

UC Davis

Agriculture and Resource Economics Working Papers

Title

Underwriting Area-based Yield Insurance to Crowd-in Credit Supply and Demand

Permalink

<https://escholarship.org/uc/item/2t07w79m>

Authors

Carter, Michael
Galarza, Francisco
Boucher, Stephen

Publication Date

2007-11-01

**Department of Agricultural and Resource Economics
University of California, Davis**

Underwriting Area-based Yield Insurance to Crowd-in Credit Supply and Demand

by

Michael R. Carter, Francisco Galarza, and Stephen Boucher

Working Paper No. 07-003

Revised November 2007



Copyright © 2007 by Michael R. Carter, Francisco Galarza, and Stephen Boucher
All Rights Reserved.

Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Giannini Foundation of Agricultural Economics

UNDERWRITING AREA-BASED YIELD INSURANCE TO CROWD-IN CREDIT SUPPLY AND DEMAND*

Michael R. Carter
University of Wisconsin,
Madison
mrcarter@wisc.edu

Francisco Galarza
University of Wisconsin,
Madison
fbgalarzaare@wisc.edu

Stephen Boucher
University of California,
Davis
boucher@primal.ucdavis.edu

November 2007

Abstract

Recent theoretical and empirical evidence suggests that risk (especially covariant risk that is correlated across producers) may discourage both the supply of agricultural credit and the willingness of small holders to utilize available credit and enjoy the higher expected incomes credit could make available to them. One possible resolution to this problem is to remove risk from the system by independently insuring it. However, conventional (all hazard) crop insurance has in almost every instance been rendered financially unsustainable by moral hazard and adverse selection problems. This paper instead analyzes two index-based insurance schemes, one based on a weather index, and a second based on measured average yields. While these index insurance products do not protect the farmer from all risks, our econometric analysis (which is based on data from the north coast of Peru) shows that they could have substantial value to the producer and could also crowd-in credit supply from lenders reluctant to carry too much covariant risk in their loan portfolios. We also show that insurance based on measured yields is markedly superior to a weather index (for both borrowers and lenders). We close by arguing that present and past public good failures justify public intervention in this area, and analyze the feasibility of a public scheme to initially underwrite the costs and uncertainties associated with area-based yield insurance.

* The work reported here has been supported by the US Agency for International Development (USAID) Agreement No. LAG-A-00-96-90016-00 through the BASIS Collaborative Research Support Program. A previous version of this paper was presented at the FAO Conference, *Rural Finance Research: Moving Results into Policies and Practice*, held in Rome, 19-21 March 2007.

UNDERWRITING AREA-BASED YIELD INSURANCE TO CROWD-IN CREDIT SUPPLY AND DEMAND

Agricultural credit markets in developing countries are shallow for several reasons. On the supply side, lenders are reluctant to increase their agricultural loan portfolio because of the high risks (climatic events and political intervention being two of the major covariate shocks that can affect repayment outcomes) and operational costs of providing loans in geographically scattered areas. Recent empirical evidence from Peru (and other developing countries, such as Bolivia) shows that public sector intervention through debt forgiveness programs in a purely private transaction can seriously damage the credit market by reducing the borrowers' incentives to repay, which results in lower credit supply (Tarazona and Trivelli, 2006).

On the demand side, recent theoretical and empirical evidence¹ suggests:

- (i) That a subset of agricultural producers will be discouraged from taking productive loans because they fear the loss of collateral that could occur under the available set of highly collateralized loan contracts;
- (ii) That these "risk rationed" producers are likely to enjoy lower levels of productive wealth than other producers; and,
- (iii) Wealth-biased risk rationing primarily affects lower-income farmers, undercutting their capacity for investment and resulting in a more inequalitarian distribution of income.

If these three observations are correct, then improving the financial performance of low-wealth agricultural producers is going to require more than land titling and other supply-side efforts. It will also require efforts to address risk constraints that limit effective demand.

¹ See Boucher et al. (2007) and Boucher and Guirkingner (2006).

One possible resolution to this problem is to remove risk from the system by independently insuring it.² However, conventional (all hazard) crop insurance has in almost every instance been rendered financially unsustainable by moral hazard and adverse selection problems (Barnett, 2000; Barnett et al., 2005; Chambers and Quiggin, 2001; Duncan and Myers, 2000; Hazell et al, 1986; Hess and Syroka, 2005; Knight and Coble, 1997; Skees et al., 1999; Skees et al., 2006).

In clear contrast with the multiple-peril crop insurance contracts, index-based insurance (*e.g.*, area-based yield insurance³ or insurance based on rainfall or other weather indices) has the virtue of being moral hazard proof in the sense that it preserves effort incentives for producers as no individual farmer can influence the probability of an insurance pay-off. It also significantly mitigates adverse selection problems, because the expected indemnities paid out by the insurer are independent of the characteristics of the pool of insured farmers.

Recently, several authors have stressed the potential benefit of bundling index-based insurance with micro loans (Alderman and Haque, 2007; Hess, 2003; Skees and Barnett, 2006; and Skees et al., 2007). The main idea underlying this proposal is that by providing an effective tool to reduce the risk of substantial losses due to catastrophic

² Other possible solutions include lending methodologies that do not depend on tangible collateral, such as group-based lending, and lending based on reputation. See Besley and Coate (1995) and Ghatak and Guinnane (1999) for theoretical treatments of advantages of group lending. De Janvry et al. (2006) and Luoto et al. (2007) provide empirical evidence from Guatemala about the importance of information sharing in reducing loan defaults. In this context, credit bureaus can increase the value of borrowers' reputation (building so-called reputation collateral), thus helping to "cream-skim" the market, with a resulting expansion of the credit market's outreach (Jappelli and Pagano, 2000).

³ In area-based yield insurance, insurance payoffs are based on the average yield of all producers in a region, irrespective of whether or not they purchase insurance. Weather index-based insurance can be viewed as a subset of area-based yield insurance in which predictors of average yields (*e.g.*, rainfall and temperature) are measured instead of realized average yields.

events, this type of insurance may also help reduce producers' loan defaults, with obvious benefits for both borrowers and lenders.⁴

In spite of its clear conceptual advantages, index-based insurance is not, of course, a silver bullet cure for the risk-related maladies of rural financial markets. Most importantly, by construction, index-based insurance only covers a fraction of the risks faced by farming households, leaving them exposed to residual uninsured, or basis, risk. A key empirical question then is whether provision of the partial protection offered by index based insurance will suffice to relax demand constraints to borrowing and empower small holders to pursue more entrepreneurial strategies. Similarly, on the supply-side, we might ask whether index insurance suffices to relax the reluctance of rural microfinance lenders to carry a larger agricultural portfolio (see Trivelli et al., 2006).

Index-based (in particular area-based) insurance programs are currently operating in several developed countries (e.g., Canada, Sweden and the U.S.) and are either at the pilot stage or have recently started operating in some developing countries, including India (Hess (2003), Kalavakonda and Mahul (2005), Lilleor et al. (2005), Manuamorn (2007), and World Bank (2003)); Mexico (Skees et al., 2002); Morocco (McCarthy, 2003; Skees et al., 2001); Mongolia (Mahul and Skees, 2006); Malawi (Hess and Syroka, 2005); and Nicaragua (Miranda and Vedenov, 2001).⁵ In Peru, where we develop our empirical analysis, both the public⁶ and private⁷ sectors have taken steps toward developing index

⁴ In addition to enhancing loan performance, Alderman and Haque (2007) argue that this loan-insurance bundling may also reduce insurance marketing costs.

⁵ Several of these experiences with weather-index insurance are summarized in World Bank (2005). With the exception of India, where a well developed weather insurance product is commercially available to small farmers in several regions, most of the other cases have not progressed beyond the pilot stage.

⁶ The Peruvian Ministry of Agriculture evaluated the feasibility of weather-indexed insurance in several valleys, with technical assistance from the World Bank. Focus groups were conducted to examine the willingness to pay (WTP) for prototypical weather-index insurance products, and in all the cases there was a positive WTP. To date, no concrete initiatives have emerged.

insurance models for agriculture. To date, however, no index insurance product has been adopted.

This paper contributes to the discussion about the benefits of index-based insurance. In particular, we analyze the effects of area-based yield insurance on producers' welfare and loan repayment outcomes. Using data from coastal Peru, we estimate the parameters for two types of actuarially fair area-based yield insurance scheme. In the first, average area yields are measured directly; while in the second they are imperfectly predicted using weather information. We then simulate and compare the value of each type of insurance to smallholder producers.

