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Rating Crop Insurance Contracts with Nonparametric Bayesian Model Averaging

Yong Liu and Alan P. Ker

Crop insurance is plagued by relatively little historical information but significant spatial information. We investigate the efficacy of using nonparametric Bayesian model averaging (BMA) to incorporate extraneous information into the estimated premium rates. Nonparametric BMA is particularly suited to this application because it does not make any assumptions about parametric form or the extent to which yields are similar. We evaluate the proposed estimator under small-to-medium sample sizes and various geographical restrictions on the distance of spatial smoothing for policy relevance. The nonparametric BMA consistently decreases error and enables statistically significant and economically important rents to be captured.

Key words: yield density estimation, crop insurance

Introduction

Over the past half century, crop insurance has been an essential part of U.S. domestic agricultural and rural policy. The United States is not alone; subsidized crop insurance has and continues to be the cornerstone of domestic agricultural policy in most developed countries, including Canada, Spain, Italy, Japan, and France (Smith and Glauber, 2012). Moreover, crop insurance programs have been integral to rural economic growth in many developing countries, including Brazil, China, India, Malaysia, Philippines, and countries in sub-Saharan Africa (Roberts, 2005; Herbold, 2010). The U.S. agricultural insurance program covers over 100 crops and has programs for livestock and dairy. The CBO (2014) estimates spending of public monies on agricultural insurance programs will be almost $90 billion for the 2014–2023 period. This does not include any *ad hoc* assistance like the recently announced $12 billion trade dispute assistance program for U.S. farmers.

Because crop insurance is the cornerstone of domestic agricultural policy in almost all developed countries and vast sums of public monies are used to subsidize crop insurance premiums, there exists a significant amount of literature on estimating yield densities and premium rates. The actuarially fair premium rate for an insurance contract is defined as expected loss divided by total liability. In practice, an estimate of the conditional yield or revenue density is required to recover premium rates. The idea of formally incorporating yield data from other densities to improve the accuracy of the estimation process started in Ker and Goodwin (2000) and continued with Racine and Ker (2006). Very recently, this literature has grown, with articles by Annan et al. (2014), Ker, Tolhurst, and Liu (2016), Park, Brorsen, and Harri (2018), and Ramsey (2020). We contribute to this literature by considering nonparametric Bayesian model averaging (BMA) to incorporate spatially extraneous yield information.

We make two contributions: (i) We include spatially extraneous information without the need to make distributional assumptions regarding the data-generating process of yields; and (ii) we evaluate various levels of geographical restrictions on the distance of spatial smoothing. Specifically, we

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consider the efficacy of the nonparametric BMA in estimating crop insurance rates under three spatial restrictions. First, we restrict extraneous yield data to within a crop-reporting district (CRD). Second, we restrict extraneous yield data to within a state. Finally, we do not impose any restrictions on extraneous yield data and use all available yield data. To evaluate our proposed methodology, we undertake two simulations. We assess statistical significance by sampling from estimated yield densities and comparing the premium rates derived from the nonparametric BMA with those derived from the standard nonparametric kernel density estimate and those from the Risk Management Agency's current method. We assess economic importance by conducting an out-of-sample retain–cede rating game, whereby the private insurer attempts to adversely select against the RMA.

A number of our findings are noteworthy. First, the nonparametric BMA estimator outperforms both the individual and the RMA estimators for all crops across all sample sizes. Second, the largest efficiency gains with BMA are in small samples, where there is relatively little information in the individual sample. Third, corn and soybean tend to make greater use of the spatially extraneous data, suggesting that their densities are more homogeneous across space than the densities of winter wheat and cotton. Fourth, although spatial correlation necessarily decreases the efficiency of the nonparametric BMA estimator, it remains more efficient. Fifth, the results are robust to restrictions on the distance of spatial smoothing.

U.S. Crop Insurance Program and Premium Rate Estimation

The U.S. crop insurance program is operated by the Risk Management Agency (RMA), an arm of the United States Department of Agriculture (USDA). The government (i.e., the RMA) sets premium rates, subsidizes those premiums, and shares in the underwriting gains and losses of the insurance contracts with private insurers. Estimated premium rates are set to be actuarially fair with an 11% top-up for reserves. That is, unlike private insurance markets, there is neither a risk premium nor premium to cover a return to capital. Private insurers approved to participate in the program sell policies to farmers, conduct claim adjustments, and share the underwriting gains and losses of the insurance contracts they sell. The structure by which the private insurers are compensated for participating is set out in the Standard Reinsurance Agreement (SRA). While the parameters have changed over time, the structure of the SRA has remained relatively intact: (i) Private insurers are reimbursed a percentage of collected premium to cover their administrative and operating (A&O) costs; (ii) underwriting gains and losses of the policies they sell are shared with RMA; (iii) there is a mechanism by which insurers can opt out of the large majority of underwriting gains and losses of policies they do not want; and (iv) the underwriting gains and losses are shared asymmetrically, where insurers receive a higher share of the underwriting gains than losses. The opt-out mechanism is necessary because private insurers do not set premium rates. The asymmetric sharing of the underwriting gains and losses is necessary to compensate private insurers for both the lack of a risk premium and the lack of a premium to cover a return to capital, both of which are absent in the government-set premium rates.[1]

In practice, estimating the premium rates requires an estimate of the conditional yield or revenue density. Parametric methods have dominated the literature. These methods include the normal (Botts and Boles, 1958), gamma (Gallagher, 1987), beta (Nelson and Preckel, 1989), logistic (Atwood, Shaik, and Watts, 2003), Weibull (Sherrick et al., 2004), inverse sine transformation method (Ramírez, 1997), maximum entropy (Wu and Zhang, 2012; Tack, Harri, and Coble, 2012), and normal mixtures (Woodard and Sherrick, 2011; Tolhurst and Ker, 2015). Recently, Zhu, Goodwin, and Ghosh (2011), Tolhurst and Ker (2015), and Ker, Tolhurst, and Liu (2016) have incorporated time-varying moments in a parametric framework. Clearly, there is no consensus in the literature on the distributional form of yields. This is not necessarily surprising, as yield distributions—albeit

[1] The SRA is far more complicated than outlined here. For more detail, see U.S. Department of Agriculture (2017), Ker (2001), or Ker et al. (2017).

unknown—appear to vary across crops, across regions within a crop, and even across time within a crop–region combination.

Nonparametric and semiparametric methods have been sparingly used. Nonparametric methods have the distinct advantage of requiring fewer assumptions; thus, there are fewer caveats associated with the results and conclusions. Moreover, parametric assumptions may not be testable or, if testable, may suffer from low power against reasonable alternatives. Conversely, one-dimensional nonparametric methods converge at a marginally slower rate ($O(n^{-4/10})$ vs. $O(n^{-5/10})$). See Goodwin and Ker (1998), Ker and Goodwin (2000), Ker and Coble (2003), and Norwood, Roberts, and Lusk (2004) for applications of nonparametric density methods to rating crop insurance contracts. Interestingly, each of these articles attempted to incorporate additional information into the density estimation process. Goodwin and Ker (1998) used yield data from surrounding counties, although weights were defined in an *ad hoc* manner. Ker and Goodwin (2000) replaced *ad hoc* weights by empirical Bayes (or shrinkage) weights that varied pointwise across the domain of the density. Ker and Coble (2003) incorporated additional information not in terms of using surrounding yield data but in terms of a parametric form; they first estimated a parametric start assuming a normal distribution and then corrected that start nonparametrically. Finally, Norwood, Roberts, and Lusk (2004) found that the nonparametric method, as proposed by Goodwin and Ker (1998), outperformed parametric methods from Gallagher (1987), Nelson and Preckel (1989), Moss and Shonkwiler (1993), Ramírez (1997), and Just and Weninger (1999).

Bayesian methods have also been used quite sparingly in the crop insurance literature. Recently, Ker, Tolhurst, and Liu (2016) proposed using BMA with parametric models to rate crop insurance contracts. Interestingly, the BMA was not done over a set of different parametric functional forms, as is common, but rather over a set of parametric density estimates based on yields from different counties. That is, the candidate set of models for the BMA was derived from different sources of data using a single parametric model rather than different parametric models estimated from a single set of data. Ker and Liu (2016) generalized this methodology to the nonparametric case by reparametrizing the nonparametric kernel density estimator into a mixture with means equal to the realizations and variances equal to the squared bandwidth. However, unlike in Ker, Tolhurst, and Liu (2016), where a likelihood is maximized over a parameter space to create the initial set of candidate models, the nonparametric generalization removes this optimization step. The main advantage of the nonparametric BMA is that parametric assumptions are not required on the individual densities. The relaxing of this restriction is particularly important as parametric forms of yield distributions are both unknown and changing across time and space.

Data and Methods

Data

Although individual farm yield and revenue insurance are the predominant programs, shallow loss and area-yield and area-revenue insurance also exist. Premium rates for farm programs are primarily based on individual yields, while rates for the shallow loss and area programs are based on county yields. The previously cited literature on rating crop insurance contracts necessarily uses county yield data because of the nonavailability of farm-level yield data. We necessarily use county yield data as well. Despite the nonavailability of individual yield data, this literature and our manuscript remain important for a number of reasons. First, methodologies that properly incorporate spatially extraneous information are more relevant at the farm-level, where historical data are more limited. Second, county-level rates are used in the farm-level rating process. Third, a methodology that does not perform well in estimating county-level rates is not likely to perform well in estimating farm-level rates.

We use county yield data collected by the USDA's National Agricultural Statistical Service (NASS) for corn, soybean, cotton, and winter wheat.[2] Corn, soybean, and wheat topped the list of insured commodities in 2017. In fact, corn and soybean together represented approximately 60% of total liabilities. For corn and soybean, we use county-level NASS yield data from the major corn- and soybean-producing states: Illinois, Indiana, Iowa, Minnesota, Missouri, Ohio, and Wisconsin. For cotton, the major producers are Arkansas, Georgia, Louisiana, Mississippi, and Tennessee. For winter wheat, we use Illinois, Indiana, Kansas, Michigan, Missouri, Ohio, Oklahoma, and Tennessee. We use yield data from 1955 to 2017 and exclude counties with incomplete histories.[3] Overall, we have yield data from 409, 399, 51, and 143 counties for corn, soybean, cotton, and winter wheat, respectively.

