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Pricing farm-level agricultural insurance: a Bayesian approach

Vitor Augusto Ozaki

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Abstract This paper applies Hierarchical Bayesian Models to price farm-level yield insurance contracts. This methodology considers the temporal effect, the spatial dependence and spatio-temporal models. One of the major advantages of this framework is that an estimate of the premium rate is obtained directly from the posterior distribution. These methods were applied to a farm-level data set of soybean in the State of the Paraná (Brazil), for the period between 1994 and 2003. The model selection was based on a posterior predictive criterion. This study improves considerably the estimation of the fair premium rates considering the small number of observations.

Keywords Rating crop insurance contracts · Hierarchical Bayesian models · Conditional autoregressive prior distribution

JEL Classification Q19

1 Introduction

All economic activities are influenced by some degree of risk. These risks and their economic consequences are especially relevant to insurance companies. In agriculture, the risk is basically related to the occurrence of some adverse climatic phenomena (e.g., drought), resulting in major economic losses, depending on the severity and extension of the phenomena.

Over time, several risk management tools were created by producers to manage these risks, including insurance schemes. Under some insurable conditions, the

V. A. Ozaki (✉)
Department of Mathematics and Statistics, College of Agriculture "Luiz de Queiroz",
University of São Paulo, Av. Pádua Dias, 11, Agronomia, Piracicaba, SP 13418-900, Brazil
e-mail: vitorozaki@yahoo.com.br

insurance allows an individual to turn a future and uncertain expenditure (loss), usually high, into an anticipated, certain and lower expenditure (premium) (Booth et al. 1999).

One of the main benefits of the insurance is the fact that it allows the insured to balance their income, whenever an adverse event occurs, to the condition in which such event does not take place. This is done through the payment of the premium and the receiving of compensation (indemnity), in case of misfortune (Arrow 1971; Rothschild and Stiglitz 1976).

However, several problems inhibit the development of a private crop insurance market: moral hazard (Chambers 1989; Goodwin and Smith 1998), adverse selection (Goodwin 1994; Quiggin et al. 1994; Skees and Reed 1986), systemic risk (Miranda and Glauber 1997) and the absence of long-term data on agricultural yield and actuarial methods to accurately calculate the fair premium rate.

Thus, in many countries, such as Brazil, USA, Japan, Canada and India, the total premium collected is lower than the total indemnity paid, which results in huge financial losses to the insurance companies. Moreover, in most of these countries, the programs are heavily subsidized by the government (Hazell et al. 1986). In Brazil, the absence of a suitable methodology is pointed as one of the main problems for the non-emergence of a private market (Rosseti 2001).

The aim of this article is to price a crop insurance contract based on farm-level yield data. In light of this, several Bayesian models are applied to the data set in order to forecast yields two steps ahead. One of the main advantages of using this approach is to derive rates directly from the posterior distribution. Moreover, the standard errors of the estimates for the premium rate provide a measure to the loading practices used by actuaries, which reflects the degree of uncertainty associated with an individual premium rate.

The individual yield crop insurance is widely available in USA (named multiperil crop insurance), Mexico, Spain and India (Miranda et al. 1999) and, is currently offered in Brazil by five insurance companies.

Basically, the compensation mechanism is triggered based on the farm-level yield. In this process, producers are indemnified when the agricultural yield observed in the harvest (in the unit or farm) falls below the guaranteed yield—chosen by the producer. This type of agricultural insurance is called individual yield crop insurance. The indemnity I for each farm i can be expressed as follows:

$$I_i = \phi_i \max\left[(y_i^c - y_i), 0\right]. \tag{1}$$

In which, ϕ_i represents the amount deductible, such that $0 < \phi_i < 1$, y_i^c is the guaranteed yield; and, y_i is the observed yield.