This preliminary *ex ante* analysis confirms that area based yield insurance would be of significant value to producers. Insurance based on directly measured yields significantly outperforms the more imprecise insurance based on a weather index, at least for the case analyzed here. In addition, under reasonable assumptions about default behavior, both types of area yield insurance significantly reduce the probability of default (and the probability that the insured borrower will forfeit their collateral). Together these observations suggest that area-based yield insurance can crowd-in both demand for and supply of credit. We then consider the reasons for the general absence of privately provided area-based insurance in low-income economies. High costs of providing insurance (innovation and marketing), together with the scarcity of reliable data to calculate the distribution of payouts, both issues with public goods nature, are the most

⁷ In 2007, a private company began offering a weather-index insurance product in the northern department of Piura. This insurance is based on an ENSO (El Niño Southern Oscillation) index, which measures the sea-surface temperature off the Peruvian coast as deviations from a long-run average temperature. This index is a good predictor of extreme rainfall resulting from an El Niño event. However, despite the seeming attractiveness of this insurance product, to our knowledge, it has not yet been purchased by any of the agriculturally oriented financial institutions that were the original target market of the product.

likely explanations for the absence of area-based insurance. Finally, we analyze the possibilities for using a public guarantee scheme (over a five year period) in order to solve this public good issue.

1. Directly Measured versus Estimated Area-based Yield Insurance

Area-based yield insurance (ARBY) makes payouts to insured beneficiaries when area yields (*e.g.*, average yields over a valley or other clearly defined geographic unit) fall below a critical threshold or strike-point. This section provides a conceptual framework to understand the underlying logic of ARBY insurance and then uses the framework to put forward two options for ARBY insurance: one based on directly measured area yields, and a second based on estimated area yields, where estimated yields are based on observed weather information. This second type of ARBY insurance is simply a particular way of expressing a weather index insurance product.

Consider an agricultural valley composed of many farmers. Viewed at the beginning of the planting season, both the yields of an individual farmer, y_i , and the average yield across all farmers in the valley, \bar{y} , are random variables. Following Miranda (1991), we can express the relationship between individual and valley average yields using the following linear regression model:

$$y_i = \mu_i^y + \beta_i^y(\bar{y} - \mu^y) + \varepsilon_i^y, \quad [1]$$

where μ_i^y is farmer i 's expected, or average, yield; μ^y is the expected valley average yield; β_i^y is a farmer-specific parameter giving the average, or systematic, relationship between the individual farmer's yield and the valley average yield; and ε_i^y represents idiosyncratic

yield variation (i.e., the variation in farmer i 's yield that is unrelated to average yields in the valley). The value of ARBY insurance to an individual farmer hinges on the value of β_i^y .⁸ A value of 1 implies that, on average, the farmer's yields move in lockstep with valley average yields. For example, when the valley average yield is 100 kilograms above its mean, we would expect that this individual farmer's yield will also be 100 kilograms above her own mean. In contrast, a value of 0 would imply that there is no systematic relationship between the farmer's yield and valley average yields. It is important to keep in mind that β_i^y represents the expected, or average, relationship between individual and valley average yields and that in any given year, the farmer's actual yield will also be affected by idiosyncratic factors, such as health shocks or plot-specific pest infestations, that are independent of those factors driving valley average yields.

Equation [1] above expressed the relationship between individual farm yields and valley average yields and thus will serve as the basis to evaluate the value of an ARBY insurance product when data on valley average yields are available. In some instances, direct data on valley average yields may not be available. Instead, data may be available on certain weather variables, such as temperature or water availability, that affect agricultural production. Letting ω denote the vector of weather variables, we can write the relationship between valley average yields and weather as follows:

$$\bar{y} = \hat{y}(\omega) + \varepsilon^y. \quad [2]$$

Equation [2] decomposes valley average yields into a systematic component, $\hat{y}(\omega)$, which gives the average relationship between valley average yields and the weather variables, and

⁸ Formally, β_i^y is equal to $\text{COV}(y_i, \bar{y}) / \text{var}(\bar{y})$, the OLS coefficient in a regression of $(y_i - \mu_i^y)$ on $(\bar{y} - \mu^y)$.

a random component, ε^y , which represents the additional variation in valley average yields unrelated to weather (e.g., the impact of insect invasions).

Note that $\hat{y}(\omega)$ is simply a particular form of a weather index. It translates weather information into predicted average yields. This specification makes it clear that writing ARBY insurance on a weather index, $\hat{y}(\omega)$, exposes the farmer to greater basis risk than does writing a contract based on directly measured yields, \bar{y} . The degree of additional basis risk, in turn, will depend on how “tight” is the relationship between valley average yields and the weather events (i.e., the magnitude of the variance of ε^y).

Before turning to the specification of the two alternative ARBY insurance contracts, we note that in irrigated systems such as the one in Peru where our empirical example is based, one reaction to water scarcity can be a reduction in area planted. Let s_i and \bar{s} denote respectively the area sown by the i 'th farmer and the average area sown by all farmers in the valley. As in equation [1], we can decompose individual sown area into a component systematically related to average sown area and an idiosyncratic term as follows:

$$s_i = \mu_i^s + \beta_i^s (\bar{s} - \mu^s) + \varepsilon_i^s, \quad [3]$$

where μ_i^s is the average area sown by farmer i ; μ^s is the average area sown throughout the valley; β_i^s gives the average relationship between individual and valley average sown areas; and ε_i^s represents idiosyncratic shocks to individual sown area. Analogous to equation [2], valley average sown area can be broken into a component systematically related to the weather variables and other factors:

$$\bar{s} = \hat{s}(\omega) + \varepsilon^s. \quad [4]$$

Using [2] and [4] we can define *directly measured adjusted valley average yields*, \tilde{y} , as:

$$\tilde{y} = \left(\frac{\bar{s}}{s^{\max}} \right) \bar{y}; \quad [5]$$

where s^{\max} is the maximum cultivable area per farmer in the valley. Similarly, we can define *estimated adjusted valley average yields*, \hat{y} , as:

$$\hat{y} = \left(\frac{\hat{s}}{s^{\max}} \right) \hat{y}. \quad [6]$$

Note that [6] is another weather index, one that accounts for the impact of water availability on both yields and area sown.

Using this same idea of an adjusted yield, we define the farmers' *realized yields per-cultivable hectare*, \tilde{y}_i , as:

$$\tilde{y}_i = y_i \left(\frac{s_i}{s_i^{\max}} \right), \quad [7]$$

where s_i^{\max} is the cultivable land available to farmer i .

We are now in a position to define alternative ARBY insurance contracts. First, let \tilde{y}^c denote the contractually predetermined “strike point.” If the relevant adjusted valley yield falls below this amount, the insurance pays out a per-hectare indemnity, ρ , equivalent to the shortfall. For ARBY insurance based on directly measured yields and sown area, the indemnity is given by:

$$\rho = \max[0, \tilde{y}^c - \tilde{y}]. \quad [8]$$

For an estimated (or weather index) ARBY insurance the payout is instead given by:

$$\hat{\rho} = \max[0, \tilde{y}^c - \hat{y}]. \quad [9]$$

In the analysis to follow, we will focus on actuarially fair insurance, which requires that the per-hectare insurance premium, π , equals the expected value of the indemnities paid out—*i.e.*, $\pi = E[\rho]$ and $\hat{\pi} = E[\hat{\rho}]$. Ignoring the fixed and other administrative costs of designing and delivering the insurance, actuarial fairness implies that the insurer will break-even in the long run as average premiums will equal average indemnity payouts.

Fixed and other administrative costs are of course non-zero. A typical assumption is that these costs lead to a 30% mark-up (or load) over the actuarially fair premium (Gollier, 2003). Such costs will of course decrease the value of the insurance to the individual, and we will later consider their impact.