RMA Methodology

We compare our methodology to the current RMA methodology to maximize policy relevance. To recover the premium rates, RMA requires an estimate of the conditional yield density for the insurance period. RMA detrends the historical yield data using a two-knot linear spline estimated with robust methods and then imposes spatial and temporal priors on the knot points:

$$y_t = \theta_1 + \theta_2 t + \delta_1 d_1(t - k_1) + \delta_2 d_2(t - k_2) + \varepsilon_t, \tag{1}$$

with $d_1 = 1$ if $t \geq k_1$ and $d_2 = 1$ if $t \geq k_2$ for knots $k_1, k_2 \in (1 + \bar{k}, \ldots, T - \bar{k})$, and $k_2 - k_1 \geq \underline{k}$. The $\underline{k}, \bar{k} \geq 10$ are *a priori* imposed bounds that prevent the knots from locating too close together ($\underline{k}$) or too close to either endpoint ($\bar{k}$). Knot locations k_i are selected using a grid search (least-squares criterion). The model is run with zero, one, and two knots, and then the number of knots used is selected using the Akaike information criterion (AIC).[4] The degree of heteroskedasticity in the residuals is estimated using the method in Harri et al. (2011). The RMA combines the prediction from their two-knot linear spline model with the heteroskedasticity-corrected residuals from their temporal model to recover a set of *assumed i.i.d.* yields from the required conditional yield density. RMA estimates county unloaded premium rates empirically and then does credibility smoothing with surrounding counties.[5] For our simulations, we focus on the unloaded rates and use the RMA detrending and heteroskedasticity adjustments in our simulations so that any rate differences are solely due to the different density estimation methodologies. We illustrate the yield data and corresponding RMA-estimated trends of selected crop-county combinations in Figure 1. Of particular note is that the RMA detrending methodology, although flexible, does not over-fit the data. This is due in part to using the AIC to choose the number of knots and in part to the robust estimation of the splines.

Nonparametric Density Estimation

We use nonparametric kernel methods to recover our initial density estimates based on the set of identically and independently distributed yields $(y_1, \ldots, y_n)$. The usual kernel density estimate can

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[2] Another source for historical crop yields is provided by RMA: https://webapp.rma.usda.gov/apps/RIRS/AreaPlanHistoricalYields.aspx.

[3] We excluded the counties with incomplete data mainly for convenience and consistency. In many instances, the percentage of missing values is well above 50%. These are generally from counties where production is very small and, in some years, nonexistent. These missing data are not missing at random and not missing just a few years. All estimators considered can accommodate missing data, although the coding is significantly more tedious.

[4] We do not impose the spatial and temporal priors on knots used by the RMA.

[5] Our proposed methodology is concerned with using spatial information to get better estimates of the unloaded rates. This does not circumvent the benefits of credibility weighting on those more efficient estimated rates. The theory behind credibility weighting comes from Stein's paradox and is applicable independent of the level of estimation error in the initial set of estimates.

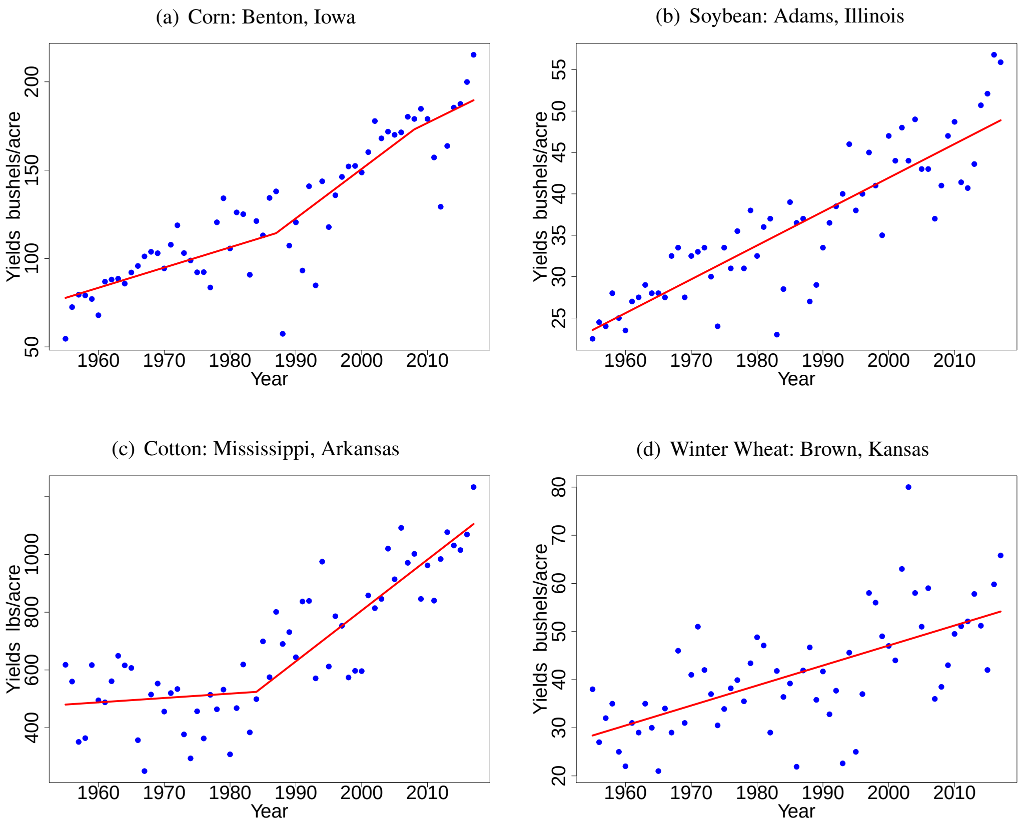

Figure 1. Yields and RMA Trend for Selected Counties

be expressed as

$$\hat{f}(y) = (1/n)\sum_{i=1}^{n} K_h(y - y_i), \tag{2}$$

where n is the number of yield observations, h is the bandwidth or smoothing parameter, $K_h(u) = 1/hK(u/h)$, K is the kernel function, and the summation is over $(y_1, \ldots, y_n)$. Throughout, K is assumed to be a square integrable symmetric probability density function with a finite second moment.

The two choices required for kernel density estimation are that of h, the smoothing parameter, and K, the kernel function. The choice of h is critical, and the literature has used various forms of direct plug-in, rules of thumb, and cross-validation methods. We use Silverman's (1986) rule of thumb, $h = 1.06\sigma n^{-0.2}$, for three reasons: (i) We estimate in excess of 100,000 densities, and this approach is the least computationally intensive; (ii) Silverman's rule of thumb has been shown to work well when the underlying densities do not differ *dramatically* from the normal, as in our case; and (iii) our simulation results are quite similar when we use cross-validation methods. Unlike the choice of h, the choice of K is well known to be relatively innocuous, because the estimate at any given point is the summation of n kernel functions evaluated at that point. This is essentially mixing and, thus, the shape of K has very little effect on the shape of the final estimate. In most empirical applications, K is chosen to be the normal density, which belongs to the family of second-order kernels. This allows us to rewrite our nonparametric estimate as

$$\hat{f}(y) = (1/nh)\sum_{i=1}^{n} \phi((y - y_i)/h), \tag{3}$$

which is a mixture of n normals with means equal to the sample realizations $(y_1, \ldots, y_n)$, variances equal to h^2, and each component receiving weight $1/n$. Recall that n is the number of yield observations. As noted by Ker and Liu (2016), using the normal as the kernel, an innocuous assumption, allows expression of the nonparametric density estimate in terms of normal mixtures, which greatly simplifies the BMA step in that the posterior weights can be defined in terms of the Bayesian information criterion (BIC).

Nonparametric Bayesian Model Averaging

Historically, Bayesian model averaging (BMA) combines different model functional forms, with a focus on model uncertainty. BMA has shown improved predictive performance in a variety of contexts, including linear regression (Raftery, Madigan, and Hoeting, 1997), generalized linear models (Raftery, 1996), and survival analysis (Volinsky et al., 1997). BMA essentially (i) assigns a prior probability to each model in a predetermined set of candidate models, (ii) estimates each of those models with the available data, (iii) evaluates the consistency of each model with the data according to a specific metric to determine posterior probabilities, and (iv) smooths (weighted average) across the models based on the posterior probability. Ker, Tolhurst, and Liu (2016) reconsidered this general ideology to introduce spatially extraneous information via the set of candidate models. Ker and Liu (2016) generalized their approach from parametric to nonparametric kernel estimators. While this generalization leads to a very different estimation procedure (as no optimization is required), the form of the posterior estimate remains a weighted average of the candidate models. The nonparametric BMA, denoted $\tilde{f}_{\mathrm{BMA}}$, is

$$\tilde{f}_{\mathrm{BMA}} = \sum_{i=1}^{J} \omega_i \hat{f}_i, \tag{4}$$

where $\hat{f}_i$ are the nonparametric density estimates and ω_i are the posterior weights which sum to 1. Appendix A summarizes the technical details, which are drawn heavily from Ker and Liu (2016).

Empirical Simulation 1

In this section, we compare the proposed methodology with the current RMA methodology for optimal policy relevance. Ideally, to compare any set of methodologies, we would like to know the true yield densities, sample from them, and compare the methodologies according to some appropriate metric. Of course, this is not doable, and so we first use the yield data to estimate (using nonparametric kernel density method) a set of densities, assume those estimated densities are the *true* densities, sample from them, and then compare the methodologies. We do this for each county-crop combination. We draw 500 samples of size 15, 20, 25, and 50. For each sample, the 90% premium rates are recovered using the three different methodologies: RMA (empirical), individual (standard nonparametric kernel density with no BMA), and nonparametric BMA. These estimated rates are then compared using mean squared error (MSE) relative to the *true* rate.