Equation (1) shows the indemnity to be paid to each producer when the agricultural yield y_i in the harvest time falls below the guaranteed yield y_i^c. In this type of contract, the producer chooses the level of coverage α_i, such as $0 \le \alpha_i \le 1$. The guaranteed yield is calculated according to the equation: $y_i^c = \alpha_i y_i^e$, in which y_i^e is the expected (forecast) agricultural yield in farm i.

In the analysis that follows, a number of alternative Bayesian models were applied to the data set aiming to model the generating process of agricultural yield data and, in particular, to properly recognize the temporal, spatial and spatio-temporal processes underlying crop yields. To select among a large number of potential candidate models, a criterion of quadratic prediction error was used. The contribution of this article is the investigation of alternative statistical methods based on Bayesian hierarchical models in a situation of small amount of available data on farm-level yield, in which the traditional statistical analysis based on asymptotic theory generates inconsistent results. Furthermore, this method captures all possible inferring uncertainties involved in predicting the insurance premium rates as opposed to the more traditional ad hoc two-stage methods based on estimation and prediction (Goodwin and Ker 1998).

This article is arranged according to the following outline. Section 2 details: (i) the design of the individual crop insurance contract; (ii) the discussion of some statistical issues regarding agricultural yield; and, (iii) the data set used in the empirical analysis. Section 3 describes the hierarchical Bayesian models and the criterion of model selection. Section 4 presents the data analysis, considering the prediction problem and the empirical application—pricing crop insurance contracts. Finally, Sect. 5 offers some concluding remarks.

2 Preliminaries

A wide variety of statistical methods are often adopted in the estimation of crop insurance rates and a number of issues regarding the modeling of crop yields are pertinent. For example, the crop yield has a substantial trend over time and tends to be significantly correlated with space due to the systemic nature of weather. One subtlety often overlooked in crop insurance pricing models refers to the fact that a degree of uncertainty also applies to the estimated parameters of any model. In this analysis, we adopt a Bayesian inferential framework that accounts for such sources of uncertainty while estimating the appropriate premium rate.

Moreover, given the increasing interest in crop insurance in Brazil by the insurance companies, pricing contracts has become an important issue. Traditionally, insurers price their contracts using what is conventionally called empirical method (Goodwin and Ker 1998), which is simply the average loss realization over liability. Because no smoothing is undertaken, a relatively large sample is necessary to accurately represent the probability of distribution.

The choice of a statistical model that adequately reflects the conditional density of yield is an important consideration in the actuarial calculation of an accurate premium rate. In doing so, one must try to recover the probability for generating the process of the yield data. Agricultural yield follows a spatio-temporal process, in the sense that if we take the average in a conditional region regarding the underlying temporal process, we can recover the conditional yield density generated by the information available at moment t (Ker and Goodwin 2000).

Along the years, statistical aspects underlying agricultural yields have been a controversial point in the literature. Particularly, the shape of the density function has been discussed extensively. On the one hand, Just and Weninger (1999) concluded that agricultural yields follow a Gaussian distribution. However, other authors found evidences against normality (Ramirez et al. 2003; Taylor 1990).

Alternatively, other distributions have been proposed: beta distribution (Nelson and Preckel 1989), inverse hyperbolic sine transformations (Moss and Shonkwiler 1993) and gamma distributions (Gallagher 1987).

One must note that, in the context of crop insurance studies, the shape of the distribution is especially important because it reflects the crop yield risk (probability of loss). In other words, when modeling an agricultural yield, one must try to estimate precisely the left tail of the distribution. Considering this fact, several statistical models have been proposed in the literature to better reflect the innovation of the agricultural yield, such as, parametric (Sherrick et al. 2004), semi-parametric (Ker and Coble 2003), non-parametric (Goodwin and Ker 1998; Ozaki et al. 2008) and empirical Bayes non-parametric approaches (Ker and Goodwin 2000).

