduction in sensitivity to outliers and hence low-quality data for some small contract areas. Buhlmann's empirical Bayes Credibility Theory (1967) has been widely used in the insurance industry for portfolio pricing. This has been used as the basis for ratemaking of the Indian Agriculture Insurance Company's modified National Agricultural Insurance Scheme since 2010 (Clarke, *et al*. 2012).

[14] In some setting, contingent debt is also used to spread covariate natural disaster risk inter-temporally.

[15] This can be evidenced from existing insurance programs in Mexico, the Caribbean, etc. In other settings, reinsurance is not in the form of stop-loss contract but rather in quota sharing to the domestic insurance pool. In Thailand, for example, reinsurer occupied 90% of the pooled risk portfolio of agricultural insurance.

[16] Guy Carpenter (2010) found that following very active hurricane seasons in 2004 and 2005, reinsurance prices increased dramatically for 2006 in the U.S. (76%) and Mexican (129%) markets comparing to ROW (2%).

[17] The market for cat bonds in the United States, Western Europe, and Japan, has been growing since the first transactions in the mid-1990s with more than 240 transactions in 1997-2007 (Swiss Re, 2007). Following the record losses from Hurricane Katrina, reinsurance premiums increased dramatically leading to greater interest in the use of cat bonds to transfer hurricane risk. This led to higher yield, which, in turn, generated more interest from investors.

[18] Additionally, there is little credit risk. Just as is done when securitising credit risks, funds are secured in a Special Purpose Vehicle (SPV) so payment upon a triggering event is assured. The key limitations, however, is that there are significant transaction costs to establishing cat bonds. These costs include risk analysis, product design, legal fees, the establishment of SPVs and the special regulatory considerations that are needed to protect investors.

[19] Returns on cat bonds are about 1% above the return on comparable BB corporate bonds. Because of the increasing diversification since 2006 with bonds issued for Mexico, Australia and the Mediterranean countries, the three-year parametric cat bonds have been issued at the lower than 2 times expected loss(Guy Carpenter, 2008).

[20] See, for example, Kunreuther and Pauly (2004).

[21]Data are obtained from the Office of Agricultural Extension, Ministry of Agriculture and Cooperatives, Thailand. There is no significant trend from the annual areas since 1980.

[22] The number of provinces has just recently increased to 77 with one additional province added in the Northeast 2011. Our spatiotemporal data are extracted using the un-updated 76-province GIS information.

[23]These results are obtained from PASCO, Co.'s study using a combination of scientific literature reviews, agro-meteorological model (DSSAT)with detailed geographical information and ground checking with the local experts in the key-growing province, Phetchabun, and flood plain modelling.

[24] USD 1= 31.81 baht (Bank of Thailand as of May 29, 2012). Figure A2 presents total budget spent in 2005-2011.

[25]At 1 rai (in Thai) = 0.16 hectare. For 2011, the subsidized price is 60 baht/rai with the payout at 606 bath/rai if lost crop is less than 60 days, or 1,400 baht/rai if lost crop is greater than 60 days of age. The scheme in 2012 continues with the same subsidized price but with single payout rate at 1,111 baht/rai. The local insurers also participate in the program in 2012 by taking some minimal percentages of insurable risk, leaving the major risk to the government.

[26] Farmers in the risky areas would, in expectation, tend to be the majority of the purchasers of the cheaper contract relative to their risk profiles. And the heavily subsidised insurance contracts for those in the risky zones could further induce excessive risk taking behaviours.

[27] This trend estimation has been commonly used in agricultural time series especially when the underlying data are not normally distributed (Ramirez, *et al*. 2003).

[28]These also include projected future climate data and are available at http://www.start.or.th/. The resolutions of these data could be improved. Attempts are current made in gridding weather data at lower resolutions.

[29] This results in 9,254 SMUs covering all the 9.1 million hectares of rice growing areas nationwide. The size of constructed SMUs ranges from 0.16 to 35,900 hectares.

[30]Data are available worldwide and cost free. See https://lpdaac.usgs.gov/content/view/full/6644.

[31] This is also common to other nationwide repeated cross sectional household socioeconomic survey data available in other developing countries, e.g., the Indonesian SUSENAS, etc. And while certain counties were sampled repeatedly, amphoe identifiers were not available to allow for construction of amphoe-pseudo panel data.

[32] Farm incomes from the last month are also available, but the large variations in cropping patterns as well as survey timing constitute great difficulties in controlling for seasonality effects.

[33]These statistics align well with findings in Isvilanonda (2009).

[34] Simple local polynomial smoothing is used over all the pixels that fall into provincial boundary over 2000-2011.