Recall that the nonparametric BMA rates use information from other counties, whereas the RMA and individual rates do not. Yield data are spatially correlated, but the simulation does not take this into account and, as such, is biased in favor of our proposed nonparametric BMA. To consider the implications of spatial correlation on the nonparametric BMA, we also take spatially correlated samples, preserving the correlation structure in the historical yield data. Drawing a random sample

Table 1. Mean Squared Error (MSE) of Estimated Premium Rates

	MSE × 1000							
	No Spatial Correlation				With Spatial Correlation			
	$N = 15$	$N = 20$	$N = 25$	$N = 50$	$N = 15$	$N = 20$	$N = 25$	$N = 50$
Corn								
RMA	1.295	0.966	0.766	0.387	1.334	1.010	0.769	0.393
Individual	1.151	0.866	0.694	0.355	1.149	0.878	0.678	0.349
BMA-CRD	0.939	0.737	0.606	0.332	1.023	0.802	0.638	0.340
BMA-State	0.795	0.639	0.537	0.309	0.936	0.746	0.611	0.332
BMA-Crop	0.780	0.616	0.512	0.293	0.917	0.734	0.604	0.328
Soybean								
RMA	0.775	0.579	0.468	0.233	0.752	0.580	0.461	0.237
Individual	0.730	0.547	0.445	0.223	0.705	0.546	0.435	0.227
BMA-CRD	0.618	0.480	0.401	0.213	0.636	0.503	0.408	0.221
BMA-State	0.540	0.431	0.367	0.204	0.597	0.480	0.390	0.219
BMA-Crop	0.521	0.429	0.365	0.200	0.573	0.467	0.380	0.210
Cotton								
RMA	1.108	0.831	0.677	0.363	1.114	0.866	0.711	0.404
Individual	0.795	0.596	0.489	0.256	0.743	0.590	0.471	0.255
BMA-CRD	0.746	0.571	0.474	0.253	0.716	0.575	0.461	0.253
BMA-State	0.702	0.548	0.460	0.250	0.699	0.566	0.454	0.250
BMA-Crop	0.652	0.512	0.439	0.247	0.652	0.540	0.435	0.247
Individual LSCV	0.809	0.605	0.494	0.272	0.817	0.600	0.482	0.267
BMA-Crop LSCV	0.686	0.561	0.471	0.256	0.719	0.585	0.480	0.252
Winter wheat								
RMA	1.166	0.877	0.709	0.351	1.229	0.903	0.741	0.366
Individual	1.094	0.827	0.672	0.337	1.145	0.846	0.696	0.347
BMA-CRD	0.988	0.765	0.628	0.325	1.069	0.798	0.659	0.340
BMA-State	0.883	0.703	0.587	0.316	1.019	0.767	0.636	0.339
BMA-Crop	0.872	0.696	0.585	0.315	1.010	0.765	0.636	0.320

from a kernel density estimate is straightforward: Draw with replacement a realization from the original data and then perturb that by adding a draw from the kernel (in our case, the normal density) with mean 0 and standard deviation h, where h is the smoothing parameter. To retrieve uncorrelated samples across the counties, we draw the initial realizations independently across the counties and perturb them. To get correlated samples across the counties, we draw a year, take all year realizations for all counties in that year, and perturb them. This maintains the correlation structure from the initial yield realizations in the samples.

Table 1 reports the MSE across each crop for the RMA, the individual kernel, and the nonparametric BMA approaches. We report both correlated and uncorrelated cases. As discussed, we consider three levels of geographical restrictions on the spatial smoothing and, therefore, on the set of candidate models in the BMA. First, we assume that the candidate models are restricted to the crop-reporting district (CRD); that is, only extraneous yield data from within the CRD are used in the BMA. Second, we assume that the candidate models are restricted to the state. Third, we impose no spatial restrictions; thus, the set of candidate models is comprised from every county in our dataset (by crop). We also consider sample sizes of 15, 20, 25, and 50 because (i) Liu and Ker (2019) argue that seed and farm management technologies have changed such that yield data beyond 25–30 years should be trimmed and (ii) the RMA requires premium rates where yield data are severely lacking, such as for nontraditional crops, nontraditional areas, and in developing countries. Finally, because of the sensitivity of kernel estimates to the choice of the smoothing parameter, we reproduced the simulation using least squares cross-validation rather than Silverman's rule of thumb for the smoothing parameter for cotton. Cotton was chosen because it has the smallest number of counties and is therefore the least computationally intensive.

A number of results in Table 1 are worth noting. First, the nonparametric BMA estimator has the smallest MSE for all crops across all sample sizes. Second, the largest efficiency gains with nonparametric BMA are in small samples, where there is less county information relative to the spatially extraneous information. Third, there are quite sizable efficiency gains (ranging from 10% to 40%) in using the nonparametric BMA across all crops. Fourth, geographically restricting the candidate set for the spatial smoothing to the CRD increases estimation error by roughly 5%–15%; conversely, restricting to the state only increases estimation error around 2%–5%. Fifth, the results for cotton using Silverman's rule of thumb and least squares cross-validation (LSCV) are quantitatively and qualitatively almost identical. Finally, spatial correlation marginally decreases (2%–8%) the relative efficiency of the nonparametric BMA. This result is not surprising given that there is less information in correlated samples relative to uncorrelated samples. Overall, these results provide strong support for the nonparametric BMA estimator.

We extend our simulations for Iowa corn to consider samples of size $N = 15$, 20, 25, 30, 40, 50, 75 and 100. Figure 2 shows the MSEs for the nonparametric BMA, the RMA, and the individual rates by sample size. Note that the MSE for the nonparametric BMA reaches an asymptote, *from below*, to the MSE of the individual. This is not surprising because, as N gets large, the weight on its own density estimate with the BMA goes to 1 relatively quickly. Also, note that for smaller sample sizes (e.g., $N = 20$), the RMA methodology requires an additional 20 yield realizations to realize the same MSE as the nonparametric BMA. Similarly, the individual kernel estimate requires an additional 10 yield realizations to achieve the same MSE as the nonparametric BMA. These results, and the results of Table 1, suggest that the nonparametric BMA estimator offers the most for situations with little historical data. This is particularly important because yield data may be severely lacking for many crop–area combinations, particularly for nontraditional crops, nontraditional areas, and in developing countries. Moreover, the small sample performance of the nonparametric BMA suggests that it may have value in rating individual farm programs.

Table 2 summarizes the BMA weights by crop and sample size with no geographical restrictions.[6] Corn and soybean make use of the spatially extraneous data more than cotton and winter wheat. As the sample size increases, the weight on the spatially extraneous data is reduced. For all crops, there is significant weight put on counties outside of their CRD. The average BMA weights from the correlated sample on the own density is roughly smaller than 10%. For example, in corn with a sample size of 25, the average weight on the own density changes from 0.153 in the uncorrelated case to 0.141 in the spatially correlated case. To better illustrate the effects of the spatial restrictions on the BMA weights, Figures B1 and B2 in Appendix B show the BMA weight placed on its own county across the various spatial restrictions. Although not surprising, it is striking to see how the weight on the own county moves closer to 1 as the spatial smoothing restriction tightens.

Empirical Simulation 2

The first empirical simulation provided insights into the estimation efficiency of the nonparametric BMA compared with other methodologies to rate crop insurance contracts. To investigate the economic implications, we conduct an out-of-sample retain–cede rating game, where two players adversely select against one another using different methodologies to estimate premium rates. The out-of-sample rating game was first proposed by Ker and McGowan (2000) and used in Ker and

[6] Table S1 in the Online Supplement (www.jareonline.org) reports corresponding BMA weights by crop and sample size with geographical restrictions.

Table 2. Summary of BMA-Unrestricted Weight during Rates Simulation

	No Correlation				Spatial Correlation			
	Own	Top 5	CRD	State	Own	Top 5	CRD	State
Corn								
$N = 15$	0.090	0.311	0.125	0.302	0.081	0.292	0.130	0.327
$N = 20$	0.122	0.377	0.159	0.334	0.110	0.359	0.163	0.359
$N = 25$	0.153	0.434	0.191	0.365	0.141	0.418	0.195	0.387
$N = 50$	0.298	0.638	0.336	0.488	0.284	0.625	0.336	0.503
Soybean								
$N = 15$	0.106	0.333	0.141	0.303	0.099	0.322	0.146	0.325
$N = 20$	0.142	0.402	0.178	0.338	0.133	0.390	0.181	0.356
$N = 25$	0.179	0.462	0.215	0.370	0.168	0.449	0.216	0.386
$N = 50$	0.345	0.668	0.378	0.507	0.333	0.658	0.376	0.516
Cotton								
$N = 15$	0.389	0.808	0.461	0.562	0.374	0.802	0.459	0.570
$N = 20$	0.465	0.866	0.529	0.617	0.454	0.861	0.527	0.623
$N = 25$	0.534	0.906	0.588	0.666	0.520	0.901	0.584	0.667
$N = 50$	0.745	0.980	0.777	0.819	0.737	0.979	0.774	0.819
Winter wheat								
$N = 15$	0.304	0.697	0.363	0.578	0.281	0.676	0.358	0.591
$N = 20$	0.380	0.770	0.436	0.629	0.357	0.752	0.431	0.640
$N = 25$	0.446	0.821	0.498	0.672	0.422	0.806	0.490	0.680
$N = 50$	0.675	0.941	0.711	0.815	0.656	0.934	0.703	0.816

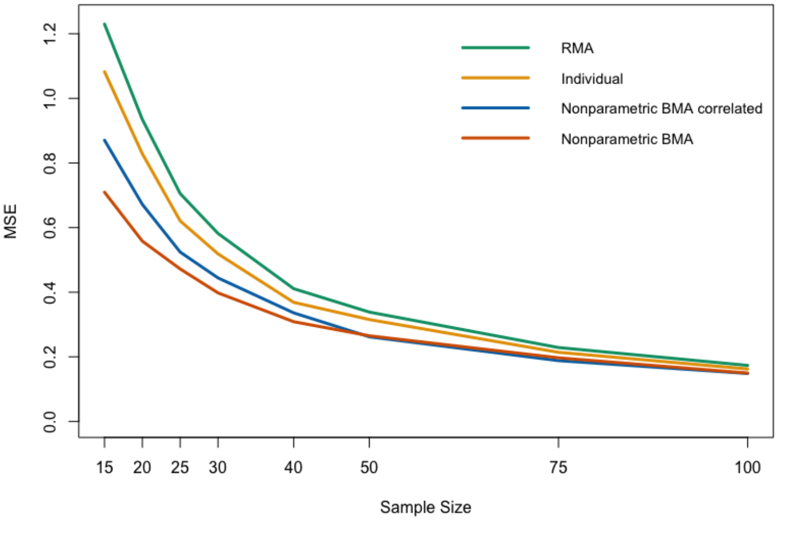

Figure 2. MSEs by Sample Size: Corn, Iowa

Coble (2003), Racine and Ker (2006), Harri et al. (2011), Annan et al. (2014), Tolhurst and Ker (2015), Ker, Tolhurst, and Liu (2016), Park, Brorsen, and Harri (2018), and Ramsey (2020). Ker, Tolhurst, and Liu (2016) modified the game with an additional test. The game is inspired by the design of U.S. crop insurance program, which involves (i) sharing of underwriting gains/losses with private insurers; (ii) mechanisms for insurers to retain or cede the vast majority of those underwriting gains or losses; (iii) the RMA, not private insurers, setting the premium rates; and (iv) private insurers selling any crop policy that is available in that state. The Standard Reinsurance Agreement outlines the specific details. Private insurers do not set the premium rates but do share the accompanying underwriting gains or losses. As a result, they estimate their own rates to decide which contracts to cede back to the government and which to retain. Those contracts in which their rate is above the RMA rate—contracts they estimate to be under-priced—they cede. Conversely, those contracts in which their rate is below the RMA rate—contracts they estimate to be over-priced—they retain. To compare the nonparametric BMA rating methodology to the RMA approach, we play the role of a private insurer using the nonparametric BMA and attempt to gain economic rents by adversely selecting against the RMA.