Agricultural yield data usually present some sort of idiosyncrasies in their structure. One of them is the spatial dependence across farms (Goodwin 2001; Wang and Zhang 2003). Other sources of systematic influences are presented in the data set: trends, autoregressive effects and heteroskedasticity. The first reflects the fact that in incorporating new technologies and more suitable and efficient methods, farmers increase the level of agricultural yields over time. Thus, yields observed in the early 1980s cannot be compared to those obtained in 2006. The autoregressive effect is important in the sense that drought or excessive moisture effects may persist from year to year. Heteroskedasticity happens because the variability is not constant or stable over time.

In this work, the temporal aspect of the data generating process is addressed, but we also incorporate the spatial dependence of the data generating process. In particular, we explicitly recognize the fact that the events that underlie yield realizations (e.g., weather, disease, and pest damages) tend to affect large areas at any single time. Thus, adjacent farms may experience substantial spatial correlations with yields over time. Taking this fact into account, space and time were combined in order to build spatio-temporal models.

The empirical analysis is based on a data set composed by 38 soybean producers located in the Castro region, in the State of Paraná, Brazil. The variable of interest is the agricultural yield, for the period between 1994 and 2003. Table 1 shows some basic statistics of the data set.

3 Empirical method

The objective of this section is to detail the empirical methodology to predict yields two steps ahead and to price a farm-level insurance contract. In light of this, we model the mean yield and assume that the precision (inverse of the variance) is conditionally constant in the analysis. Gelfand et al. (1998) show that more effective results can be achieved when modeling the mean component rather than the precision in forecasting problems.

Therefore, $E(y_{it}) \equiv \mu_{it}$, in which i represents the space variable index and t the temporal index. Thus, y_{it} is the agricultural yield in farm i in time t, where $i = 1, 2, \ldots, S$ and $t = 1, 2, \ldots, N$.

Modeling the dependence structure through hierarchical models is intuitive and facilitates the visualization of each component in the analysis instead of modeling

Table 1 Exploratory analysis of the soybean agricultural yield

	Year									
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Mean	2,802	2,854	2,769	2,657	2,882	2,891	2,720	2,954	3,104	3,317
	(59)	(60.6)	(65.2)	(86.4)	(75.2)	(67.2)	(68.4)	(51.8)	(48)	(77.1)
5° Percentile	2,046	2,094	2,117	1,843	1,955	2,254	2,077	2,481	2,569	2,533
50° Percentile	2,846	2,924	2,749	2,679	2,874	2,932	2,782	2,913	3,064	3,304
95° Percentile	3,329	3,467	3,550	3,562	3,738	3,683	3,221	3,529	3,604	4,001
Standard deviation	363.6	373.5	402.2	532.9	463.7	413.9	421.5	319.5	295.8	475.3
Coefficient of variation	12.98	13.09	14.53	20.06	16.09	14.32	15.5	10.82	9.528	14.33
Maximum	3,474	3,484	4,089	3,861	3,885	3,766	3,387	3,669	3,712	4,979
Minimum	2,008	2,085	2,015	1,261	1,639	2,053	1,371	2,265	2,437	2,351
Skewness	−0.43	−0.36	0.871	−0.12	−0.29	0.083	−0.97	0.277	−0.14	0.928
Kurtosis	−0.49	−0.61	2.005	0.18	0.616	−0.52	1.314	−0.23	−0.24	2.99

Standard error in parenthesis

such structure directly through the y_{it}.[1] However, assigning non-informative prior distributions can lead to improper posterior distribution (Hobert and Casella 1996).

Taking this fact into account, proper prior distributions will be chosen assuring that the Gibbs sampling process will be well-behaved. In this case, ignorance can be represented as values for the precision parameter close to zero (Gelfand and Smith 1990).

The temporal component will be initially modeled considering a deterministic trend model according to: $y_{it} = \sum_{j=1}^{p} \beta_j T^j + \varepsilon_t$, $\varepsilon_t \overset{iid}{\sim} N(0, \sigma^2)$ and $p = 1, 2$. For this type of trend model, the variable T was centered in order to improve the Markov Chain Monte Carlo (MCMC) algorithm speed of convergence, such as $T^* = [T - (N + 1) \times 0.5]$. Moreover, the empirical plot checking indicated that a quadratic trend was sufficient to capture trend effects.