[35] Current contract piloted by JBIC and Sompo Japan insurance in Khon Kaen relies on simple cumulative rainfall are taken from July to September.

[36] For example, drought index insurance for maize piloted in Thailand since 2007.

[37] Note that for $y(w_t), CR_t, MD_t, ME_t$, we standardise at the SMU and pixel first (using SMU and pixel specific moments) before aggregate them into provincial indices. This is different from taking average of index first then dividing by overall long-term average later. The latter case will result in index with lower variations since most the SMU-level variations are already smoothed out in the aggregation process.

[38]There are two values for each of the weather indices in the two-crop zones, one for each crop cycle. Summary in Table 1 and Figure 5 reflect the average of the two values each year.

[39]We reintroduce provincial subscript l here for clarification. The alternative approach of using pseudo provincial panel in estimating (1) controlling for provincial fixed effect would not take full advantage of these rich household data, as it would not yield household-level variations of basis risks.

[40] Ideally, we want to estimate provincial-specific β_l. The temporal observations per province are simply not enough with 6 years in Thai SES data.

[41]2-day cumulative rainfall exceeding 25 mm is chosen to trigger the start of each crop cycle, as it provides the best results comparing to others. This chosen trigger might not serve as an appropriate trigger for crop cycle just yet.

[42]As the estimated coefficients are specific at provincial level (not household), the simulated households' optimal coverage scales are specific at provincial level.

[43] We note that these estimated levels of welfare improvement rely extensively on the assumed functional form of utility. Inferences from these results are for comparison of hedging effectiveness across contracts only.

[44] And so we would expect that specific strike level for each payout frequency to be different across indices and provinces depending on their specific underlying distributions.

[45] Reported pricings are established using burn rate approach. We also price these contracts using Monte Carlo simulations with marginal distribution of the provincial indices are estimated parametrically based on the best-fit distribution (according to chi-square criteria). Because the underlying risk (index) does not exhibit long tail associated with extreme event, our simulation results using best-fit distributions also confirm the same pricing patterns and are available upon request.

[46]LIBOR rate as of May 30, 2012 from www.global-rate.com.

[47] For example, an investor who purchased a cat bond with required return of 4%, 50% cap with 110% strike at the price = USD0.8823 and received USD1 principle back one year later when reinsurance is not triggered, would realise a total compounded return of 12.4%. The rate can be

interpreted as including a risk free LIBOR rate of 1.07%, 2.93% premium associated with bond default and other risks not associated with the insured reinsurance risk, and an additional 8.4% premium associated with this catastrophic risk associated with the reinsurance.

[48] This mark up is comparable to other existing index insurance programs in other part of the world. These market rates are comparable to other pilot projects for rice insurance in Thailand. For example, 4.64% rate changed for recently piloted deficit rainfall index insurance covering only drought peril for only the main rice production in Khon Kaen province during July-September.

[49] Because the extreme layers of risk are not so catastrophic, capping at higher level beyond 40% of sum insured will result in more or less the same effects to market premium rates. The market premium rates for 130% strike contract do not change with payout caps, as the contracts' maximum payout rates are already well below the caps.

[50]We rescale the simulated representative sample to represent the current 9.2 hectares of growing areas nationwide. The current sample represents 63 similar households (9,200,000/(76,000×1.92)).

[51] Without actual payout statistics, we assume that under the existing program, if household's actual crop income falls below its 1-in-3 year trigger level, they will be paid 3,787 baht per hectare (606 bath/rai) under disaster relief program and an extra 6,944 baht per hectare (1,111 baht/rai) if they pay for disaster insurance coverage at a subsidised price of 375 baht per hectare (60 baht/rai). We believe this assumption is reasonable, as (i) the program covers larger sets of disasters and (ii) it makes payout conditional on government's declaration of disasters at very local levels with required actual loss verification. Because government disaster insurance is offered at highly subsidised price, our welfare optimisation implies that all representative risk-averse households will purchase full coverage. Hence 100% insurance penetration rate is used. Note that we abstract from all the incentive problems associated with existing program that could result in larger exposure on government spending.

[52] Gridded weather data from WMO stations across Asia are available online at NOAA Global Daily Climatology Network (daily, 1900-present). Various satellite imagery Normalised Difference Vegetation Index (NDVI) available from NASA MODIS at 250m resolution (15-day; 2000-present) and from NOAA AVHRR at 8km resolution (10-day; 1982-2000). RADARSAT-1 and RADARDAT-2 with cloud-penetrating SAR sensor at 25m resolution (every 15 day, 1995-present) have been increasingly used for flood monitoring.

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