More specifically, the rating game uses yield data on a county–crop basis from 1955 to 1997 to estimate the premium rates for 1998 using the two rating methodologies. In our case, both the private insurer and the RMA use the RMA's rating methodology for detrending and correcting for possible heteroskedasticity; the only difference is the density estimates. RMA uses the empirical rate while the private insurer uses the nonparametric BMA. The two sets of rates are plugged into the above decision rule to recover the set of contracts retained by the private insurer. For each county–crop combination, the contract is either retained or ceded. The underwriting gains or losses for the set of retained and ceded contracts are calculated using the actual realized yields in 1998. This process is repeated using data from 1955–1998 to estimate the premium rates for 1999, the subsequent sets of retained and ceded contracts in 1999, and, finally, the underwriting gains and losses for the two sets of retained and ceded contracts. We repeat this analysis for the most recent 20 years (1998–2017).

The underwriting gains/losses and premium rates are aggregated across counties within a state. The average yearly loss ratios for both methodologies are reported. Statistical significance is ascertained using a binomial test based on the relative loss ratios in each of the 20 years. The null assumes a probability of 0.5 and corresponds to the case where the loss ratio of the retained and ceded contracts is equivalent. This represents the first p-values reported in our game results tables. We also calculate a second binomial test, as outlined in Ker, Tolhurst, and Liu (2016), to ascertain the efficacy of using the nonparametric BMA relative to the RMA approach; this tests corrects for the inherent advantage to the private insurer in that the RMA rate is revealed first. Note that in both tests, p-values close to 0 support the efficacy of the nonparametric BMA relative to the RMA methodology, while p-values close to 1 support the efficacy of the RMA methodology relative to the BMA methodology.

Table 3 reports the results of the rating game between the nonparametric BMA and the RMA methodology. From left to right, the columns of results table show the crop–state combination, the number of counties, the percentage of contracts retained, the loss ratio of the contracts ceded (loss ratio government), the loss ratio of the contracts retained (loss ratio private), the p-value from the adverse selection game (denoted p-value 1), and finally, the p-value that the nonparametric BMA estimator is statistically equal or more efficient than the RMA estimator (denoted p-value 2). For 24 of the 27 crop–state combinations, the mean of the yearly private insurer loss ratios is lower than the mean of the yearly government loss ratios. More importantly, statistical significance of a yearly lower loss ratio using BMA methodology to choose which contracts to retain versus cede is found in 20 of the 27 crop–state combinations (see p-value 1). The results are most favorable for corn and soybean. With respect to the methodological hypothesis that the nonparametric BMA is as or more efficient than the RMA rating methodology, 15 of the 27 cases are statistically significant. Note that in no cases is the RMA methodology statistically significantly preferred to the nonparametric BMA. These results are consistent with our first empirical simulation and consistent with others

Table 3. Rating Game Results: RMA versus BMA-Unrestricted, Full Sample

Crop and State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-Value 1	*p*-Value 2
Corn						
Illinois	73	74.2	0.972	0.548	0.000	0.001
Indiana	60	85.0	1.116	0.679	0.000	0.000
Iowa	91	71.9	0.425	0.384	0.001	0.252
Minnesota	56	84.7	0.320	0.206	0.021	0.001
Missouri	24	94.4	0.801	0.655	0.000	0.058
Ohio	58	87.0	0.791	0.690	0.000	0.006
Wisconsin	47	81.2	0.489	0.450	0.058	0.748
Soybean						
Illinois	82	75.9	0.712	0.597	0.021	0.021
Indiana	59	71.2	0.952	0.549	0.000	0.001
Iowa	93	87.2	1.089	0.735	0.000	0.006
Minnesota	56	78.6	0.755	0.714	0.021	0.058
Missouri	27	77.0	1.129	0.786	0.001	0.058
Ohio	50	90.3	1.456	0.703	0.001	0.006
Wisconsin	32	79.5	0.898	0.793	0.132	0.132
Cotton						
Arkansas	7	42.1	0.625	0.549	0.001	0.006
Georgia	20	58.0	0.568	0.518	0.412	0.252
Louisiana	6	66.7	2.212	1.308	0.000	0.021
Mississippi	11	66.8	0.701	0.713	0.021	0.058
Tennessee	7	80.0	0.609	0.586	0.021	0.132
Winter wheat						
Illinois	8	62.5	0.426	0.350	0.001	0.000
Indiana	19	75.3	0.489	0.377	0.021	0.006
Kansas	33	57.3	1.372	1.100	0.132	0.412
Michigan	27	37.4	0.325	0.225	0.006	0.021
Missouri	13	33.5	0.508	0.571	0.058	0.132
Ohio	17	55.3	0.465	0.470	0.058	0.021
Oklahoma	16	66.9	1.689	1.637	0.132	0.412
Tennessee	10	73.5	0.384	0.437	0.006	0.001

in the literature (Ker, Tolhurst, and Liu (2016), Park, Brorsen, and Harri (2018), Ramsey (2020)); incorporating spatially extraneous data into the rating process can increase efficiency relative to the RMA methodology, which does not do so.

In Table 4, the results of the two tests are illustrated at the reduced sample sizes.[7] These results are particularly relevant because historical yield data are lacking for many regions, for nontraditional crops, and in developing countries and dramatic changes in on-farm seed and production technologies over the past half-century can negate the usefulness of yield data older than 25–30 years. We find that statistically significant rents can be recovered by the private insurer using the nonparametric BMA estimator for 23, 22, and 22 of the 27 crop–state combinations for sample sizes 25, 20, and 15 (*p*-value 1), respectively. We find significant efficiency gains in 16, 16, and 17 of the 27 crop–state combinations using the nonparametric BMA for sample sizes of 25, 20, and 15, respectively. Again, in no cases is the RMA methodology statistically significantly preferred to the

[7] All results for the rating game are located in Tables S2–S4 of the Online Supplement.

Table 4. Summary of Rating Games Results: *p*-Values, RMA versus BMA-Unrestricted

	p-Value 1				*p*-Value 2			
	15 Years	20 Years	25 Years	Full	15 Years	20 Years	25 Years	Full
Corn								
Illinois	0.001	0.001	0.000	0.000	0.006	0.021	0.021	0.001
Indiana	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
Iowa	0.000	0.006	0.000	0.001	0.001	0.001	0.001	0.252
Minnesota	0.000	0.000	0.000	0.021	0.000	0.000	0.000	0.001
Missouri	0.000	0.000	0.000	0.000	0.001	0.006	0.001	0.058
Ohio	0.000	0.006	0.000	0.000	0.001	0.006	0.006	0.006
Wisconsin	0.058	0.252	0.058	0.058	0.412	0.412	0.588	0.748
Soybean								
Illinois	0.006	0.058	0.001	0.021	0.412	0.252	0.006	0.021
Indiana	0.000	0.000	0.000	0.000	0.006	0.058	0.058	0.001
Iowa	0.006	0.000	0.000	0.000	0.021	0.132	0.001	0.006
Minnesota	0.000	0.001	0.006	0.021	0.006	0.006	0.006	0.058
Missouri	0.021	0.021	0.132	0.001	0.252	0.021	0.252	0.058
Ohio	0.000	0.000	0.000	0.001	0.058	0.001	0.058	0.006
Wisconsin	0.000	0.000	0.000	0.132	0.252	0.058	0.001	0.132
Cotton								
Arkansas	0.006	0.001	0.000	0.001	0.058	0.006	0.000	0.006
Georgia	0.001	0.021	0.058	0.412	0.021	0.058	0.132	0.252
Louisiana	0.001	0.001	0.000	0.000	0.006	0.006	0.058	0.021
Mississippi	0.252	0.000	0.001	0.021	0.588	0.412	0.412	0.058
Tennessee	0.000	0.000	0.000	0.021	0.006	0.021	0.021	0.132
Winter wheat								
Illinois	0.000	0.000	0.000	0.001	0.006	0.000	0.000	0.000
Indiana	0.000	0.000	0.000	0.021	0.000	0.058	0.006	0.006
Kansas	0.588	0.588	0.252	0.132	0.868	0.868	0.748	0.412
Michigan	0.058	0.058	0.001	0.006	0.058	0.021	0.006	0.021
Missouri	0.006	0.021	0.006	0.058	0.021	0.021	0.058	0.132
Ohio	0.000	0.000	0.000	0.058	0.021	0.000	0.001	0.021
Oklahoma	0.058	0.132	0.252	0.132	0.412	0.588	0.412	0.412
Tennessee	0.006	0.000	0.001	0.006	0.021	0.132	0.058	0.001

nonparametric BMA. These results are, again, consistent with the results of empirical simulation 1, where the nonparametric BMA realized greater efficiency gains in smaller samples.

To focus further on whether or not to incorporate spatially extraneous information, we repeat the above analysis with the RMA using the individual kernel-estimated rate rather than the empirical rate. That is, we compare the nonparametric BMA estimate to the individual nonparametric estimate. The only difference is the incorporation of spatially extraneous data via the BMA. These results are located in the Online Supplement (see Tabls S5–S8) and are quite similar to the above results. The nonparametric BMA is preferred, suggesting that incorporating spatially extraneous information into the rating process is preferred. We also repeated the game, restricting our spatial smoothing to the CRD and state levels. The results, again, do not change qualitatively for either *p*-value 1 or *p*-value 2 (see Tables S9 and S10 in the Online Supplement).