In addition to the deterministic models, an autoregressive AR (1) term was included and fitted to the data, such as: $y_t = \rho y_{t-1} + \varepsilon_t$, $-1 \leq \rho \leq 1$. At this point, assumptions regarding the specification of the model must be made. First, the correlation parameter ρ in the stochastic models changes according to the farm. Second, an exchangeable[2] Gaussian prior was assigned to the parameter ρ and Gaussian and inverse Gamma hyper-distributions for the mean and variance parameters, respectively.

The interaction between the deterministic and stochastic models was analyzed considering a first-order polynomial function in t added to the stochastic component, as follows: $y_t = \rho y_{t-1} + \beta_0 + \beta_1 T^* + \varepsilon_t$.

[1] Alternative approaches model the temporal and spatio-temporal dependences through the error term (Anselin 1988).

[2] For more details see Casella and Berger (2002), De Finetti (1972) and Migon and Gamerman (1999).

Univariate Gaussian prior distributions were assigned to β_0, β_1 and β_2 with zero mean and precision parameter $\tau \rightarrow 0$. Considering a random effect model, then all β's will be exchangeable. This result is convenient and it is reasonable to assume that the parameters may differ from one another, although they arise from the same population distribution.

The spatial effect can be represented as random effects υ_i were introduced in order to capture the heterogeneity (unobserved features) among different regions. Moreover, a latent variable was introduced to catch the spatial effect ξ_i representing the geographic nature of each farm. Thus, υ_i is the spatially non-structured latent variable (heterogeneity) and ξ_i is the spatially structured latent variable (clustering).

In this study, we incorporate the unobserved farm-effects features that affect agricultural yield through these latent variables. More specifically, υ_i captures the socio-economical factors (such as, agricultural techniques and technologies in each farm) and ξ_i reflects the soil and climatic conditions particular to each location. This approach is particularly appealing because of the nature of the agriculture yield data.

These random effects are separated by using the hierarchical structure of the model. Under the exchangeability assumption we can estimate the heterogeneity variable through its prior distribution and estimate the clustering variable assuming a special form of spatial prior distribution. This framework addresses the problem of spatial dependence between farms.

Identification of the parameters in the likelihood function in this case is verified in the hierarchical model by assuming a conditional autoregressive[3] (CAR) prior distribution for ξ_i and exchangeable Gaussian priors for υ_i. We assume that the non-structured variable follows a Gaussian distribution, so that $\upsilon_i \sim N(\mu_\upsilon, \sigma_\upsilon^2)$, and the spatially structure variable $\xi_i|\xi_j(j \neq i)$, was represented according to $\xi_i \sim N(\bar{\xi}_i, \sigma_\xi^2/n_i)$, in which $\bar{\xi}_i$ is the average of the ξ_j's, in which j indexes the neighboring sites of i. The variance parameters σ_υ^2 and σ_ξ^2 are assigned an inverse Gamma prior distribution (Besag 1974; Besag et al. 1991; Bernardinelli et al. 1995a; Clayton and Kaldor 1987; Cressie and Chan 1989).

A restriction must be imposed to the random effects parameters, so that those effects amount to zero. In other words, an intercept parameter must be included in the model to assign an improper (uniform) prior distribution (Thomas et al. 2002). If both parameters were placed in the model, then $E(\upsilon_i) = 0$. Likewise, if both parameters υ_i and ξ_i were included to the model and one attributed a non-informative point prior to υ_i, then we would have either $\upsilon_i = 0$ or $\sum \upsilon_i = 0$. Due to convergence issues in the MCMC algorithm, one must include either the spatially non-structured variable or the structured variable, but not both (Gelfand et al. 1998).

