Simultaneous Borrowing of Extraneous Information across Space and Time for Estimating Crop Insurance Premium Rates

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Institute Working Paper 2019.9

Abstract

There has been a recent surge in the literature outlining methodologies that make use of spatially extraneous yield data in estimating crop insurance premium rates. The idea of borrowing information across space to better estimate tail probabilities is appealing. Along a different vein, recent research has questioned the validity of using whatever limited historical yield data exists given the number of technological changes in seed and farm management technologies as well as climate change. This literature has suggested historical yield data be trimmed to the most recent 25-30 years, thereby making the historically discarded yield data temporally extraneous. In this manuscript, we present three successively flexible data-driven methodologies to nonparametrically smooth across both space and time simultaneously. We apply these methodologies in estimating U.S. corn and soybean county-level crop insurance premium rates. We find significant borrowing of information across both time and space. We also find all three methodologies improve both the stability and accuracy of crop insurance premium rates.

Some key words: spatial smoothing, temporal smoothing, crop insurance

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Introduction

There is a great deal of methodological literature on estimating conditional yield distributions and corresponding crop insurance premium rates.[2] Most recently, the idea of borrowing spatially extraneous yield data to better estimate tail probabilities has attracted significant attention. For example, Park, Brorsen, and Harri (2018) proposed a Bayesian Kriging method for spatial smoothing. Ramsey (2019) presented a Bayesian quantile process for yield density estimation where the spatial information is introduced through a Gaussian spatial process. Ker, Tolhurst, and Liu (2016) developed a Bayesian model averaging technique to exploit possible similarities across space. Finally, Annan et al. (2014) used a distributional testing procedure to identify possible sets of yield pooling. For earlier works on exploiting possible spatial similarities in estimating yield distributions and premium rates, see Ker and Goodwin (2000) and Racine and Ker (2006). All of these methods can be considered some form of smoothing or weighting between the individual yield data of interest and the spatially extraneous yield data.

Literature questioning the use of historical yield data in empirical analyses has also started to surface; not surprising given the significant changes in seed technology (such as the introduction of genetically modified seeds), changes in farming practices (such as precision farming), and changes in climate. With respect to crop insurance, it does not seem likely that yield losses from the 1950s and 1960s can inform, to the same degree as yield losses from the 2000s, about possible losses in 2019. Shen, Odening, and Okhrin (2018), using adaptive smoothing, found that yields should be trimmed after approximately 20 years. Liu and Ker (2019), using nonparametric hypothesis tests, found that yields should be trimmed after 25-30 years. Moreover, many have found statistically significant changes in the higher moments of yields (see Tack, Harri, and Coble, 2012; Tolhurst and Ker, 2015; Ker and Tolhurst, 2019; Goodwin and Piggott, 2019), thereby violating the common assumption in the literature of only correcting for time-varying changes in the first two moments of yields; this necessitates historical trimming. Similar to extraneous spatial yield data, the trimmed yield data can be considered *temporally* extraneous.

[2]Examples include parametric estimation (Gallagher, 1987; Atwood, Shaik, and Watts, 2003; Sherrick et al., 2004; Tack, Harri, and Coble, 2012; Tolhurst and Ker, 2015) and nonparametric estimation (Goodwin and Ker, 1998; Ker and Goodwin, 2000; Ker and Coble, 2003; Norwood, Roberts, and Lusk, 2004).

The objective of this manuscript is to generalize three methods -- previously used to smooth only across space -- to smooth simultaneously across both space and time for estimating crop insurance rates. No assumptions are made as to the degree or form of similarity between the underlying data generating processes, either temporally or spatially. The first approach we consider pools all extraneous yield data across both space and time to form a start estimate. The start estimate is then corrected using the individual yield data. Note that this approach optimizes the smoothing between the individual yield data and the temporally and spatially extraneous yield data. However, it is naive in that the methodology treats all extraneous data identically. The second approach is generally used for smoothing across discrete and continuous variables. In our case, we have two discrete variables: time and space. As a result, we require an additional smoothing parameter compared to the first method. However, the additional smoothing parameter does enable the weights or smoothing across space and time to differ. The final methodology is Bayesian and smooths across time and space using posterior weights. The Bayesian methodology is the most flexible in that the weight varies not only between space and time but within space and time as well. Note, all three proposed methods allow historical trimming (as per Shen, Odening, and Okhrin (2018) and Liu and Ker (2019)) without completely discarding the trimmed yield data. Moreover, the proposed methods capture possible efficiency gains from smoothing across space (as found by Ker, Tolhurst, and Liu, 2016; Park, Brorsen, and Harri, 2018; Ramsey, 2019).