Table 5 illustrates the average weights by crop–state combination for the BMA estimate in the full sample with no spatial restrictions. There are a number of interesting results: (i) Corn

Table 5. BMA-Unrestricted Weight during Rating Game: Full Sample

	Cumulative Weight on *N* Counties								Weight within	
	1	**2**	**3**	**5**	**10**	**25**	**50**	**100**	**CRD**	**State**
Corn (409 counties)										
Illinois	0.193	0.343	0.418	0.523	0.677	0.865	0.957	0.995	0.245	0.394
Indiana	0.181	0.335	0.411	0.513	0.661	0.847	0.948	0.993	0.235	0.378
Iowa	0.229	0.392	0.472	0.579	0.725	0.890	0.967	0.996	0.314	0.530
Minnesota	0.332	0.513	0.591	0.687	0.804	0.925	0.978	0.998	0.408	0.538
Missouri	0.203	0.376	0.477	0.612	0.794	0.951	0.990	0.999	0.270	0.453
Ohio	0.178	0.330	0.406	0.512	0.665	0.851	0.952	0.994	0.232	0.419
Wisconsin	0.357	0.526	0.606	0.705	0.824	0.939	0.983	0.998	0.432	0.565
Soybean (399 counties)										
Illinois	0.363	0.542	0.627	0.730	0.849	0.953	0.989	0.999	0.446	0.623
Indiana	0.225	0.372	0.451	0.556	0.702	0.875	0.961	0.997	0.256	0.391
Iowa	0.264	0.412	0.491	0.598	0.744	0.904	0.974	0.998	0.335	0.568
Minnesota	0.356	0.498	0.573	0.666	0.786	0.914	0.974	0.998	0.413	0.498
Missouri	0.480	0.641	0.722	0.816	0.916	0.983	0.997	1.000	0.507	0.615
Ohio	0.199	0.344	0.424	0.533	0.687	0.868	0.959	0.996	0.263	0.427
Wisconsin	0.442	0.602	0.682	0.772	0.873	0.958	0.990	0.999	0.500	0.619
Cotton (51 counties)										
Arkansas	0.841	0.931	0.960	0.984	0.998	1.000	1.000	1.000	0.872	0.878
Georgia	0.673	0.830	0.897	0.959	0.996	1.000	1.000	1.000	0.742	0.888
Louisiana	0.618	0.800	0.884	0.960	0.997	1.000	1.000	1.000	0.660	0.682
Mississippi	0.659	0.828	0.901	0.966	0.998	1.000	1.000	1.000	0.706	0.775
Tennessee	0.665	0.874	0.940	0.985	0.999	1.000	1.000	1.000	0.831	0.831
Winter wheat (143 counties)										
Illinois	0.598	0.781	0.857	0.924	0.978	0.999	1.000	1.000	0.653	0.772
Indiana	0.441	0.621	0.714	0.818	0.931	0.997	1.000	1.000	0.487	0.633
Kansas	0.616	0.782	0.852	0.922	0.981	1.000	1.000	1.000	0.682	0.884
Michigan	0.545	0.705	0.782	0.866	0.951	0.998	1.000	1.000	0.625	0.772
Missouri	0.724	0.853	0.902	0.949	0.988	1.000	1.000	1.000	0.791	0.817
Ohio	0.687	0.832	0.885	0.932	0.977	0.999	1.000	1.000	0.761	0.835
Oklahoma	0.631	0.813	0.899	0.967	0.996	1.000	1.000	1.000	0.719	0.922
Tennessee	0.623	0.797	0.867	0.932	0.982	1.000	1.000	1.000	0.709	0.730

and soybean borrow the most from the spatially extraneous data while wheat and cotton do not, suggesting more heterogeneity amongst the underlying wheat and cotton yield densities across space, (ii) significant weights for corn and soybean are outside their CRD, and (iii) the heterogeneity in weights for a crop between states is significantly less than the heterogeneity in weights between crops. These results are consistent with the first simulation results; as the sample size increases, the weight on the spatially extraneous data decreases, and corn and soybean put more weight on the spatially extraneous data.

Conclusions

We proposed a nonparametric BMA estimator to recover U.S. crop insurance premium rates for area-type (county-based) programs. We conducted a finite sample simulation using nonparametric estimates of county-crop yield densities for corn, soybean, cotton, and winter wheat. A number of

Table 6. Summary of BMA-Unrestricted Weight during Rating Games

	Own Weight				Top 5			
	15 Years	20 Years	25 Years	Full	15 Years	20 Years	25 Years	Full
Corn								
Illinois	0.045	0.055	0.064	0.193	0.214	0.250	0.289	0.523
Indiana	0.045	0.057	0.070	0.181	0.218	0.257	0.307	0.513
Iowa	0.049	0.060	0.071	0.229	0.225	0.278	0.322	0.579
Minnesota	0.065	0.078	0.092	0.332	0.277	0.339	0.404	0.687
Missouri	0.077	0.098	0.115	0.203	0.322	0.383	0.441	0.612
Ohio	0.048	0.056	0.062	0.178	0.223	0.251	0.280	0.512
Wisconsin	0.120	0.152	0.189	0.357	0.362	0.443	0.519	0.705
Soybean								
Illinois	0.116	0.144	0.165	0.363	0.386	0.449	0.495	0.730
Indiana	0.056	0.075	0.096	0.225	0.238	0.282	0.330	0.556
Iowa	0.052	0.076	0.099	0.264	0.254	0.308	0.349	0.598
Minnesota	0.100	0.131	0.154	0.356	0.329	0.402	0.451	0.666
Missouri	0.149	0.189	0.225	0.480	0.457	0.527	0.583	0.816
Ohio	0.039	0.053	0.072	0.199	0.213	0.263	0.315	0.533
Wisconsin	0.039	0.052	0.070	0.442	0.229	0.274	0.332	0.772
Cotton								
Arkansas	0.435	0.518	0.602	0.841	0.813	0.884	0.917	0.984
Georgia	0.289	0.375	0.454	0.673	0.705	0.797	0.851	0.959
Louisiana	0.218	0.296	0.374	0.618	0.590	0.698	0.776	0.960
Mississippi	0.223	0.297	0.339	0.659	0.671	0.761	0.827	0.966
Tennessee	0.301	0.344	0.407	0.665	0.730	0.804	0.868	0.985
Winter wheat								
Illinois	0.192	0.236	0.278	0.598	0.609	0.687	0.735	0.924
Indiana	0.114	0.155	0.205	0.441	0.484	0.558	0.630	0.818
Kansas	0.171	0.228	0.300	0.616	0.546	0.628	0.704	0.922
Michigan	0.222	0.248	0.292	0.545	0.594	0.654	0.714	0.866
Missouri	0.305	0.394	0.455	0.724	0.665	0.733	0.781	0.949
Ohio	0.234	0.305	0.364	0.687	0.596	0.671	0.727	0.932
Oklahoma	0.226	0.254	0.285	0.631	0.674	0.722	0.762	0.967
Tennessee	0.273	0.297	0.345	0.623	0.672	0.722	0.772	0.932

results are worth reiterating: (i) The nonparametric BMA estimator outperforms the individual and the RMA estimators for all crops across all sample sizes; (ii) the largest efficiency gains with BMA are in small samples, where there is relatively little information in the individual sample; (iii) corn and soybean tend to make greater use of the spatially extraneous data, suggesting that their densities are more homogeneous across space than winter wheat and cotton; (iv) although spatial correlation necessarily decreases the efficiency of the nonparametric BMA estimator, it remains more efficient; and (v) the results are robust to restrictions on the distance of spatial smoothing.

An out-of-sample retain–cede rating game between the private insurer and the RMA highlighted the policy implications. Again, we considered various sample sizes and spatial smoothing restrictions. These results are consistent with the first simulation: (i) The nonparametric BMA estimator is more efficient at estimating premium rates than either the current RMA methodology or the individual kernel method, (ii) the largest efficiency gains with BMA are in small samples, where there is relatively little information in the individual sample, (iii) corn and soybean tend to make greater use of the extraneous data, and (iv) the results are robust to restrictions on the distance of spatial smoothing.

Given the size of the public monies directed toward crop insurance in the United States, these results are interesting. Consider the average absolute difference in premium rates between the nonparametric BMA and the current RMA methodology for 2019: Corn is 20.25%, soybean is 17.02%, cotton is 7.85%, and winter wheat is 7.66%. There are larger absolute rate differences in corn and soybean, where there is more spatial smoothing. If we also consider that the total premiums for corn were $3.7 billion in 2019, this represents a reallocation of $740 million in premium dollars across producers and between producers and the RMA. This assumes that the nonparametric BMA methodology is applied to individual farm programs as well as area programs. Similarly, for soybean, cotton, and wheat, the nonparametric BMA methodology would represent the reallocation of roughly $300 million, $75 million, $85 million, respectively.

The nonparametric BMA estimator contributes to the growing literature making use of spatial information in estimating premium rates (for other approaches, see Ker, Tolhurst, and Liu (2016), Park, Brorsen, and Harri (2018), and, Ramsey (2020)). The next two questions the literature should consider are (i) can these methods which incorporate spatially extraneous information be used to rate farm-level programs? and (ii) which of these methodologies is most efficient? The latter answer is likely dependent on the crop–region combination, suggesting that there may be a set of methodologies that could be used to rate crop insurance contracts at the farm level.

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Appendix A: Nonparametric BMA

This appendix draws heavily from Ker and Liu (2016). Bayesian model averaging (BMA) historically combines different model functional forms with a focus on model uncertainty. BMA has shown improved predictive performance in a variety of contexts, including linear regression (Raftery, Madigan, and Hoeting, 1997), generalized linear models (Raftery, 1996), and survival analysis (Volinsky et al., 1997). BMA can be summarized by the following steps: Suppose M_1, M_2, …, M_J are the candidate models to be considered and Λ is the quantity of interest. The posterior distribution of Λ given data D is

(A1) $$\text{pr}(\Lambda \mid D) = \sum_{i=1}^{J} \text{pr}(\Lambda \mid M_i, D)\text{pr}(M_i \mid D),$$

where $\text{pr}(\Lambda \mid M_i, D)$ is the posterior distribution of Λ under model M_i and $\text{pr}(M_i \mid D)$ is the posterior model probability of model M_i. The posterior distribution, $\text{pr}(\Lambda \mid D)$, is a weighted average of the posterior distributions under each of the models considered, where the weight is from their individual posterior model probability. The posterior probability of model M_i, by Bayes' theorem, is given as

(A2) $$\text{pr}(M_i \mid D) = \frac{\text{pr}(D \mid M_i)\text{pr}(M_i)}{\sum_{i=1}^{J} \text{pr}(D \mid M_i)\text{pr}(M_i)},$$

and the probability of observing data D under the model assumption M_i is given by

(A3) $$\text{pr}(D \mid M_i) = \int \text{pr}(D \mid \theta_i, M_i)\text{pr}(\theta_i \mid M_i)\, d\theta_i,$$

where $\boldsymbol{\theta}_i$ is the vector of parameters of model M_i, $\text{pr}(\theta_i \mid M_i)$ is the prior for θ_i under model M_i, and $\text{pr}(M_i)$ is the prior probability of model M_i. A general guidance for the implementation of BMA, including several typical methods and related software, can be found in Hoeting et al. (1999).