The spatio-temporal models were based on the works of Bernardinelli et al. (1995b), Dreassi (2003) and Waller et al. (1997). In their work, Waller et al. (1997) consider a nested model, in which the spatial effect and the heterogeneity variable vary in time.

Because of the conditional interchangeability associated with time, the resulting prior distribution assigned to the heterogeneity can be represented by $\upsilon_i^{(t)} \overset{iid}{\sim}$

[3] The reader must not confuse the term "autoregressive" commonly used in the time series analysis. In spatial statistics or econometrics, autoregressive refers to the mean of the variable in the neighbor regions.

$N(\mu_{\upsilon}^{(t)}, \sigma_{\upsilon}^{2(t)})$. For the spatial effect $\xi_i^{(t)}$ in the i-th region in year t, Waller et al. (1997) adopted an intrinsic CAR prior distribution. Thus, $\xi_i^{(t)} \sim N(\bar{\xi}_i^{(t)}, \sigma_{\xi}^{2(t)}/n_i)$, where $\bar{\xi}_i^{(t)}$ is the average of the jth contiguous areas of i. An inverse Gamma was used to form hyper-priors for $\sigma_{\upsilon}^{2(t)}$ and $\sigma_{\xi}^{2(t)}$.

We also allow the spatial effects to be nested within the temporal process, in such a way that the parameters of the deterministic trend (β's) are modeled by using the CAR prior. Intuitively, one can think of the trend parameters as being spatially correlated, given time. The stochastic term was incorporated to the general expression and exchangeable prior distributions were assigned to the AR(1) term. Thus, we have the following general expressions:[4]

$$y_{it} = \rho_i y_{t-1} + \beta_{0i} + \beta_{1i} T^* + \beta_{2i} T^{*2} + v_i^{(t)} + \varepsilon_{it}. \tag{2}$$

As one can note, several models emerge as potential candidates. Traditional criteria of model selection, such as the Bayes factor, are not applicable in this case as they are, where non-informative or conditional autoregressive (CAR) prior distributions are used. Improper prior distributions result in improper conditional predictive distributions, limiting the use of Bayes factor as a model selection criterion in these cases (Carlin and Louis 2000, p. 220).

Classical approach to model selection is also difficult. Penalized likelihood criteria based on asymptotic efficiency require the determination of the dimension of the model or the number of the parameters, which is difficult to estimate in hierarchical models with random effects such as those used in this paper.

In this article, the model selection criteria will be based on predictive densities (Laud and Ibrahim 1995). Working on the predictive space, the penalty appears without the necessity of asymptotic definitions. The objective is to minimize the posterior predictive loss (Gelfand and Ghosh 1998). The posterior predictive distribution is given by:

$$f(y_{new}|y_{obs}) = \int f(y_{new}|M)p(M|y_{obs})dM \tag{3}$$

in which, M represents the set of all parameters in a given model and y_{new} is the replication of the vector of observed data y_{obs}.

The criterion is based on a discrepancy function $d(y_{new}, y_{obs})$, and the objective is to choose the model that minimizes the expectation of the discrepancy function, conditional on y_{obs} and M_m, where M_m represents all the parameters in the model m. The penalty is considered in the analysis regardless of model dimension. If we consider Gaussian models D_m is given by:

$$D_{M_m} = E[(y_{new} - y_{obs})^T (y_{new} - y_{obs})|y_{obs}, M_m]. \tag{4}$$

[4] When including the heterogeneity variable, the clustering variable must be excluded and vice versa.