2. Statistical Properties for Area-based Yield Insurance Indices for Lambayeque Valley in Peru

This section defines and estimates the probability distributions needed to simulate the value of the area based yield insurance schemes defined in the prior section. For illustrative purposes, we use information on irrigated rice production in the Lambayeque valley on the north coast of Peru. As with all of Peru's coastal valleys, agricultural production in Lambayeque depends on water that flows down from the Andean highlands. While the upstream Tinajones reservoir provides some degree of water management in the Lambayeque valley, its limited capacity leaves producers vulnerable to fluctuations in the river flows that feed into the reservoir.⁹ A year of scarce water has two impacts on farmers. First, if water scarcity is revealed prior to planting decisions, it may lead to a

⁹ Of the 52 valleys on the Peruvian coast, only five have dams with sufficient capacity to allow significant inter-year water storage and transfer. In principal, fluctuation in water availability in the other 47 valleys should be even more severe, making ARBY insurance even more valuable than what is calculated here for Lambayeque.

reduction in area sown. Second, water scarcity reduces yields on those areas which are sown. The empirical analysis reported in this section looks at these dual effects both at the valley and individual household levels.

In order to analyze the value of both types of ARBY insurance, we need to first estimate four things: 1) The parameters of the distribution of water availability in the valley; 2) The parameters describing the relationship between valley average yield and water availability (equation [2]); 3) The parameters describing the relationship between valley sown area and water availability (equation [3]) and; 4) The parameters of the relationship between individual farmer yields and valley average yields (equation [1]). We estimate the first three sets of parameters using time series data composed of 36 annual observations (1969 – 2004) on water flows, average yields and area sown in the Lambayeque valley. We use a shorter panel of data (2002-2004) from a sample of 176 rice producers in the same valley to estimate the parameters of the individual yield distributions.

Consider first water availability. Our empirical measure of availability is the annual volume of water outflows from the Tinajones reservoir, the primary source of irrigation in the Lambayeque valley. Let ω_t denote outflows in year t and $f(\omega_t)$ its probability density function. We assume that the function $f(\cdot)$ follows the generalized beta distribution with parameters $(a, b, p$ and $q)$:

$$f(\omega; a, b, p, q) = \frac{(\omega - a)^{p-1} (b - \omega)^{q-1}}{B(\omega; p, q)(b - a)^{p+q-1}}, \quad [10]$$

where: $a \leq \omega \leq b$; $p, q > 0$ and $B(\omega; p, q) = \int_0^1 \omega^{p-1} (1 - \omega)^{q-1} d\omega$. The parameters of this density function were estimated by maximum likelihood using the 36-year time series data

on water outflows from the Tinajones reservoir. Table A-1 in the Appendix reports the parameter estimates and compares the distribution of the historical data to 100 draws from the estimated beta distribution.

Our next step is to empirically estimate the relationship between valley average yields and water flows (equation [2]) and between valley average sown area and water flows (equation [4]). We do so using the time series data (again for the period 1969 – 2004) on average valley yields and area sown published by the Ministry of Agriculture. We assume that both relationships are quadratic in water flows so that the empirical specifications of equations [2] and [4] are given by the following two equations:

$$\bar{y}_t = \alpha_0 + \alpha_1 \omega_t + \alpha_2 \omega_t^2 + \varepsilon_t^y; \quad [11]$$

$$\bar{s}_t = \gamma_0 + \gamma_1 \omega_t + \gamma_2 \omega_t^2 + \varepsilon_t^s. \quad [12]$$

We estimate the parameters of equations [11] and [12] using OLS. The regression results are reported in table A2 in the Appendix. The parameter estimates allow us to construct weather indices that are denominated in interpretable units of kilograms of rice per-sown hectare (\hat{y}_t) and sown hectares (\hat{s}_t).¹⁰ Using [6], these two indices can then be combined to generate an estimated adjusted area yield index. As reported in the Appendix, the R^2 of these regressions are between 10% and 50%, meaning that less than half of the variation in valley average yields can be explained by weather fluctuations, and hence that less than half of the insurable covariant risk can be covered by the simple weather index proposed here.¹¹

¹⁰ The indices themselves are simply linear functions of the measured weather variables.

¹¹ More sophisticated yields models, especially those that rely on an expanded set of weather variables, could of course improve the explanatory power of these regressions and ultimately increase the value of a weather index based ARBY insurance.

Finally, we use the three year panel of data on individual producers to estimate the farmer-specific parameters of individual yields specified in equation [1]. We assume the idiosyncratic error component (ε_{it}^y) is normally distributed with mean zero and estimate this random coefficients model using maximum likelihood.¹² This exercise allows us to estimate the farmer-specific β_i^y parameters from equation [1]. Appendix Table A-3 summarizes the results from estimating equation [1] using the Lambayeque panel data. As discussed above, these parameters measure the sensitivity of individual yields to average valley yields. Note that while the distribution of the $\beta_i^{y's}$ will be centered on one, some farmers will be hypersensitive to average outcomes (with their $\beta_i^y > 1$, perhaps the ‘tail-enders’ in the irrigation system), while others will have yields and sown area that are more insulated from average outcomes (with their $\beta_i^y < 1$, perhaps those located at the head of irrigation canals). ARBY insurance will of course be less valuable for producers with lower values of β_i^y . Finally, note that the distribution of the error term, ε_{it}^y , permits us to evaluate the magnitude of idiosyncratic risk faced by individual producers. With these four sets of parameter estimates in hand, we turn now to analyze the value of the two types of ARBY insurance contracts to both farmers (borrowers) and lenders.

3. Benefits to Borrowers of Area-based Yield Insurance

The expressions linking individual farmer i 's yields and sown area to valley averages are given in equations [1] and [3]. Note that the insurance is written on valley

¹² Note that while we could estimate the individual farmer's sown area in a similar fashion using [3], we will here assume that local irrigation commissions restrict all individuals to sow the same fraction of their cultivable area.

averages, not individual outcomes. While this resolves moral hazard and adverse selection problems, it also limits the value of the insurance to the individual. The actual value of insurance to the farmer will depend on the variance of idiosyncratic risk (the ε_{it} 's), and on the values of β_i^y and β_i^s which determine how closely the individual's yields and sown area track the valley averages. In addition, for ARBY insurance based on estimated yields, the value of insurance further depends on the accuracy with which average valley yields can be predicted with weather information (*i.e.*, on the variances of $\bar{\varepsilon}^y$ and $\bar{\varepsilon}^s$). If all the variance terms were zero, and if $\beta_i^y = \beta_i^s = 1$, then the ARBY insurance would perfectly cover all production risk faced by the farmer. As those variances increase, or as the β_i decline, the insurance becomes less valuable to the farmer.

How valuable ARBY will be is an empirical question and context specific. Using the econometric results summarized in the prior section, we will now simulate the value of various ARBY contracts to agricultural producers in Lambayeque. Later sections will return to consider some of the limitations of this sort of *ex ante* analysis.

To get an idea of the benefits to farmers from an ARBY scheme, we use the results of the estimations described above to generate a 100-year simulated time series of outcomes for the valley and for 500 individual rice farmers. To ensure that the 500 farmers are representative of Lambayeque, each farmer is assigned a β_i^y drawn from the estimated distribution of this parameter. Each farmer is assumed to own five hectares of land and, in order to produce on their land, is assumed to take out a working capital loan. Each farmer also has the option to purchase an ARBY product. Finally, to keep matters simple, we assume that all farmers have the same average yield.

The simulation proceeds in the following six steps.

1. First, we took 100 draws from the estimated Beta distribution (see table A1 in the Appendix) to generate a simulated time series of valley water flows $(\omega_1, \omega_2, \dots, \omega_{100})$.
2. We then used the simulated water flow data along with 100 draws from the estimated distribution of ε_t^y and the parameter estimates of equation [11] to generate a 100 year time series of average yields in the valley $(\bar{y}_1, \bar{y}_2, \dots, \bar{y}_{100})$.
3. Similarly, we used the simulated water flow data along with 100 draws from the estimated distribution of ε_t^s and the parameter estimates of equation [12] to generate a 100 year time series of average area sown in the valley $(\bar{s}_1, \bar{s}_2, \dots, \bar{s}_{100})$.
4. For each farmer, we then generated a time series of 100 idiosyncratic yield shocks by taking draws from the estimated distribution of ε_{it}^y .
5. We next combined these simulated data according to equation [1] to generate a 100 year time series of individual yields, $(y_{i1}, y_{i2}, \dots, y_{i100})$, for each of the 500 farmers.
6. Finally, we used equation [7] to generate the time series of realized yields per cultivable hectare for each farmer, $(\tilde{y}_{i1}, \tilde{y}_{i2}, \dots, \tilde{y}_{i100})$. We made the additional assumption that there is no idiosyncratic area shock (i.e., $\varepsilon_{it}^s = 0, \forall t$) so that the ratio $\left(\frac{s_{it}}{s_{it}^{\max}} \right)$ in equation [7] is equal to $\left(\frac{\bar{s}_t}{s_{it}^{\max}} \right)$.