There are two major difficulties in the implementation of BMA. First, the number of candidate models in the summation of equation (A1) can be unbounded. This is resolved in our application as the number of models is equal to the number of counties we wish to include. We consider three levels of geographic restrictions: (i) restrict the set of candidate models to the crop-reporting district (CRD), (ii) restrict the set of candidate models to the state, and (iii) include all counties in our dataset (unrestricted). Second, the posterior model probability $\text{pr}(M_i \mid D)$ is difficult to compute because it generally involves high-dimensional integrals. This is resolved in our setting because we have expressed the kernel estimator as a normal mixture.[8] That is, for a specific normal mixture model M_i, the likelihood that it generates the data D with sample size m $(d_1, \ldots, d_m)$ can be calculated as

(A4) $$\text{pr}(D \mid M_i) = L_i = \prod_{j=1}^{m} (1/mh) \sum \phi((d_j - Y_i)/h),$$

which is simply the likelihood function of data D under the model assumption M_i that is specified by sample Y_i and corresponding bandwidth h. Assuming each model has equal prior probability, the weight for each of J models considered, $\text{pr}(M_i \mid D)$, is given from equation (A2) as

(A5) $$\text{pr}(M_i \mid D) = \frac{L_i}{\sum_{i=1}^{J} L_i}.$$

Given that $\hat{f}_i$ is the nonparametric density estimate of each model, the final $\tilde{f}_{\text{BMA}}$ is

(A6) $$\tilde{f}_{\text{BMA}} = \sum_{i=1}^{J} \text{pr}(M_i \mid D)\hat{f}_i,$$

[8] The BMA can be extended to non-normals, although the computations are nontrivial.

which is an average of all densities considered, weighted by their corresponding model probabilities.

Specifically, we consider a set of Q county crop yield densities with sample realizations $\{y_{11}, \ldots, y_{1n_1}, \ldots, y_{Q1}, \ldots, y_{Qn_Q}\}$. The individual density estimates, $\hat{f}_1, \ldots, \hat{f}_Q$, comprise the model space and are estimated nonparametrically using sample data exclusively from their own county. Then, the nonparametric BMA density estimate for county i is

$$\tilde{f}_i = \sum_{j=1}^{Q} \omega_j^i \hat{f}_j, \quad \text{where} \quad \omega_j^i = \frac{L_j^i}{\sum_{q=1}^{Q} L_q^i}. \tag{A7}$$

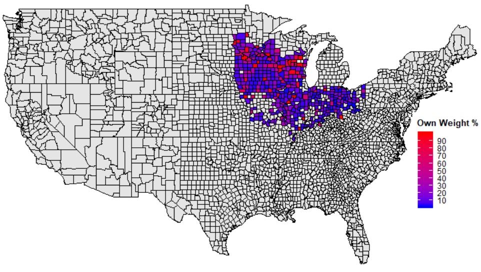
L_j^i is evaluated using the sample realizations from county i at $\hat{f}_j$, the individual density estimate from county j. That is,

$$L_j^i = \mathrm{pr}(D_i \mid M_j) = \prod_{l=1}^{n_i} (1/n_j h) \sum_{k=1}^{n_j} \phi((d_l - Y_k)/h), \tag{A8}$$

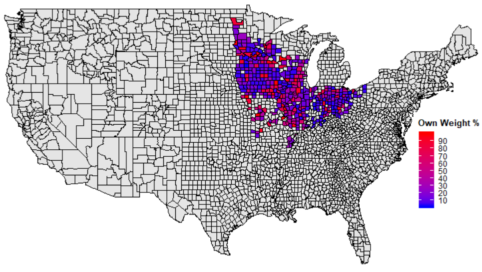
where $D_i = \{d_1, \ldots, d_{n_i}\}$ is the sample realization from county i with sample size n_i; M_j represents the model that uses county j's data $Y_1, \ldots, Y_{n_j}$ to estimate the yield density. Here, we are not refitting the models but rather taking densities estimated for other counties and averaging them using weights based on the fit of that density to the target county's data. The weights necessarily sum to 1.

Appendix B

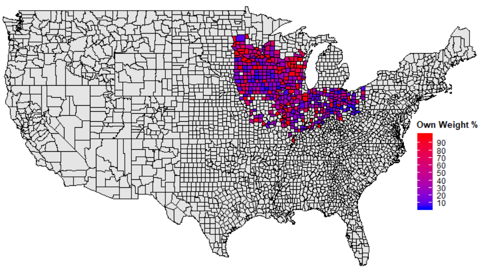
(a) Unrestricted Case: Corn



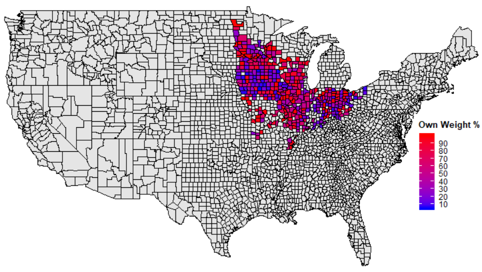
(b) Unrestricted Case: Soybean



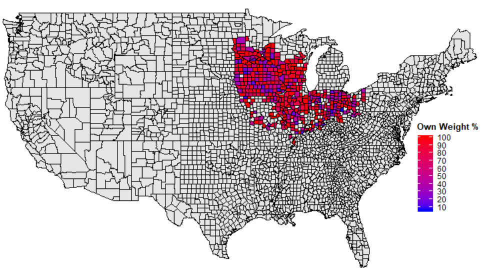
(c) State-Restricted: Corn



(d) State-Restricted: Soybean



(e) CRD-Restricted: Corn



(f) CRD-Restricted CRD: Soybean

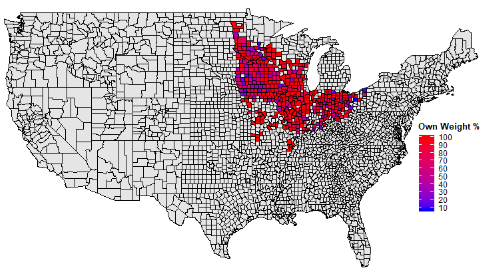


Figure B1. BMA Weight on Own County in Different Levels: Corn & Soybean

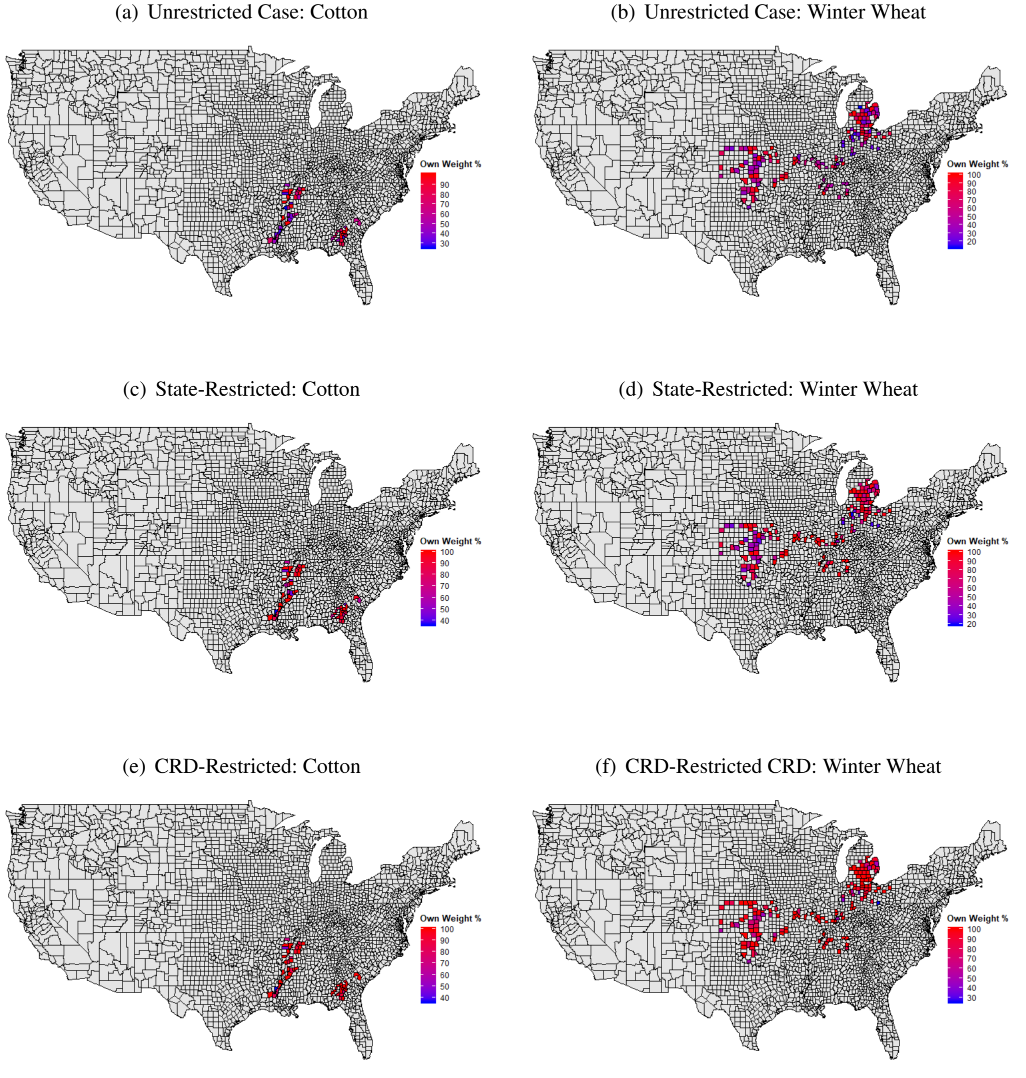


Figure B2. BMA Weight on Own County in Different Levels: Cotton & Winter Wheat

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Online Supplement: Rating Crop Insurance Contracts with Nonparametric Bayesian Model Averaging