We evaluate the three proposed methods with respect to estimating crop insurance premium rates. Crop insurance programs have been the pillar of U.S. domestic agricultural policy for the past 25 years. As of 2017, over 100 crops are now covered under various programs. According to the estimate of the U.S. Congressional Budget Office in 2014, the total spending on agricultural insurance programs will be almost $90 billion over the coming decade. Crop insurance represents the largest expenditure in the farm bill after food stamps. The program is administered by the United States Department of Agriculture's Risk Management Agency (RMA). The three proposed methodologies are of primary interest to rating both area-yield and shallow loss products. Interestingly, the RMA methodology for area-yield products uses all historical county-level yield data, whereas the Agency's methodology for shallow loss products discards historical yield data prior to 1991. Additionally, the proposed methodologies are of relevance to the farm-level crop insurance programs for two reasons:

(i) county level rates are used in the rating process for base farm level rates; and (ii) the proposed methodologies perform very well in small samples given their smoothing properties.

The remainder of this manuscript proceeds as follows. The next section details the yield data. The third section presents RMA's detrending and heteroscedasticity methodologies. The fourth section outlines how the proposed methodologies are generalized to borrow information across both space and time. The fifth section presents estimated premium rates and results of an out-of-sample retain-cede rating game. The final section summarizes our findings.

Data

We use historical county level yield data for corn and soybean from 1951 to 2017, collected from USDA's National Agricultural Statistical Service (NASS) Quick Stats portal.[3] We focus on states that account for the majority of national production. We removed states that have less than 25 producing counties. We also removed states that had more than 10% of their acreage as irrigated in the 2012 Census of Agriculture. For each state selected, counties with missing observations were also removed. Following these criteria, we ended up with seven states for corn: Illinois (IL), Indiana (IN), Iowa (IA), Minnesota (MN), Ohio (OH), South Dakota (SD), and Wisconsin (WI). These states accounted for 57.8 percent of harvested acreage and 61.8 percent of national corn production in 2017. All corn states except South Dakota met the inclusion criteria for soybean. These six states accounted for 50.5 and 53.9 percent of national harvested acreage and production of soybean in 2017, respectively. In total, our data comprises 414 corn and 373 soybean counties.

RMA Methodology

In the vast majority of the crop insurance literature, premium rates are estimated using a two-stage process. First, a trend function is assumed and estimated using the historical yields. Both deterministic and stochastic trends have been used in the literature. Examples include linear, median regression, two-knot linear spline (Skees and Reed, 1986), polynomial (Just and Weninger, 1999), nonparametric regression (Goodwin and Hungerford, 2015), Kalman filter (Kaylen and Koroma, 1991) and ARIMA (Goodwin and Ker,

[3]NASS Quick Stats: `https://quickstats.nass.usda.gov`

1998). The residuals from the trend estimation are adjusted for possible heteroscedasticity via Harri et al. (2011). The detrended and heteroscedasticity adjusted yield data, referred to throughout as *adjusted* yields, are then used to estimate conditional yield distributions and recover premium rates. Zhu, Goodwin, and Ghosh (2011) noted, this two-stage procedure is by far the most common practice employed in the literature. In this manuscript, we use the current RMA methodology for trend estimation and heteroscedasticity adjustment given the relevance of our results to crop insurance.[4] Currently, RMA estimates the county level historical yields, denoted as $y_t = (y_1, ..., y_T)$, with a robust two-knot linear spline:

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

where d_1 and d_2 are indicator functions so that $d_1 = 1$ if $t \geq k_1$ and $d_2 = 1$ if $t \geq k_2$, and are zeros otherwise; k_1, k_2 are two knots such that $k_1, k_2 \in (1 + \bar{k}, \ldots, T - \bar{k})$ and $k_2 - k_1 \geq \underline{k}$. To maintain the proper length of each knot section, the conditions $\underline{k}, \bar{k} \geq 10$ are imposed to prevent the knot locations from being too close to each other or too close to the end points. Knot locations k_i are selected through a grid search based on minimizing least squares. The number of optimal knots (0, 1, 2) is selected based on Akaike information criterion (AIC). Given the number of knots, parameters are estimated through two robustness procedures where the spline is iterated to convergence with Huber weights and then twice passed through a bisquare function.