In subsequent analysis, we will treat these 500 individuals as if they were the clientele (the loan portfolio) of a single microfinance organization. For purposes of the simulation, we assume that all farmers borrow working capital equal to 40 percent of the expected value of production (that is, we assume that financed inputs constitute 40 percent of the value of production).¹³ Matching the reality of agricultural microfinance lending in

¹³ This assumption roughly corresponds to conditions in northern Peru, where loans for rice production range from \$300 - \$500 per hectare and revenues per hectare average around \$1,000. The main purpose of this assumption is to reflect the use of external financing in agricultural production. Varying this proportion will only affect farmers' consumption (*ceteris paribus*, the higher the proportion of loan, the lower the consumption, keeping unchanged the full loan repayment result) in the case of buying a *measured* ARBY insurance. In the case of not buying insurance or buying insurance indexed by the *estimated* average valley yields (estimated ARBY, with weather index) a higher proportion of loans will decrease farmers' consumption and reduce returns on lending. As we will see in Table 1, ARBY insurance will have more value to farmers when computed using the measured valley yields.

coastal Peru, the interest rate was set to 21.7 percent (in Soles, non-annualized) for a five-month loan.¹⁴ We further assume that farmers have the option to take out an insurance contract for all 5 of their hectares. Initially, we will assume that the strike point is equal to long-run average valley yields—*i.e.*, $\tilde{y}^c = \mu^y$. Later, we will also consider contracts with other strike points (*e.g.*, $\tilde{y}^c = 0.8\mu^y$).

Farmers' full-repayment-net-income is defined as the residual income, after paying any insurance premium, receiving any insurance indemnity payments and repaying a loan of L at a nominal interest rate, r . Note that, since insurance is actuarially fair, the average full-repayment-net-income of insured farmers will equal that of uninsured farmers (who also obtain a loan, but not insurance, to finance their production). However, to properly value the insurance for farmers and lenders, we need to make assumptions regarding loan repayment. While full repayment is an option, we more realistically assume that the borrower always pays back as much as is feasible after meeting a subsistence consumption level, \underline{c} (set at a fraction of long-run average production). Under these assumptions, the net income available for the farmer's consumption is:

$$c_{it}^{ARBY} = 5 \times (\max[\underline{c}, (\tilde{y}_{it} - \pi_t - (1+r)L) + \rho_t]) \quad [13]$$

if she buys insurance. Similarly, the farmer's net income without insurance is:

$$c_{it}^{NI} = 5 \times (\max[\underline{c}, (\tilde{y}_{it} - (1+r)L)]). \quad [14]$$

Note that under this specification, default can either be total or partial. In addition, because borrowers repay as much as possible after reserving \underline{c} for themselves, insured borrowers will end up repaying more on average and hence have lower average consumption levels

¹⁴ This interest rate corresponds to current interest rates charged for agricultural loans by microfinance lenders (the Cajas Municipales) in Peru.

than their more frequently defaulting counterparts. For simplicity, the lender's income is total repayments received minus the value of loans made.¹⁵

Equations [13] and [14] above are the critical objective inputs into the farmer's valuation of ARBY insurance as they compare his consumption levels with and without insurance for each possible joint outcome of his individual yield and average yields in the valley. Ultimately, the value of ARBY and the decision of whether or not to purchase the insurance will also depend on each farmer's preferences with respect to (i.e., sensitivity to) risk. We assume that farmers' preferences are given by the following Constant Relative Risk Aversion (CRRA) utility function:¹⁶

$$U(c_{it}) = \frac{c_{it}^{1-g}}{1-g}, \quad \text{for } g > 0, g \neq 1; \quad [15]$$

where g is the Arrow-Pratt coefficient of relative risk aversion. The higher the parameter g , the more risk averse the individual. The analysis below will consider various degrees of risk aversion.

In order to make the implications of risk aversion more transparent, we will use our assumptions on the nature of risk aversion to express the value of a given risky prospect (e.g., a risky income stream without insurance, or with imperfect ARBY insurance) in certainty equivalence terms. In particular, the certainty equivalent of the risky consumption stream $c_{it}(\omega_t; \beta_i^y, \varepsilon_{it}^y)$ ¹⁷ is defined as the value of consumption that, if received with certainty, would yield the same level of well-being as the expected utility of

¹⁵ Abstracting from other costs (e.g., operating costs) will allow us to concentrate on examining repayment rates only.

¹⁶ These preferences were assumed by similar studies for the U.S., such as Coble et al. (2004) and Wang et al. (1998).

¹⁷ Note that in this exercise we focus on yield variability and neglect variability in sown area so that consumption depends only on ε_{it}^y and β_i^y ; not ε_{it}^s nor β_i^s .

the risky income stream. The certainty equivalent of contract k , c_{ce}^k , is thus implicitly defined by the following equation:

$$U(c_{it}^k) = EU \left[c_{it} \left(\omega_t, \pi^k, \tilde{y}^{c,k}; \beta_i^y, \varepsilon_{it}^y \right) \right]; \quad [16]$$

where π^k and $\tilde{y}^{c,k}$ are the premium and strike point for contract k .

To complete the empirical specification, we set the minimum (subsistence) consumption level, \underline{c} , equal to 20% of long-term expected income.¹⁸ Yields, and other values, are converted to US dollars. Throughout the exercise we set the rice price at \$0.16 per kilo, which is the price that prevailed in Lambayeque in 2004.

Tables 1 and 2 present the results of this simulation analysis. The top panel of table 1 reports the mean values of farmer income, the insurance premium and indemnities, consumption and loan performance for a farmer with $\beta_i^y = 1$. The first two columns compare these values across measured versus estimated ARBY contracts with a strike-point set at 100% of long term valley yields. The third column gives these values without insurance. The bottom panel of the table reports the certainty equivalents corresponding to each of these three options for five different degrees of risk aversion, ranging from “Very Low” to “Very High.” For a person with Very High risk aversion, the uninsured consumption stream has a certainty equivalence value of \$1,565 (see bottom right entry of Table 1). Given that the uninsured consumption stream has a mean of \$1,971, this implies that the most risk averse individual would be willing to pay \$406, or 20.6% of expected annual consumption, in order to completely eliminate risk. The size of this risk premium of course diminishes as risk aversion diminishes (and would be zero for a risk neutral

¹⁸ While this proportion is arbitrary, the important feature from reality this intends to capture is that farmers will not give away everything in order to repay the loans. They would rather satisfy their basic needs before repaying any loan.

farmer). An individual with Very Low risk aversion, for example, has a certainty equivalent of \$1,878 and thus is only willing to give up \$93, or just under 5% of expected annual consumption, to completely eliminate risk.

So how valuable is area-based yield insurance to borrowers? For an individual with Very High risk aversion, the certainty equivalence of *measured* ARBY insurance is \$1,825 (see bottom left entry in Table 1). This figure indicates that the highly risk averse person would be willing to pay up to \$260, beyond the total annual premium of \$547, in order to buy the measured ARBY insurance. Farmers are willing to pay these amounts because the insurance reduces consumption variability, as shown by the standard deviation figures in the top half of Table 1. These willingness-to-pay figures of course decline as risk aversion diminishes, as shown in Table 1.

The corresponding figures for a weather index based estimated ARBY insurance are shown in the middle column of Table 1. For a highly risk averse farmer, the certainty equivalence of the weather index is \$130 (=1,925-1,695) less than the value this farmer would assign an ARBY contract based on measured yields. Put differently, this farmer would be willing to pay up to \$130 (=1,695-1,565) *more* than the actuarially fair premium for the weather-index insurance, whereas the same farmer would be willing to pay up to additional \$260 for an ARBY insurance based on measured yields. It should be noted that the actuarially fair premium for the measured ARBY insurance is \$33 more than that for weather index-based insurance. As risk aversion declines, the differences between all three contracts (no insurance, measured ARBY and weather index-based ARBY) diminish.¹⁹

¹⁹ It should also be noted that the analysis here only examines the favorable case in which $\beta_i^y = 1$. Further analysis could identify farmer types (with β_i^y approaching zero) for whom the insurance would cease to be valuable.