Yong Liu and Alan P. Ker

Table S1. BMA Weight During Rates Simulation: State & CRD Restricted

	No Correlation				*Spatial Correlation*			
	Own	Top 5	CRD	State	Own	Top 5	CRD	State
Corn								
BMA-State								
n=15	0.264	0.655	0.382	1.000	0.225	0.608	0.376	1.000
n=20	0.322	0.718	0.436	1.000	0.279	0.677	0.426	1.000
n=25	0.374	0.766	0.482	1.000	0.332	0.732	0.471	1.000
n=50	0.566	0.895	0.650	1.000	0.527	0.877	0.634	1.000
BMA-CRD								
n=15	0.647	0.982	1.000	−−	0.557	0.968	1.000	−−
n=20	0.699	0.988	1.000	−−	0.617	0.979	1.000	−−
n=25	0.739	0.992	1.000	−−	0.666	0.985	1.000	−−
n=50	0.852	0.998	1.000	−−	0.807	0.997	1.000	−−
Soybean								
BMA-State								
n=15	0.296	0.688	0.418	1.000	0.264	0.655	0.414	1.000
n=20	0.361	0.751	0.476	1.000	0.326	0.722	0.468	1.000
n=25	0.418	0.797	0.525	1.000	0.383	0.771	0.516	1.000
n=50	0.623	0.915	0.698	1.000	0.593	0.902	0.686	1.000
BMA-CRD								
n=15	0.670	0.982	1.000	−−	0.601	0.971	1.000	−−
n=20	0.723	0.988	1.000	−−	0.661	0.980	1.000	−−
n=25	0.763	0.992	1.000	−−	0.708	0.986	1.000	−−
n=50	0.875	0.998	1.000	−−	0.843	0.996	1.000	−−
Cotton								
BMA-State								
n=15	0.675	0.983	0.815	1.000	0.645	0.980	0.804	1.000
n=20	0.740	0.992	0.852	1.000	0.717	0.991	0.844	1.000
n=25	0.790	0.996	0.880	1.000	0.768	0.995	0.872	1.000
n=50	0.905	1.000	0.947	1.000	0.896	1.000	0.944	1.000
BMA-CRD								
n=15	0.828	0.999	1.000	−−	0.803	0.999	1.000	−−
n=20	0.868	1.000	1.000	−−	0.851	1.000	1.000	−−
n=25	0.899	1.000	1.000	−−	0.881	1.000	1.000	−−
n=50	0.956	1.000	1.000	−−	0.948	1.000	1.000	−−
Winter wheat								
BMA-State								
n=15	0.545	0.911	0.650	1.000	0.499	0.889	0.628	1.000
n=20	0.617	0.938	0.707	1.000	0.574	0.922	0.688	1.000
n=25	0.672	0.955	0.750	1.000	0.632	0.943	0.731	1.000
n=50	0.828	0.988	0.872	1.000	0.804	0.985	0.862	1.000
BMA-CRD								
n=15	0.821	0.999	1.000	−−	0.772	0.999	1.000	−−
n=20	0.858	1.000	1.000	−−	0.817	1.000	1.000	−−
n=25	0.884	1.000	1.000	−−	0.849	1.000	1.000	−−
n=50	0.945	1.000	1.000	−−	0.927	1.000	1.000	−−

Table S2. Rating Game Results: RMA versus BMA-Unrestricted, $n = 15$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	50.3	2.027	1.123	0.001	0.006
Indiana	60	61.7	2.299	0.890	0.000	0.001
Iowa	91	45.9	3.344	1.046	0.000	0.001
Minnesota	56	53.0	1.217	0.575	0.000	0.000
Missouri	24	79.0	2.361	1.094	0.000	0.001
Ohio	58	72.4	1.214	0.710	0.000	0.001
Wisconsin	47	45.0	1.804	0.679	0.058	0.412
Soybean						
Illinois	82	44.6	0.962	0.699	0.006	0.412
Indiana	59	41.8	1.248	0.617	0.000	0.006
Iowa	93	66.7	1.070	0.646	0.006	0.021
Minnesota	56	69.6	1.120	0.730	0.000	0.006
Missouri	27	66.9	2.006	0.885	0.021	0.252
Ohio	50	74.7	1.566	0.649	0.000	0.058
Wisconsin	32	84.8	1.725	1.075	0.000	0.252
Cotton						
Arkansas	7	39.3	1.559	1.273	0.006	0.058
Georgia	20	53.8	1.520	0.784	0.001	0.021
Louisiana	6	55.0	1.712	1.197	0.001	0.006
Mississippi	11	45.0	0.903	0.926	0.252	0.588
Tennessee	7	65.0	1.656	0.488	0.000	0.006
Winter wheat						
Illinois	8	51.9	0.676	0.412	0.000	0.006
Indiana	19	57.9	1.095	0.471	0.000	0.000
Kansas	33	47.9	1.462	0.989	0.588	0.868
Michigan	27	46.5	0.687	0.540	0.058	0.058
Missouri	13	25.0	0.864	0.738	0.006	0.021
Ohio	17	46.8	1.023	0.498	0.000	0.021
Oklahoma	16	64.7	1.402	1.113	0.058	0.412
Tennessee	10	55.5	1.742	1.057	0.006	0.021

Table S3. Rating Game Results: RMA versus BMA-Unrestricted, $n = 20$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	p-value 1	p-value 2
Corn						
Illinois	73	54.2	1.481	0.912	0.001	0.021
Indiana	60	72.5	1.960	0.900	0.000	0.000
Iowa	91	56.0	0.639	0.482	0.006	0.001
Minnesota	56	66.0	0.635	0.335	0.000	0.000
Missouri	24	83.3	1.926	0.988	0.000	0.006
Ohio	58	77.3	0.964	0.745	0.006	0.006
Wisconsin	47	50.3	1.248	0.523	0.252	0.412
Soybean						
Illinois	82	51.7	0.855	0.590	0.058	0.252
Indiana	59	44.6	1.077	0.634	0.000	0.058
Iowa	93	68.1	0.895	0.635	0.000	0.132
Minnesota	56	75.8	1.028	0.758	0.001	0.006
Missouri	27	69.8	1.719	0.866	0.021	0.021
Ohio	50	78.7	1.687	0.711	0.000	0.001
Wisconsin	32	89.7	1.504	1.120	0.000	0.058
Cotton						
Arkansas	7	49.3	1.473	0.657	0.001	0.006
Georgia	20	56.0	1.064	0.702	0.021	0.058
Louisiana	6	60.8	2.314	1.363	0.001	0.006
Mississippi	11	50.9	1.007	0.818	0.000	0.412
Tennessee	7	64.3	1.177	0.573	0.000	0.021
Winter wheat						
Illinois	8	46.9	0.639	0.196	0.000	0.000
Indiana	19	62.4	0.763	0.376	0.000	0.058
Kansas	33	51.1	1.377	0.901	0.588	0.868
Michigan	27	49.4	0.459	0.314	0.058	0.021
Missouri	13	25.4	0.561	0.694	0.021	0.021
Ohio	17	48.2	0.887	0.416	0.000	0.000
Oklahoma	16	68.8	1.348	1.227	0.132	0.588
Tennessee	10	56.5	0.669	0.404	0.000	0.132

Table S4. Rating Game Results: RMA versus BMA-Unrestricted, $n = 25$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	p-value 1	p-value 2
Corn						
Illinois	73	60.8	1.116	0.520	0.000	0.021
Indiana	60	82.2	1.676	0.676	0.000	0.000
Iowa	91	59.5	0.601	0.316	0.000	0.001
Minnesota	56	75.0	0.411	0.243	0.000	0.000
Missouri	24	88.8	1.579	0.819	0.000	0.001
Ohio	58	78.9	1.033	0.727	0.000	0.006
Wisconsin	47	60.7	0.572	0.544	0.058	0.588
Soybean						
Illinois	82	60.0	0.788	0.561	0.001	0.006
Indiana	59	45.9	1.027	0.579	0.000	0.058
Iowa	93	70.5	1.063	0.691	0.000	0.001
Minnesota	56	80.6	1.175	0.817	0.006	0.006
Missouri	27	76.7	1.101	0.883	0.132	0.252
Ohio	50	80.5	1.605	0.749	0.000	0.058
Wisconsin	32	92.8	2.266	1.159	0.000	0.001
Cotton						
Arkansas	7	50.0	1.770	0.637	0.000	0.000
Georgia	20	57.5	0.647	0.574	0.058	0.132
Louisiana	6	56.7	2.175	1.291	0.000	0.058
Mississippi	11	55.0	0.945	0.668	0.001	0.412
Tennessee	7	70.0	1.531	0.567	0.000	0.021
Winter wheat						
Illinois	8	50.0	0.607	0.201	0.000	0.000
Indiana	19	66.1	0.653	0.397	0.000	0.006
Kansas	33	56.2	1.363	0.980	0.252	0.748
Michigan	27	50.7	0.377	0.193	0.001	0.006
Missouri	13	26.5	0.534	0.503	0.006	0.058
Ohio	17	45.6	0.776	0.496	0.000	0.001
Oklahoma	16	70.6	1.677	1.420	0.252	0.412
Tennessee	10	59.0	0.595	0.383	0.001	0.058

Table S5. Rating Game Results: Individual versus BMA-Unrestricted, $n = 15$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	49.6	2.025	1.160	0.000	0.006
Indiana	60	46.8	2.231	0.914	0.000	0.001
Iowa	91	39.0	2.651	1.103	0.000	0.001
Minnesota	56	46.4	1.040	0.734	0.001	0.021
Missouri	24	82.7	1.989	1.181	0.000	0.001
Ohio	58	64.6	1.103	0.733	0.000	0.006
Wisconsin	47	38.6	1.894	0.675	0.252	0.588
Soybean						
Illinois	82	30.0	0.953	0.775	0.058	0.588
Indiana	59	30.6	1.207	0.603	0.000	0.021
Iowa	93	52.8	1.173	0.626	0.006	0.058
Minnesota	56	58.8	1.185	0.774	0.000	0.006
Missouri	27	62.0	1.889	0.950	0.000	0.021
Ohio	50	65.8	1.387	0.712	0.006	0.021
Wisconsin	32	84.2	1.630	1.126	0.000	0.058
Cotton						
Arkansas	7	35.7	1.196	1.142	0.006	0.001
Georgia	20	67.0	1.328	0.795	0.000	0.132
Louisiana	6	55.0	1.662	1.235	0.000	0.001
Mississippi	11	42.3	0.931	0.861	0.132	0.588
Tennessee	7	52.1	1.459	0.473	0.000	0.001
Winter wheat						
Illinois	8	51.2	0.648	0.184	0.000	0.001
Indiana	19	47.6	0.929	0.533	0.000	0.021
Kansas	33	53.0	1.474	1.005	0.252	0.748
Michigan	27	44.3	0.475	0.564	0.252	0.412
Missouri	13	25.4	0.710	1.151	0.006	0.021
Ohio	17	32.6	0.998	0.482	0.001	0.058
Oklahoma	16	57.2	1.437	1.125	0.252	0.412
Tennessee	10	61.0	1.314	1.073	0.001	0.132