Table 2 Model selection

M	D_m	Model (μ_{it})
1	208,100	$\rho_i y_{t-1} + \beta_{1_i} + \beta_{2_i}^C t^*$
2	264,700	$\rho_i y_{t-1} + \beta_{1_i}^C + \beta_{2_i} t^*$
3	269,500	$\rho_i y_{t-1} + \zeta_i^t$
4	270,300	AR(1)
5	279,900	$\rho_i y_{t-1} + \beta_{1_i}^C + \beta_{2_i}^C t^*$
6	305,500	$\rho_i y_{t-1} + \beta_{1_i} + \beta_{2_i} t^* + \zeta_i^t$
7	306,800	$\rho_i y_{t-1} + \beta_{1_i} + \beta_{2_i} t^*$
8	307,500	$\beta_{1_i} + \beta_{2_i} t^* + \zeta_i^t$
9	308,200	$\beta_{1_i} + \beta_{2_i} t^*$
10	363,500	$\beta_{1_i} + \beta_{2_i} t^* + \beta_{3_i} t^{*2}$

4 Results and empirical application

Altogether, ten models were adjusted to the data set. Table 2 shows that the first seven models present the stochastic trend component. Thus, it is evident that the temporal effect is relevant in the analysis. The model that minimizes the mean squared predictive error has the stochastic and the deterministic term (model 1). Moreover, the intercept parameter varies according to the i-th farm. In this case the spatial correlation is detected by the slope parameter through the CAR prior distribution.

The difference between models 1 and 2 relies on the prior distribution assigned to the β's. The superscript "C" indicates a conditional autoregressive prior distribution. Furthermore, a Gaussian prior distribution is assigned to β. One can note that the values of D_m between models 1 and 2 are considerably different. This fact suggests that the inclusion of the spatial dependence results in better agricultural yield predictions.

Considering models 3 and 4, the inclusion of the spatially structured latent variable changing over time associated to the stochastic trend term reduces the value of D_m when compared to the first-order autoregressive model. Assigning CAR priors to both parameters of the deterministic trend component improve the prediction results ($D_5 < D_7$). The difference between models 8 and 9 is the addition of the clustering variable changing over time, which is preferable to the situation where the variable is absent ($D_8 < D_9$). Finally, the polynomial model shows the highest value of D_m, thus the worst result in terms of prediction.

In order to check the mixing and convergence of the Markov sequence we run three chains. Results showed that all parameters achieved good convergence and mixing. Because of the small temporal number of observations, we do not correct to conditional heteroskedasticity. Instead, we assume that series are conditionally homoskedastic. Table 3 shows prediction results using model 1 (Table 2).

After choosing the best model and predicting yields two steps ahead, we use this prediction to calculate the premium rate. The premium rate (PR) is calculated considering the level of coverage $\alpha (0 \leq \alpha \leq 1)$ of the expected yield y^e and given by the following equation (Goodwin and Ker 1998):

Table 3 Predicted yield of the 38 producers, in kg/ha

Producer	Year	Predict. yield	Producer	Year	Predict. yield	Producer	Year	Predict. yield	Producer	Year	Predict. yield
1	2004	3,110	11	2004	3,276	21	2004	3,416	31	2004	2,650
	2005	3,232		2005	3,295		2005	3,528		2005	2,693
2	2004	3,268	12	2004	3,126	22	2004	3,561	32	2004	3,175
	2005	3,346		2005	3,224		2005	3,672		2005	3,181
3	2004	3,346	13	2004	2,810	23	2004	3,693	33	2004	3,080
	2005	3,386		2005	2,894		2005	3,721		2005	3,155
4	2004	3,042	14	2004	3,813	24	2004	3,411	34	2004	3,259
	2005	3,094		2005	3,762		2005	3,489		2005	3,316
5	2004	3,707	15	2004	3,784	25	2004	3,533	35	2004	3,203
	2005	3,738		2005	3,868		2005	3,626		2005	3,271
6	2004	2,725	16	2004	3,386	26	2004	3,647	36	2004	3,165
	2005	2,872		2005	3,469		2005	3,763		2005	3,243
7	2004	3,817	17	2004	3,382	27	2004	3,866	37	2004	3,198
	2005	3,809		2005	3,442		2005	3,911		2005	3,289
8	2004	4,837	18	2004	3,691	28	2004	2,476	38	2004	3,307
	2005	4,809		2005	3,756		2005	2,593		2005	3,399
9	2004	3,703	19	2004	3,207	29	2004	3,281			
	2005	3,655		2005	3,335		2005	3,307			
10	2004	3,438	20	2004	2,961	30	2004	2,727			
	2005	3,520		2005	2,999		2005	2,755			

$$PR = \frac{F_Y(\alpha y^e)E_Y[\alpha y^e - (Y|y < \alpha y^e)]}{\alpha y^e}. \tag{5}$$

In which E is the expectation operator and F is the cumulative distribution of yields.