Table 1
The Value of Actual and Estimated ARBY Insurance
(Coverage = 100% acreage & $\beta_i^y = 1$)

	With Insurance (Strike Point 100% of Long-run Average Valley Yields)		No Insurance
	Measured ARBY Mean	Estimated ARBY (Weather Index) Mean	Mean
Net income, \$	2,601	2,601	2,601
Insurance payment (total), \$	547	514	0
Expected indemnity (total), \$	547	514	0
Consumption, \$	1,932 (797) ^a	1,945 (990) ^a	1,971 (1,276) ^a
Loan repayment, \$	669 (0) ^a	656 (77) ^a	631 (118) ^a
Lending return (%)	21.7	19.4	14.7
Certainty Equivalent Value to Borrower (\$'s)			
Very Low Risk Aversion (g=0.2)	1,904	1,889	1,878
Low Risk Aversion (g=0.33)	1,885	1,849	1,813
Middle Risk Aversion (g=0.5)	1,862	1,798	1,726
High Risk Aversion (g=0.67)	1,846	1,742	1,643
Very High Risk Aversion (g=0.8)	1,825	1,695	1,565

^a Standard errors in parentheses.

Note: Average loan: \$ 550; Interest rate: 21.7%.

To put these numbers in context, it is useful to compare them to the additional costs that a private sector insurance provider might charge to recover the fixed costs related to product development, marketing and administration. Under the assumption that the loading factor is 1/3 of the premium, the insurance schemes analyzed here would cost about another \$130/year. This amount is approximately equal to the farmer's total excess willingness to pay for weather index-based ARBY insurance, and about half the amount

the farmer would be willing to pay for measured ARBY insurance. These crude calculations suggest that there could be demand for ‘fully loaded’ measured ARBY insurance, but not for fully loaded weather index-based ARBY insurance.

Figure 1
Area-based Yield Insurance Simulation
 Typical Farmer, Strike Value = 100% mean

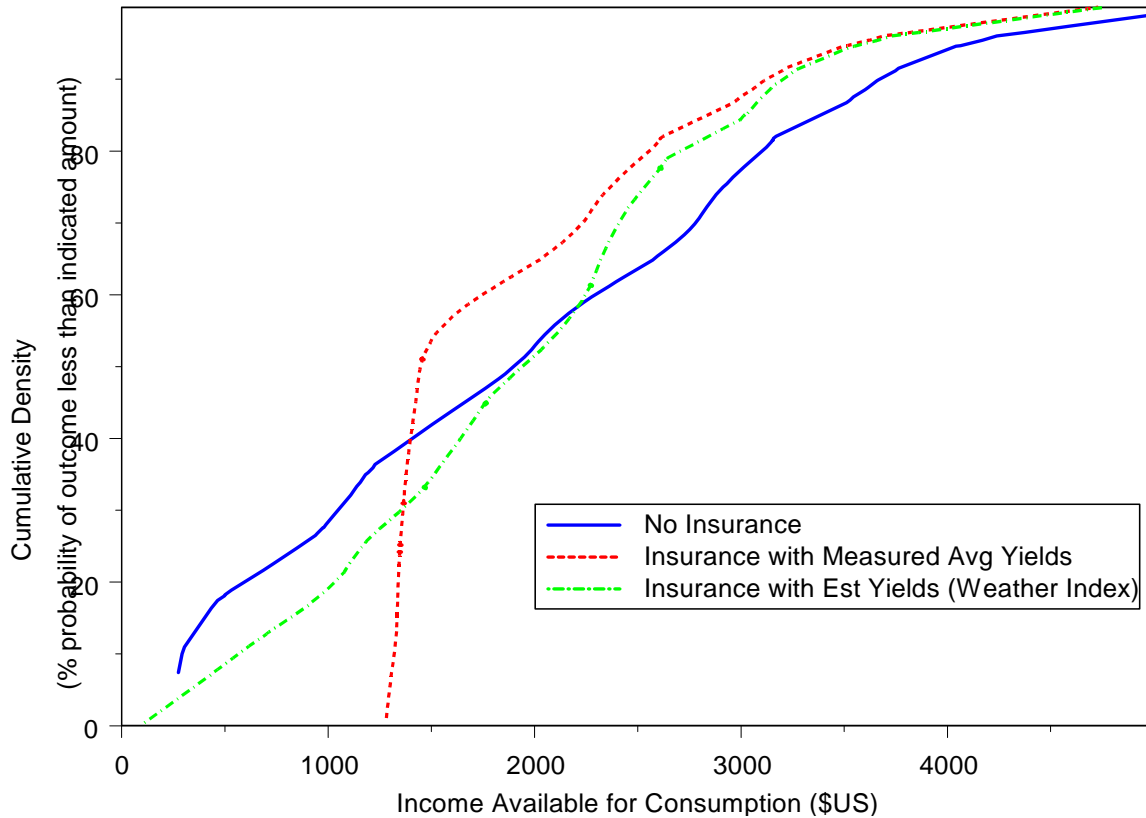


Figure 1 provides an alternative depiction of the same information, showing the cumulative distribution of consumption (as defined in equations [13] and [14]). As can be seen, both types of ARBY insurance contracts reduce the probability of extreme outcomes. Without insurance, there is a 20% probability that the producer’s net income falls below \$600 (or 3,750 kilos of rice on their 5 hectares). Under measured ARBY insurance, that probability drops to zero, while it is 10% under a weather index-based estimated ARBY

insurance. Because of the insurance premium, the probability of high outcomes is of course also reduced under both ARBY schemes. But as the certainty equivalent values in Table 1 show, risk averse borrowers prefer this swap. A risk neutral borrower would of course be (almost) indifferent between the three distributions.²⁰

Table 2
Typical Farmer and Lender: Value to Borrower by Strike Point

(Coverage = 100% acreage & $\beta_i = 1$. Farmer has high risk aversion)

	Measured ARBY		Estimated ARBY	
	Certainty Equivalent, \$'s	Insurance Premium Per-Hectare, π_t (\$'s)	Certainty Equivalent, \$'s	Insurance Premium Per-Hectare, π_t (\$'s)
No insurance	1,643	0	1,643	0
Insurance Strike Point, \tilde{y}_t^c (% of Long-run Average Valley Yields)				
40%	1,615	11	1,640	5
50%	1,670	20	1,647	11
75%	1,770	55	1,695	42
90%	1,817	86	1,729	75
100%	1,846	109	1,742	103

Finally, Table 2 explores the impact of lowering the strike point. As can be seen, the actuarially fair premium drops quickly (more so for the estimated ARBY) as the strike point declines. While expected utility is strictly increasing in the strike point for the typical farmer being analyzed, this will not necessarily be true for farmers with different values of β_i^y . The analysis above can be easily extended to different values of the β_i^y . Using

²⁰ The risk neutral farmer would prefer no insurance as it allows greater amounts of default under the consumption minimum repayment rule.

information on the valley-wide distribution of the β_i^y ,²¹ it would then be possible to estimate the potential demand for any particular ARBY scheme.

4. Area-based Yield Insurance and the Reduction of Default Probabilities: Crowding-in Demand and Supply in the Credit Market

If we were to make the draconian assumption that individuals always repay lenders as much as is financially possible (i.e., set $\underline{c}=0$), then loan default would not be a major issue in our simulations. However as we make the more realistic assumption that farmers will retain enough income to at least feed their families (setting \underline{c} to 20% of long-term expected income), loan default becomes an issue. We find that under this repayment assumption, a larger share of the benefits of ARBY insurance will pass to the lender in the form of even lower default rates and higher earnings. In particular, simulation results show that ARBY insurance eliminates loan default and increases realized returns on the lender's loan portfolio by between 4% and 6%, depending on the ARBY index used (measured or estimated). This shift of benefits to the lender means,²² however, that the insurance is less valuable to borrowers in the short term sense. However, additional value would accrue to borrowers once we take into account their gain in future utility from not having defaulted, and thus not having lost valuable collateral or reputation, in the present. Additional analysis can further explore these points.

²¹ Econometric estimation of equation [1] yields the distribution of the β_i^y . Experimental data would provide further insights about the demand for ARBY insurance for various β_i^y -type farmers given different insurance strike points.

²² These results provide a rationale for the participation of lenders in delivering ARBY insurance, bundled with an agricultural loan (this could also reduce insurance marketing costs). Recent field visit to a southern coastal valley in Peru confirmed the interest of the main agricultural lender in delivering ARBY-type insurance as an add-on to the loans already offered.