Table S6. Rating Game Results: Individual versus BMA-Unrestricted, $n = 20$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	p-value 1	p-value 2
Corn						
Illinois	73	52.9	1.450	1.001	0.001	0.021
Indiana	60	60.2	1.850	0.947	0.000	0.000
Iowa	91	47.0	0.753	0.457	0.000	0.006
Minnesota	56	58.0	0.589	0.566	0.001	0.001
Missouri	24	83.5	2.011	1.032	0.000	0.001
Ohio	58	70.3	0.979	0.780	0.000	0.021
Wisconsin	47	42.2	1.112	0.589	0.412	0.588
Soybean						
Illinois	82	37.4	0.892	0.625	0.006	0.588
Indiana	59	34.7	1.081	0.659	0.000	0.006
Iowa	93	56.0	1.042	0.606	0.021	0.058
Minnesota	56	64.4	1.126	0.808	0.006	0.006
Missouri	27	64.4	1.732	0.857	0.006	0.001
Ohio	50	69.7	1.493	0.752	0.000	0.001
Wisconsin	32	86.7	1.785	1.157	0.000	0.006
Cotton						
Arkansas	7	50.7	0.961	0.697	0.000	0.001
Georgia	20	71.2	1.288	0.666	0.000	0.058
Louisiana	6	63.3	2.020	1.270	0.000	0.021
Mississippi	11	44.5	0.982	0.730	0.001	0.588
Tennessee	7	61.4	1.912	0.439	0.000	0.001
Winter wheat						
Illinois	8	50.0	0.609	0.263	0.000	0.000
Indiana	19	48.7	0.732	0.348	0.000	0.006
Kansas	33	56.4	1.491	0.870	0.006	0.748
Michigan	27	49.1	0.496	0.292	0.006	0.021
Missouri	13	21.5	0.548	0.685	0.006	0.021
Ohio	17	38.8	0.783	0.417	0.001	0.006
Oklahoma	16	61.6	1.405	1.217	0.132	0.412
Tennessee	10	63.0	0.729	0.486	0.000	0.132

Table S7. Rating Game Results: Individual versus BMA-Unrestricted, $n = 25$ Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	58.8	1.136	0.559	0.000	0.132
Indiana	60	70.0	1.421	0.707	0.000	0.001
Iowa	91	52.6	0.598	0.306	0.001	0.001
Minnesota	56	70.0	0.418	0.231	0.000	0.000
Missouri	24	87.3	1.729	0.840	0.000	0.006
Ohio	58	71.6	1.064	0.754	0.000	0.006
Wisconsin	47	50.2	0.583	0.560	0.058	0.412
Soybean						
Illinois	82	45.7	0.781	0.597	0.001	0.132
Indiana	59	36.9	1.089	0.547	0.000	0.006
Iowa	93	58.4	1.185	0.706	0.058	0.021
Minnesota	56	69.6	1.264	0.863	0.006	0.252
Missouri	27	66.1	1.418	0.840	0.001	0.132
Ohio	50	71.1	1.559	0.783	0.006	0.006
Wisconsin	32	91.1	1.602	1.238	0.000	0.021
Cotton						
Arkansas	7	50.7	1.513	0.749	0.000	0.000
Georgia	20	69.5	0.765	0.549	0.000	0.252
Louisiana	6	65.8	1.983	1.409	0.000	0.021
Mississippi	11	52.3	0.947	0.754	0.006	0.132
Tennessee	7	58.6	0.917	0.456	0.000	0.001
Winter wheat						
Illinois	8	50.0	0.631	0.182	0.000	0.000
Indiana	19	54.7	0.681	0.399	0.000	0.006
Kansas	33	60.6	1.363	1.003	0.058	0.412
Michigan	27	52.8	0.295	0.248	0.021	0.021
Missouri	13	28.1	0.611	0.438	0.006	0.058
Ohio	17	39.4	0.761	0.486	0.000	0.021
Oklahoma	16	66.9	1.724	1.415	0.058	0.748
Tennessee	10	67.5	0.519	0.433	0.001	0.252

Table S8. Rating Game Results: Individual versus BMA-Unrestricted: Full Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	67.2	0.935	0.576	0.000	0.001
Indiana	60	73.4	0.974	0.715	0.000	0.000
Iowa	91	60.1	0.493	0.362	0.058	0.132
Minnesota	56	79.8	0.351	0.199	0.001	0.001
Missouri	24	89.2	0.789	0.696	0.000	0.132
Ohio	58	80.1	0.836	0.721	0.006	0.006
Wisconsin	47	68.8	0.538	0.466	0.058	0.748
Soybean						
Illinois	82	60.7	0.805	0.579	0.058	0.252
Indiana	59	61.0	0.861	0.571	0.000	0.001
Iowa	93	73.9	1.252	0.709	0.000	0.058
Minnesota	56	72.1	0.984	0.659	0.006	0.058
Missouri	27	72.2	1.159	0.786	0.000	0.021
Ohio	50	86.3	1.804	0.681	0.000	0.006
Wisconsin	32	81.1	0.912	0.799	0.412	0.058
Cotton						
Arkansas	7	38.6	0.716	0.543	0.000	0.021
Georgia	20	65.5	0.664	0.508	0.021	0.252
Louisiana	6	66.7	2.280	1.322	0.000	0.021
Mississippi	11	59.1	0.780	0.715	0.001	0.000
Tennessee	7	69.3	0.933	0.547	0.000	0.001
Winter wheat						
Illinois	8	53.8	0.657	0.287	0.000	0.000
Indiana	19	65.8	0.497	0.374	0.021	0.001
Kansas	33	63.8	1.513	1.067	0.132	0.058
Michigan	27	48.3	0.315	0.232	0.001	0.021
Missouri	13	41.9	0.510	0.499	0.021	0.058
Ohio	17	49.7	0.547	0.391	0.006	0.006
Oklahoma	16	64.7	1.584	1.712	0.412	0.021
Tennessee	10	81.0	0.206	0.415	0.006	0.021

Table S9. Rating Game Results: RMA versus BMA-CRD: Full Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	74.7	0.704	0.622	0.006	0.001
Indiana	60	83.3	0.962	0.688	0.000	0.000
Iowa	91	78.4	0.302	0.409	0.252	0.252
Minnesota	56	79.5	0.209	0.222	0.252	0.021
Missouri	24	88.8	0.555	0.683	0.058	0.058
Ohio	58	79.6	0.868	0.686	0.000	0.058
Wisconsin	47	82.9	0.382	0.469	0.252	0.058
Soybean						
Illinois	82	80.1	0.660	0.623	0.132	0.006
Indiana	59	74.4	0.849	0.593	0.021	0.006
Iowa	93	82.9	0.748	0.782	0.132	0.021
Minnesota	56	77.9	0.708	0.719	0.001	0.021
Missouri	27	66.5	0.783	0.867	0.132	0.132
Ohio	50	76.5	0.755	0.754	0.021	0.132
Wisconsin	32	60.9	0.811	0.822	0.058	0.252
Cotton						
Arkansas	7	43.6	0.664	0.571	0.001	0.001
Georgia	20	49.2	0.611	0.478	0.252	0.252
Louisiana	6	56.7	1.867	1.437	0.058	0.021
Mississippi	11	67.7	0.573	0.777	0.868	0.588
Tennessee	7	71.4	0.230	0.701	0.021	0.021
Winter wheat						
Illinois	8	65.0	0.219	0.411	0.058	0.021
Indiana	19	68.7	0.416	0.436	0.021	0.006
Kansas	33	47.3	1.158	1.186	0.132	0.412
Michigan	27	35.4	0.320	0.210	0.021	0.132
Missouri	13	30.0	0.595	0.348	0.001	0.058
Ohio	17	45.3	0.431	0.554	0.006	0.006
Oklahoma	16	56.6	1.916	1.551	0.021	0.412
Tennessee	10	50.0	0.458	0.400	0.006	0.021

Table S10. Rating Game Results: RMA versus BMA-State: Full Sample

Crop-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	*p*-value 1	*p*-value 2
Corn						
Illinois	73	75.3	0.755	0.615	0.001	0.000
Indiana	60	82.6	0.953	0.690	0.000	0.000
Iowa	91	80.5	0.369	0.392	0.006	0.132
Minnesota	56	80.3	0.220	0.216	0.021	0.000
Missouri	24	79.2	0.546	0.686	0.058	0.000
Ohio	58	72.8	0.901	0.677	0.000	0.001
Wisconsin	47	81.7	0.438	0.464	0.132	0.412
Soybean						
Illinois	82	81.0	0.650	0.622	0.021	0.021
Indiana	59	73.7	0.940	0.556	0.000	0.021
Iowa	93	81.0	1.018	0.720	0.001	0.021
Minnesota	56	77.7	0.853	0.680	0.006	0.058
Missouri	27	74.3	0.852	0.831	0.058	0.058
Ohio	50	81.2	1.030	0.688	0.001	0.021
Wisconsin	32	66.7	0.863	0.809	0.058	0.001
Cotton						
Arkansas	7	42.9	0.664	0.571	0.001	0.001
Georgia	20	53.0	0.578	0.511	0.412	0.412
Louisiana	6	61.7	1.895	1.419	0.021	0.021
Mississippi	11	66.8	0.647	0.761	0.588	0.252
Tennessee	7	71.4	0.230	0.701	0.021	0.021
Winter wheat						
Illinois	8	68.1	0.249	0.364	0.021	0.000
Indiana	19	67.4	0.458	0.410	0.132	0.006
Kansas	33	53.6	1.231	1.154	0.412	0.588
Michigan	27	42.8	0.329	0.225	0.001	0.006
Missouri	13	29.2	0.529	0.550	0.021	0.132
Ohio	17	52.6	0.464	0.486	0.006	0.021
Oklahoma	16	59.1	1.903	1.541	0.132	0.252
Tennessee	10	48.5	0.456	0.508	0.001	0.021

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