After the trend estimation, we denote the residuals as $\hat{\varepsilon}_t$ and the fitted values as $\hat{g}(t) = \hat{y}_t$. Heteroscedasticity is corrected for using Harri et al. (2011):[5]

$$\ln(\hat{\varepsilon}_t^2) = \alpha + \gamma \ln(\hat{y}_t) + v_t. \tag{2}$$

Note, constant and proportional variance in the underlying yield data corresponds to $\gamma = 0$ and $\gamma = 2$, respectively. Yields are adjusted based on a one-step ahead forecast ($\hat{y}_{T+1}$) and

[4] Our results are robust to simple linear trend, median regression, and nonparametric local smoothing.

[5] See Ker and Tolhurst (2019) for an alternative methodology. Our findings are robust to either heteroscedasticity treatment.

the heteroscedasticity coefficient ($\hat{\gamma}$):[6]

$$\hat{y}_t^* = \hat{y}_{T+1} + \hat{\varepsilon}_t \left(\frac{\hat{y}_{T+1}}{\hat{y}_t} \right)^{\frac{\hat{\gamma}}{2}} \tag{3}$$

The adjusted yields can then be used to estimate conditional yield distributions or generate empirical premium rates:

$$\pi_{T+1}^* = \frac{1}{T} \sum_{t=1}^{T} \max\left\{0,\ \lambda \hat{y}_{T+1}^* - \hat{y}_t^*\right\} \tag{4}$$

where λ is the coverage level such that $\lambda \hat{y}_{T+1}^*$ is the yield guarantee.

Methods: Incorporating Extraneous Data across Space and Time

As mentioned, we wish to consider three methods that can simultaneously smooth yields across both space and time. Consider we have Q counties each with T adjusted yields where y_t^j represents the adjusted yield realization in time t from county j.[7] We follow the literature (Shen, Odening, and Okhrin, 2018) and trim the yield data into sets of 20 years. Given that we have yield data from 1951-2017, we have three sets of historical yield data: 1998-2017; 1978-1997; and 1958-1977. Note, the two historically trimmed reference sets are 1958-1977 and 1978-1997, while the current yield set is 1998-2017. We divide the data as follows:

$$\begin{array}{r} \textit{Temporal Set 2} \left\{ \begin{array}{l} \\ \\ \\ \end{array} \right. \\ \textit{Temporal Set 1} \left\{ \begin{array}{l} \\ \\ \\ \end{array} \right. \\ \textit{Temporal Set 0} \left\{ \begin{array}{l} \\ \\ \\ \end{array} \right. \end{array} \begin{bmatrix} y_{1958}^1 & y_{1958}^2 & \cdots & y_{1958}^Q \\ \vdots & \vdots & \ddots & \vdots \\ y_{1977}^1 & y_{1977}^2 & \cdots & y_{1977}^Q \\ \hline y_{1978}^1 & y_{1978}^2 & \cdots & y_{1978}^Q \\ \vdots & \vdots & \ddots & \vdots \\ y_{1997}^1 & y_{1997}^2 & \cdots & y_{1997}^Q \\ \hline y_{1998}^1 & y_{1998}^2 & \cdots & y_{1998}^Q \\ \vdots & \vdots & \ddots & \vdots \\ y_{2017}^1 & y_{2017}^2 & \cdots & y_{2017}^Q \end{bmatrix}$$

[6] RMA uses a two-step ahead forecast because of data availability/timing issues. We chose a one-step ahead forecast for our analysis simply to gain an additional degree of freedom given we are truncating an already very short time series.

[7] For notational convenience and without loss of generality, we assume all counties have equal T although all three estimators can handle an unbalanced design.

All three proposed methods are nonparametric and based on the Nadaraya-Watson (NW), or standard kernel, estimator. The standard kernel estimator is defined as:

$$\hat{f}(y) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{y - y_i}{h}\right), \tag{5}$$

where $K()$ is kernel function assumed to be a square integrable symmetric probability density function with a finite second moment, and h is the bandwidth or smoothing parameter. Nonparametric based methods have been used throughout the crop insurance literature (see Goodwin and Ker, 1998; Ker and Coble, 2003, for examples).

Possibly Similar Estimator (PS)

The possibly similar (PS) estimator uses a *start* estimate and then nonparametrically corrects the *start*. This estimator uses the extraneous yield data to reduce bias. See Ker (2016) for technical details (rate of convergence and bounded neighbourhood of reductions in asymptotic mean integrated squared error). If the *start* is sufficiently close to the density of interest then the correction function is less rough (as measured by the integrated second derivative) and bias is reduced in the overall estimation. Of importance for our application is that there are no restrictions beyond continuity placed on the data entering the *start* estimate. That is, the *start* estimate can be comprised of data from both time and space. Because the data is simply pooled across space and time for the *start* estimate, the PS estimator is relatively naive.