The likelihood that ARBY insurance can reduce default suggests that it could have impacts on both the demand and supply sides of the credit market. From the demand side, the elimination of the probability of default eliminates the risk that borrowers will lose their collateral. As discussed by Boucher *et al.* (2007), studies in Guatemala, Honduras, Nicaragua and Peru suggest that between 15% and 30% of all potential borrowers are “risk rationed,” refusing available loan contracts (and retreating to safer, lower return activities) in order to avoid the risk of default and collateral loss. The returns, in terms of higher investment and productivity levels, to ARBY insurance that brings these individuals into the market are potentially quite high (see Boucher and Guirking, 2006).

In addition, as documented by Tarazona and Trivelli (2006) and Trivelli et al. (2006) for the case of the north coast of Peru, local agricultural lenders (the *Cajas Municipales*) are extremely reluctant to carry a large loan portfolio. At the root of this reluctance is a two-sided fear of covariant risk. Directly, locally based lenders clearly do not want to carry a large fraction of their portfolio in loans where the likelihood of default is highly correlated (as would happen in a drought year). In addition, covariant risk of this sort also generates a secondary political risk. When a large number of producers face default, they have obvious political incentives to demand a bail-out or other form of debt forgiveness. Precisely this scenario took place following the 1998 El Niño event. The resulting governmentally mandated *Rescate Financiero* (Financial Rescue), which required lenders to restructure certain overdue loans, further reduced lenders’ willingness to lend to agriculture (see Trivelli et al., 2006). Seen in this light, ARBY insurance potentially offers a double benefit to lenders. If uptake is sufficiently high, ARBY insurance can reduce

both the direct risk of correlated default as well as the risk of political default which, as made evident in the case of Peru, is also produced by covariant shocks.

5. Implementation Issues for Area-based Yield Insurance: From Theory to Practice

The *ex ante* analysis above indicates large private and social gains to area-based yield insurance. ARBY would appear to be an attractive option precisely because it promises to crowd-in supply and demand in rural credit markets, enhancing the productivity of the sector.

These observations raise the question as to why the private insurance market (in Peru and elsewhere) generally fails to offer ARBY insurance products.²³ There are at least three reasons for the failure of the private market to provide this insurance:

1. The novelty of the product and the costs associated with its innovation;
2. Scarcity of reliable, long-term data on area yields or the weather indices needed to estimate them (meaning that potential insurance providers face parameter uncertainty as they try to write insurance contracts); and,
3. Costs of marketing the product, especially to the smallholder sector (where returns are likely to be highest).

Following the example of other micro-insurance products, a potential solution to problem 3 is to bundle ARBY contracts with microfinance products. Indeed this bundling strategy has already been proposed elsewhere.²⁴ In a country like Peru, where the private insurance sector has virtually no experience in offering agricultural insurance, the strategy of channeling an ARBY insurance product through micro-finance institutions, which have

²³ In the context of the US, it is often argued that government subsidized conventional insurance products crowd-out market supply of ARBY insurance contracts. Such crowding out is not the issue in Peru and most other areas in the developing world. A review of the design, and viability, of the ARBY-like US contracts, offered under the Group Risk Plan (GRP), can be found in Skees et al. (1997) and Deng et al. (2007), respectively.

²⁴ See Alderman and Haque (2007) and Hess and Syroka (2005) for the case of crop insurance, and Karlan and Zinman (2005) for an example of this bundling in the case of micro health insurance.

extensive outreach and clientele amongst the target population of small-farmers, is particularly attractive.²⁵

The other two problems have a public good character. Problem 2 in a very direct sense reflects past public good failures in the form of a public sector that has not maintained credible long-term yield and, or weather information. Problem 1 also presents an important obstacle since no individual insurance provider may have incentives to pay innovation costs, especially given problems 2 and 3.

These observations suggest that there may be a public role in underwriting innovation costs, creating reliable long-term information,²⁶ and sharing some of the excess risk (that results from parameter uncertainty) until experience and more reliable long-term information come on-line. But how costly would it be for a public sector entity to underwrite the risk of an ARBY insurance scheme over a short term period until sufficient learning had occurred to permit the private sector to bear the full risk of the program?

Over the long-term, the expected cost of an underwriting guarantee is of course zero. That is, if the program were run for a long-time, then the premiums collected would almost surely cover the indemnity payments. In the short term, in contrast, it is possible that accumulated premiums would be insufficient to cover indemnity payouts. To get a handle on the magnitude of this risk, Table 3 shows the probability of losses of different magnitudes associated with insurance underwriting.²⁷ The table is based on the simulation analysis of Lambayeque rice producers used above. Two alternative insurance contracts

²⁵ Needless to say, careful attention must be paid to institutional details such as regulation of the insurance product and cost-sharing of marketing and administrative expenses between the micro-finance institution and the private insurance sector.

²⁶ As discussed above, ARBY insurance will become more valuable to farmers as direct reliable yield measurement can replace the reliance on weather indices and estimated average yields.

²⁷ For purposes of this analysis, administrative costs are assumed to be zero.

are illustrated. The first (Contract I) sets the strike point at 80% of long-run average valley yields. The actuarially fair premium for this contract is \$65 per-planted hectare. This amount represents 11.8% of the production loan taken by a typical rice farmer. Rolling this cost into the interest rate would increase the annual interest on the loan by approximately 25.6 percentage points. The second contract (Contract II) sets the strike point at 100% of long-run average valley yields. With its higher strike point, this second contract is more expensive, requiring a premium of \$109 per-planted hectare.

The rows of the table display the probabilities that per-hectare *insurance* losses take on certain amounts. Gains and losses over a T -year time horizon are calculated as follows:²⁸

$$T\pi - \sum_{t=1}^T (\rho_t),$$

where π is the per-hectare premium and ρ_t is the indemnity payment for year t . Note that premiums are pooled over the T years and, under this definition, losses appear as negative values.

As can be seen in Table 3, for the case of the 80% ARBY plan, over a single year time horizon, there is a 2% probability that insurance losses exceed \$300 per-hectare financed (recall however, that the farmer's debt obligation is \$110 per-hectare). When risk is pooled over just two years, this probability drops to almost zero. When risk (and premiums) are pooled over a five year period, the probability that losses exceed \$100 is only 3%, while the probability that losses are between zero and \$100 is 26%. Put differently, premiums collected are sufficient to cover losses 74% of the time even when risk is pooled only over a five year horizon.

²⁸ Note that we are not discounting the indemnity payments.