If we reparameterize y, so that, $y^* = y/\lambda y^e$, then Eq. (5) becomes:

$$PR = P(w > 0)E_w[w|w > 0)]. \tag{6}$$

In which $w = 1 - y^*$.

After some simplification, the premium rate equation reduces to:

$$PR = \int_0^1 w\, f(w)dw. \tag{7}$$

Premium rates were monitored through the posterior mean of w. In Table 4 we show the average premium rate (38 producers), maximum and minimum, by level of coverage. In addition to the calculation of the PR we derive standard error estimates,

Table 4 Average, minimum and maximum premium rates (PR)—38 producers—by level of coverage, and Monte Carlo standard error (MC SE)

Level of coverage (%)	Average PR (%)	Minimum PR (%)	Maximum PR (%)	MC SE
70	0.0934	0.002505	0.5593	0.000056
75	0.3030	0.014720	1.3150	0.000117
80	0.7753	0.069410	2.6300	0.000213
85	1.6395	0.241200	4.5500	0.000339
90	2.9792	0.648000	6.9720	0.000480

which in our context are called Monte Carlo standard errors of the mean.[5] The estimates of the premium rate standard errors provide a natural metric process to guide "loading practices"[6]—a measure of the uncertainty associated with an individual premium rate estimate. In particular, higher load adjustments can be applied to those rates which reflect a higher degree of uncertainty.

5 Concluding remarks

The premium rate is one of the most important pieces of information of any insurance contract. An actuarially fair premium rate is a rate that is set so that premiums collected are equal to expected indemnities. An inaccurate premium rate results in distortions to the insurance pool and thus may result in losses as agents adversely select against the insurance provider.

For example, consider an insurance company selling contracts to soybean producers located in the Castro region charging 3.5% of premium rate. In Brazil, rates are regionalized and charged equally among producers. Further, consider that the premium rate (level of coverage of 90%) calculated using the Bayesian method is equal to 4.87% to producer 1 and 1.84% to producer 5.

In this situation, the insurer will overprice producer 5 and underprice producer 1. In a market where historically indemnities paid are higher than the total amount of premiums collected, better actuarial methods (such as, the one proposed in this paper) should be taken into account by insurance companies to calculate accurate premium rates and reduce their historical high loss ratio. This approach makes the premium rate calculation less ad hoc, in the sense that rates are derived after the simulation through MCMC algorithm. Moreover, when we calculate the rates we capture their uncertainty through the standard error.

This study is appealing from both economic and political perspectives because it improves the actuarial methods used by the insurance companies and better addresses the spatial and temporal correlation. Results show a high variance of the

[5] For further details see Spiegehalter et al. (2003).

[6] Loading refers to additive factors that are applied to premium rates to account for uncertainty and is commonly used to build reserves, to cover administrative and operating costs and to ensure a positive profit for the insurer.

rates among producers at the same level of coverage. This fact suggests that the risk varies considerably in this sample. If the insurance companies continue to charge equal premium rates by regions indistinctly, they might end up increasing their losses.

The fact of the matter is that producers have better information about their own risk than the insurance companies do. Thus, without enough volume of accurate information to assess the farmer's risk, insurers might concentrate their operations in the regions of lower risk. Considering the political perspective, this is the situation to be avoided by the government, which is trying to develop a financially sound crop insurance plan to better support agricultural producers nationwide.

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