Define $\hat{g}(y)$ as our initial *start* estimate with smoothing parameter h_g based on all the space and historical data pooled together. The correction factor function in the PS estimator is then given as

$$\hat{r}(y) = \sum_{t=1}^{T} \frac{1}{hT} K\left(\frac{y - y_t}{h}\right) / \hat{g}(y_t), \tag{6}$$

where y_t is the individual sample realizations $(y_1, ..., y_t)$ and, again, $\hat{g}(y_t)$ is the *start* estimate. The PS estimator is given by the product of the pooled estimate and the individual correction factor, which is

$$\tilde{f}(y) = \hat{g}(y)\hat{r}(y) = \sum_{t=1}^{T} \frac{1}{hT} K\left(\frac{y - y_t}{h}\right) \frac{\hat{g}(y)}{\hat{g}(y_t)}. \tag{7}$$

Two smoothing parameters, h_g and h, are chosen by likelihood cross-validation.

Although the PS estimator is naive in that it necessarily treats the temporal and spatial extraneous data identically, it has many attractive features. First, Ker (2016) found the PS estimator to significantly outperform the standard kernel estimator, more so in small samples. Second, likelihood cross-validation is used to determine the relative smoothing between the *start* and the individual estimates. Finally, no assumptions about the form or extent of similarity across space and time are required.

Li-Racine Estimator (LR)

The Li-Racine (LR) estimator smooths across mixed data-types, both continuous and discrete. Technical details about the LR estimator can be obtained from Li and Racine (2003), Racine and Li (2004), and Li, Simar, and Zelenyuk (2016). In our application, the continuous variable is the adjusted yields, whereas space and time represent discrete variables. As a result, we have three smoothing parameters: one to smooth the adjusted yields, one to smooth the adjusted yields across time, and one to smooth the adjusted yields across space.[8] In this case, the LR estimator is

$$\begin{aligned}\hat{f}(y) = (Nh)^{-1}\Bigg[& \underbrace{\sum_{t=1}^{2}\sum_{j=1}^{T}\lambda_1 K\left(\frac{y-y_{tj}}{h}\right)}_{\text{historical data}} + \underbrace{\sum_{j=1}^{T}\lambda_2 K\left(\frac{y-y_{0j}}{h}\right)}_{\text{current data}} \\ & + \underbrace{\sum_{i=1}^{(Q-1)}\sum_{j=1}^{T}(1-\lambda_1-\lambda_2) K\left(\frac{y-y_{0ij}}{h}\right)}_{\text{spatial data}}\Bigg]\end{aligned} \tag{8}$$

where T is the length of yield data set ($T = 20$ in our case), y_{tj} represent the historical yields for the county of interest, y_{0j} represent the current set (1998-2017) of yields for the county of interest, and y_{0ij} represent the current yields for the other $Q-1$ counties. Note, $t = 0$ refers to the current or temporal set 0 (1998-2017), $t = 1$ refers to temporal set 1 (1978-1997) and $t = 2$ refers to temporal set 2 (1958-1977).

The LR estimator also has many attractive features. It has been shown to outperform the conventional frequency or bin estimator that was previously used to handle mixed data

[8]Because we choose different smoothing parameters across space and time, the estimator more closely resembles the generalization of LR by Li, Simar, and Zelenyuk (2016).

types (Racine and Li (2004)). The LR estimator uses likelihood cross-validation to choose the amount of smoothing over both space and time simultaneously. As a result, if the data are very different (as measured by likelihood cross-validation metric) across space and/or time, LR smooths very little. Like the PS estimator, the LR estimator requires no assumptions about the form or extent of similarity across space and time. Asymptotic normality is established by Racine and Li (2004); the rate of convergence is the same as the case when there are only continuous random variables. Finally, the LR estimator is less naive than the PS estimator in that it recovers different smoothing weights for the extraneous time versus space yield data.

Bayesian Model Averaging Estimator (BMA)

The final estimator uses Bayesian model averaging (BMA) to recover a set of posterior weights and smooth across space and time. Recall, we have Q counties, each with a current yield set and two historical yield sets. Usually, BMA is used to average over models, but as shown in Ker, Tolhurst, and Liu (2016), BMA can be used to smooth across space.[9] We extend their approach to smooth across both space and time.