Table 3
Short-term Costs and Risks of Underwriting ARBY Insurance

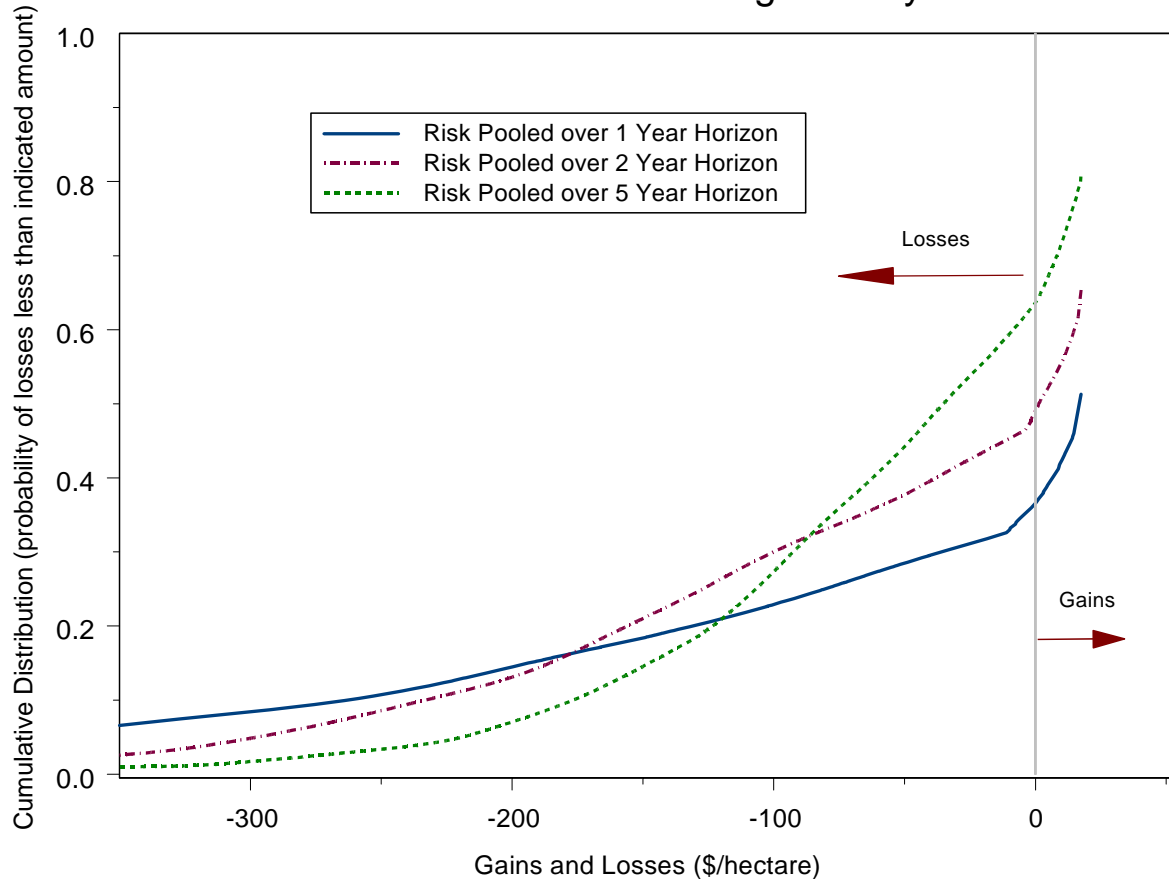
	<i>Contract I</i> (Strike point = 80% of long-run average valley yields)			<i>Contract II</i> (Strike point = 100% of long-run average valley yields)		
Expected Yield per Cultivable Hectare (\$US)	\$916			\$916		
Actuarially Fair Annual Premium per Planted Hectare	\$65			\$109		
Premium as % of Typical Loan*	11.8%			19.8%		
<i>Time Horizon Over which Loss Probabilities Calculated (years)</i>	1	2	5	1	2	5
Expected Loss	0	0	0	0	0	0
Probability of loss greater than \$300/hectare	2%	0%	0%	8%	5%	2%
Probability of loss between \$200 and \$300/hectare	2%	2%	~0%	7%	8%	5%
Probability of loss between \$100 and \$200/hectare	2%	3%	3%	8%	6%	20%
Probability of loss between \$50 and \$100/hectare	2%	5%	7%	6%	7%	16%
Probability of loss between \$0 and \$50/hectare	3%	25%	19%	5%	20%	19%

* Average loan: \$ 550.

The full estimated cumulative distribution function for losses (on which the figures in Table 3 are based) for the 100% ARBY plan is presented in Figure 2. As can be seen, the risk of losses over a one-year horizon is not trivial. However, this risk diminishes rapidly if the underwriter takes on a long-term commitment. Note also that this risk exposure could be reduced further by raising the premium to farmers, or by charging a usage fee to participating lenders (who would benefit from diminished default risk).

Figure 2

Insurance at 100% of Average Valley Yields



6. Conclusions

The analysis presented here has used real data to illustrate the potential for area-based yield insurance to crowd-in supply and demand for agricultural finance.²⁹ While this potential has been recognized at least in part by a number of other authors (such as Hess (2003) and Skees and Barnett (2006)), the actual implementation of area-based yield insurance has often floundered over the lack of credible long-term statistical information

²⁹ It should be stressed that the valuation of insurance presented here assumes that producers behave in accordance with the axioms of the expected utility hypotheses. Behavioral research indicates that in reality individuals may depart from a number of these axioms. In an effort to get a sharper insight into the real world value of ARBY insurance, the authors of this study are planning to run field experiments to explore individuals' willingness to pay for ARBY insurance.

needed to make area-based yield insurance immediately attractive to the private sector. But as argued in this paper, this lack of information reflects a past history of public good failures. An appropriate response would thus seem to be a dual approach in which (1) needed informational infrastructure is created and (2) short term parameter uncertainty is resolved by public sharing of risk (through subsidies to the cost of insurance, for instance). The returns to such a dual approach would seem to be large, both in terms of rural income generation, but also in terms of underwriting the income growth of the small farm sector that suffers most from risk and incomplete financial markets.

Finally, efforts should be made to avoid distorting interventions from the public sector in rural financial markets. Recent history in several developing countries alerts us of the harmful effects of political intervention.

References

- Alderman Harold and Haque Trina, "Insurance Against Covariate Shocks: The Role of Index-Based Insurance in Social Protection in Low-Income Countries of Africa", *World Bank Working Paper No.95*, Africa Region Human Development Department, The World Bank, Washington, D.C., 2007.
- Barnett Barry, "The U.S. Federal Crop Insurance Program," *Canadian Journal of Agricultural Economics* Vol. 48, No.4, 2000, pp.539-551.
- Barnett Barry, Black J. Roy, Hu Yingyao and Skees Jerry, "Is Area Yield Insurance Competitive with Farm Yield Insurance", *Journal of Agricultural and Resource Economics* Vol. 30, No.2, 2005, pp.285-301.
- Besley Timothy and Coate Stephen, "Group lending, repayment incentives, and social collateral", *Journal of Development Economics* Vol. 46, No.1, 1995, pp.1-18.
- Boucher Steve, Carter Michael R., and Guirkinger Catherine, "Risk Rationing and Wealth Effects in Moral Hazard-Constrained Markets: Theory and Implications for Land Titling and Rural Finance", *American Journal of Agricultural Economics*, forthcoming, 2007.
- Boucher Steve and Guirkinger Catherine, "Credit Constraints and Productivity in Peruvian Agriculture", working paper, UC-Davis, 2006.
- Coble Keith, Miller J. Corey, Zuniga Manuel, and Heifner Richard, "The joint effect of government crop insurance and loan programmes on the demand for futures hedging", *European Review of Agricultural Economics* Vol. 31, No.3, 2004, pp. 309-330.
- Chambers Robert and Quiggin John, "Decomposing Input Adjustments under Price and Production Uncertainty", *American Journal of Agricultural Economics* Vol. 83, No.1, 2001, pp.20-34.
- De Janvry Alain, McIntosh Craig, and Sadoulet Elizabeth, "The Supply and Demand Side of Credit Market Information" Working Paper, UC-Berkeley, UC-San Diego, 2006.
- Deng Xiaohui, Barnett Barry, and Vedenov Dmitry, "Is there a viable market for Area-Based Crop Insurance?", *American Journal of Agricultural Economics* Vol. 89, No.2, 2007, pp.508-519.
- Duncan John and Myers Robert J., "Crop Insurance Under Catastrophic Risk", *American Journal of Agricultural Economics* Vol. 82, No.4, 2000, pp.842-855.
- Karlan Dean and Zinman Jonathan, "Microfinance in Theory and Practice", Research project, BASIS Research Program, University of Wisconsin-Madison, 2005.

- Ghatak Maitresh and Guinnane Timothy, “The economics of lending with joint liability: Theory and practice”, *Journal of Development Economics* Vol. 60, No.1, 1999, pp.195-228.
- Gollier Christian, “To Insure or Not to Insure?: An Insurance Puzzle”, *The Geneva Papers on Risk and Insurance Theory* Vol.28, No.1, 2003, pp.5-24.
- Hazell Peter, Pomareda Carlos, and Valdes Alberto (editors), *Crop Insurance for Agricultural Development: Issues and Experience*. Johns Hopkins University Press, Baltimore, 1986.
- Hess Ulrich, “Innovative Financial Services for Rural India: Monsoon-Indexed Lending and Insurance for Smallholders”, *Agricultural and Rural Development Discussion Paper* No.9, The World Bank, Washington, D.C., 2003.
- Hess Ulrich and Syroka Joanna, “Weather-Based Insurance in Southern Africa: The Case of Malawi”, *Agriculture and Rural Development Discussion Paper* No. 13, The World Bank, Washington, D.C., 2005.
- Jappelli Tullio and Pagano Marco, “Information sharing in Credit Markets: A Survey”, *CSEF Working Paper* No.36, Center for Studies in Economics and Finance (CSEF), University of Salerno, Italy, 2000.
- Kalavakonda Vijay and Mahul Olivier, “Crop Insurance in Karnataka”, *Policy Research Working Paper Series* No.3654, The World Bank, Washington, D.C., 2005.
- Knight Thomas and Coble Keith, “Survey of U.S. Multiple Peril Crop Insurance Literature Since 1980”, *Review of Agricultural Economics* Vol. 19, No.1, 1997, pp.128-156.
- Lilleor Helene, Gine Xavier, Townsend Robert, and Vickery James, “Weather Insurance in Semi-Arid India”, Paper prepared for the Commodity Risk Management Group, Agricultural and Rural Development Department, The World Bank, Washington, D.C., 2005.
- Luoto Jill, Wydick Bruce, and McIntosh Craig, “Credit Information Systems in Less-Developed Countries: A Test with Microfinance in Guatemala”, *Economic Development and Cultural Change* Vol. 55, No.2, 2007, pp.128-156.
- Mahul Olivier and Skees Jerry, “Piloting Index-Based Livestock Insurance in Mongolia”, *World Bank Report*, Mimeo, 2006.
- Manuamorn Ornsaran P., “Scaling up microinsurance: the case of weather insurance for smallholders in India”, *Agriculture and Rural Development Discussion Paper* No. 36, World Bank, Washington, D.C., 2007.

- McCarthy Nancy, “Demand for Rainfall-Index Based Insurance: A Case Study from Morocco”, *EPTD Discussion Paper* No. 106. International Food Policy Institute, Environment and Production Technology Division (EPTD), Washington, D.C., 2003.
- Miranda Mario, “Area Crop Yield Insurance Reconsidered”, *American Journal of Agricultural Economics*, Vol. 83, No.3, 1991, pp.650-665.
- Miranda Mario and Vedenov Dmitry, “Innovations in Agricultural and Natural Disaster Insurance”, *American Journal of Agricultural Economics* Vol. 83, No. 3, 2001, pp. 650-655.
- Skees Jerry and Barnett Barry, “Enhancing micro finance using index-based risk transfer products”, *Agricultural Finance Review* Vol. 66, 2006, pp.235-250.
- Skees Jerry, Black J. Roy, and Barnett Barry, “Designing and rating an area yield crop insurance contract,” *American Journal of Agricultural Economics* Vol. 79, No.2, 1997, pp.430-438.
- Skees Jerry, Hartell Jason, and Goes Anne, “Using index-based risk transfer products to facilitate micro lending in Peru and Vietnam”, Mimeo, 2007.
- Skees Jerry, Hartell Jason, and Hao Jianqiang, “Weather and index-based insurance for developing countries: Experience and possibilities”, in Sarris Alexander and Hallam David (eds.), *Agricultural Commodity Markets and Trade: New Approaches to Analyzing Market Structure and Instability*, Edward Elgar Publishing, Cheltenham, UK and Northampton, MA, 2006, pp.256-281.
- Skees Jerry, Hazell Peter, and Miranda Mario, “New Approaches to Crop Yield Insurance in Developing Countries”, *Environment and Production Technology Division Discussion Paper* No.106, International Food Policy Research Institute, Washington, D.C., 1999.
- Skees, Jerry, Varangis Panos, Larson Donald, and Siegel Paul, “Can Financial Markets be Tapped to Help Poor People Cope with Weather Risks?”, *Policy Research Working Paper* No.2812, The World Bank, Washington, D.C., 2002.
- Skees Jerry, Gober Stephanie, Varangis Panos, Lester Rodney, and Kalavakonda Vijay, “Developing Rainfall-Based Index Insurance in Morocco”, *Policy Research Working Paper* No.2577, The World Bank, Washington, D.C., 2001.
- Tarazona Alvaro and Trivelli Carolina, “Financiamiento Rural en Chepen y Piura”, Research Report, Instituto de Estudios Peruanos (IEP), Lima, Peru, 2006.
- Trivelli Carolina, Carter Michael R., Galarza Francisco, Tarazona Alvaro, and Yancari Johanna, “Can Insurance Unlock Agricultural Credit and Promote Economic

Growth”, *BASIS Brief* No.46, BASIS Research Program, University of Wisconsin-Madison, 2006.

Varangis Panos, Skees Jerry, and Barnett Barry, “Weather Indexes for Developing Countries”, in Dischel Robert S. (ed.), *Climate Risk and the Weather Market: Financial Risk Management with Weather Hedges*, Risk Books, London, 2002.

Wang H. Holly, Hanson Steven D., Myers Robert J., and Black J. Roy, “The Effects of Crop Yield Insurance Designs on Farmer Participation and Welfare”, *American Journal of Agricultural Economics* Vol. 80, No.4, 1998, pp.806-820.

World Bank, “Piloting Weather Insurance in India”, Mimeo, 2003.

World Bank, *Managing Agricultural Production Risk. Innovations in Developing Countries*, Report No. 32727-GLB, Agriculture and Rural Development Department, World Bank, 2005.

Zegarra Eduardo and De los Rios Carlos, “Agricultural Insurance Policy and Farmers’ Exposure to Covariant and Idiosyncratic Risk in the Peruvian Coast”, Research Report, Grupo de Analisis para el Desarrollo (GRADE), Lima, Peru, 2006.

Appendix: Econometric Results

Table A1
Data fitting for water outflows from the Tinajones Reservoir
Density: Beta (335.07, 1832; 2.53, 2.98)

	Historical Data	Fitted Data
Mean	1,038	1,021
Standard Deviation	323	281
Median	1,021	1,055
Minimum	443	494
Maximum	1,745	1,730
Number of observations	36	100

Note: See equation [10] in the text. Units expressed in millions of cubic meters.

Table A2
Regression Results for Parametric Functions Between Water Outflows and:

	Coefficient	T Statistic
<i>Average Valley Yield, Kg/Ha (Eqn. [11])</i>		
Water Outflows (ω_t)	6.45	1.52
Water Outflows squared (ω_t^2)	-0.0026	-1.28
Constant	2,030	0.95
R-squared	0.1031	
N	36	
<i>Sown Valley Area, Has (Eqn. [12])</i>		
Water Outflows (ω_t)	112.36	2.79
Water Outflows squared (ω_t^2)	-0.0396	-2.08
Constant	-37,880	-1.87
R-squared	0.4191	
N	36	

The residuals were fitted to mean zero normal distributions with standard deviations of 1,231 (average valley yields, ε_i^y) and 1,629 (valley sown area, ε_i^s).

Table A3
Regression of Individual Yields on Average Valley Yields
 (Random Coefficients)

	Estimated Data		Simulated Data*	
	Mean	Standard Deviation	Mean	Standard Deviation
Idiosyncratic shock, ε_{it}^y (Kg/Ha)	~0	137	0.2	137
Individual farmers' beta, β_i^y	1.02	0.23	1.03	0.24

* Simulations are based on random draws from normal distributions with the above indicated means and standard deviations.

Note: See equation [1] in the text. n = 528 (= 176 observations X 3 years).

Table A4
Descriptive Statistics

	Mean	Median	Standard Deviation	Minimum	Maximum
Estimated betas, β_i^y	1.024	1.019	0.230	0.241	1.511
Simulated betas	1.032	1.034	0.237	0.098	1.852
Simulated Individual yield, y_{it} , (Kg/Ha)	5,870	5,871	273 ^a	371	10,527
Simulated valley average yield, $y(\omega_t)$ (Kg/Ha)	5,727	5,898	389	4,587	6,066
Adjusted individual sown area (Ha) ^b	2.72	2.74	1.22	0.63	5.00
Adjusted average valley yield, \tilde{y}_t (Kg/Ha) ^c	3,160	3,183	1,634	411	7,613
Idiosyncratic shock, ε_{it}^y (Kg/Ha)	0.20	1.08	137 ^a	-601	533
Historical water outflows, ω_t (millions of cubic meters, MCM)	1,038	1,021	323	443	1,745
Simulated water outflows, MCM	1,021	1,055	281	494	1,730
Estimated error from regressing y_t on ω_t , ε_t^y (Eqn.[11])	-37	-83	1,028	-2,468	2,200
Estimated error from regressing s_t on ω_t , ε_t^s (Eqn.[12])	-1,577	-865	21,253	-26,711	10,731

^a Average standard deviation across 100 years.

^b It equals $\frac{\bar{s}_t}{s_{\max}}$ x5, where \bar{s}_t is truncated between 7,200 and 57,200 hectares.

^c $\tilde{y}_t = \bar{y}_t \frac{\bar{s}_t}{s_{\max}}$ (Eqn. [5]).

Note: Simulations assume subsistence consumption equal to 20% of expected income (\$275); and loan size equal to 40% of expected income (\$ 550). Expected income (\$ 1,375) results from multiplying the adjusted average valley yield (in Kg/Ha) times the average adjusted sown area (in Has.) times the price of a Kg of rice (3,160x2.72x0.16).