In our application, we have $3Q$ individually estimated densities in the first stage to comprise our set of candidate models. We define the BMA estimator for county i as:

$$\tilde{f}_i = \sum_{t=0}^{2} \sum_{j=1}^{Q} \omega_{tj}^{i} \hat{f}_{tj}, \tag{9}$$

where Q is the total number of counties, $t = 0$ again represents the current period while $t = 1$ and $t = 2$ represent the two temporal reference sets, and $\hat{f}$ are the standard kernel density estimates based on the individual data sets. We are smoothing across all $3Q$ estimated densities with the weights chosen by an empirical likelihood. Note, the weights (ω) are defined as

$$\omega_{tj}^{i} = \frac{L_{tj}^{i}}{\sum_{t=0}^{2} \sum_{q=1}^{Q} L_{tq}^{i}}, \tag{10}$$

where L_{tj}^{i} is evaluated using current yields from county i at density estimate $\hat{f}_{tj}$. The weights necessarily sum to one. Because we recover individual weights for all estimated densities in

[9] For a comprehensive introduction to the general purpose of BMA, we refer to Hoeting et al. (1999).

the model averaging, we can calculate the overall weight of the historical data versus the spatial data in our final county estimates.

The BMA estimator has many attractive features. It has been shown to outperform the standard kernel estimator (Ker and Liu (2017)). The BMA estimator uses an empirical likelihood measure to choose the amount of smoothing over both space and time simultaneously. As a result, if the data are very different across space and/or time, BMA smooths very little and behaves much like the kernel estimator. Conversely, if the data are similar across space or time or both, the BMA smooths accordingly, and gains in efficiency tend to be realized. As with the PS and the LR estimators, the BMA estimator requires no assumptions about the form or extent of similarity across space and time. The BMA estimate $\tilde{f}$ converges to the kernel estimate as the current yield set grows. Finally, the BMA estimator is less naive than both the LR and the PS estimators in that it recovers different weights not only between but also within space and time. Note, each extraneous set of yield data receives a different posterior weight.

Estimating Crop Insurance Premium Rates

We estimate the set of conditional yield densities and accompanying premium rates for the 414 corn counties and 373 soybean counties using standard nonparametric kernel methods (which do not borrow information) and the BMA, LR, and PS methods (which borrow information across space and time). We plot in Figure 1 representative examples of both crops. Interestingly, the proposed estimates tend to be very different from the standard kernel estimate suggesting significant borrowing of information from the extraneous yields across both space and time.

Table 1 summarizes the amount of borrowing of yield data across space and time for the LR and BMA method. For comparison, a standard estimate involves no spatial smoothing ($\omega_{space} = \lambda_{space} = 0$) and equal weight to all historical yields ($\omega_{time} = \lambda_{time} = 2/3$). Consistent with Figure 1, the results in Table 1 indicate significant smoothing. Note that the weight given to extraneous spatial yield data tends to be higher than the weight given to the historical yield data for both LR and BMA methods. Also, BMA gives noticeably more weight to the extraneous yield data relative to LR. Finally, there tends to be more smoothing with soybean versus corn.

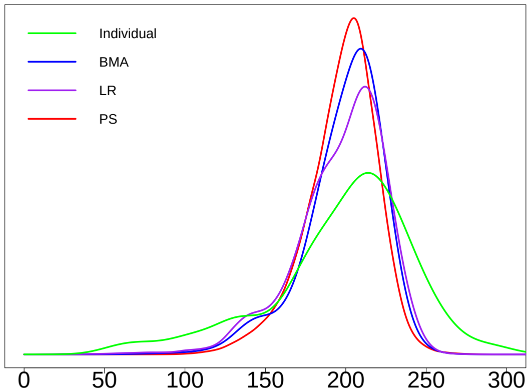
County specific estimates of the temporal and spatial weights are depicted in maps in Figure 2-3 for corn (corresponding estimates for soybean are in the Appendix). Given that the temporal, spatial, and individual weights add to one, counties with greater temporal weight tend to exhibit lower spatial weight. Interestingly, they illustrate very different patterns between the BMA and the LR methodologies. For the BMA estimator, the majority of corn counties in Iowa, Minnesota, and Wisconsin have temporal BMA weights below the average. Counties with relatively high temporal BMA weights are sparsely distributed along the state lines between South Dakota and the adjacent counties in Illinois and Indiana. With respect to the LR estimator, the majority of corn counties illustrate fairly constant temporal weights. Counties with relatively high temporal weight are sparsely located in the outlying areas of the seven states considered. With respect to the spatial BMA weights, we find that greater weight is given to the central midwest counties. With respect to the spatial LR weights, the majority of counties in Wisconsin, Iowa, and South Dakota show relatively low spatial weights; they correspond to areas with relatively high temporal weights. In summary, the results show non-trivial spatial and temporal smoothing differences between the BMA and the LR; recall that the two estimators use different smoothing metrics.

Table 1. Table of Average Weight (%) of BMA and LR for 2019 Estimated Densities

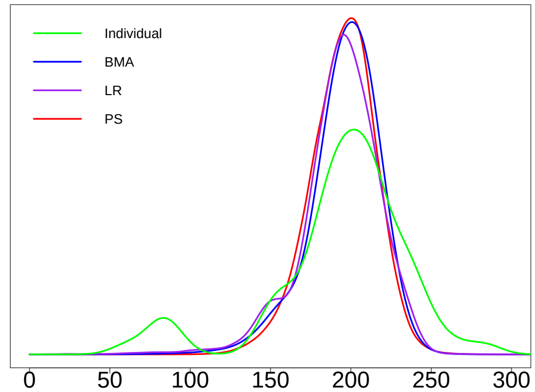
	BMA (%)			LR (%)		
Crop	ω_{own}	ω_{time}	ω_{space}	λ_{own}	λ_{time}	λ_{space}
Corn	22.69	33.35	43.96	52.29	18.46	29.24
Soybean	19.39	41.13	39.48	38.49	32.18	29.33

We derive the 90% coverage level premium rates for both corn and soybean from our estimated 2019 conditional yield densities. We compare these to the base empirical rates recovered using the current RMA methodology. The actuarially fair premium rate for an insurance contract, denoted as π, is the expected loss divided by total liability. That is, defining the random variable crop yield as Y, the actuarially fair premium rate for insurance coverage below a guarantee, denoted Y_G, is:

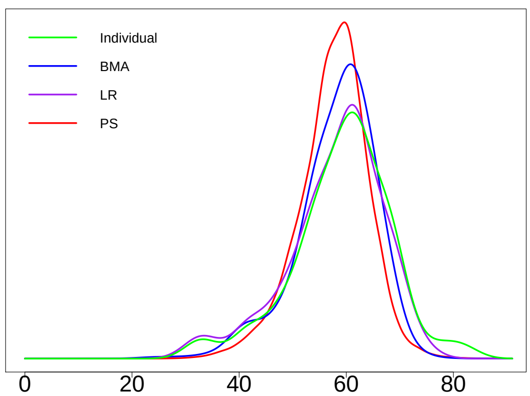
$$\pi = \frac{1}{Y_G}\int_0^{Y_G}(Y_G - y)f_Y(y)dy, \tag{11}$$



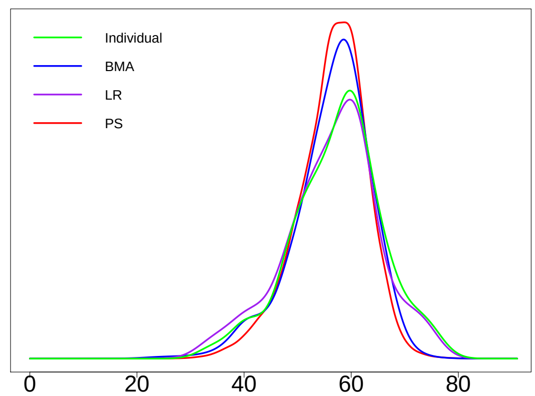
(A) Corn Iowa, Bremer



(B) Corn Iowa, Buchanan



(C) Soybean Illinois, Champaign



(D) Soybean Illinois, Edgar

Figure 1. Estimated 2019 Conditional Yield Densities by Method

where the density $f_Y(y)$ is recovered using any of the BMA, LR, or PS estimators. The estimated premium rate $\hat{\pi}$ is defined as a percent of the guarantee Y_G and is recovered by substituting $\hat{f}_Y(y)$ into equation 11. The box plots in Figure 4 show that for both corn and soybean, the three proposed estimators produce premium rates with lower median, less outliers, and smaller interquartile range (IQR) than the RMA estimator. The lower rates are a reflection of the yield density becoming markedly less skewed in the most recent period. Recall that weights given the two historical periods are much less than 2/3. This result was also found by Goodwin and Piggott (2019) and is attributable to the introduction of

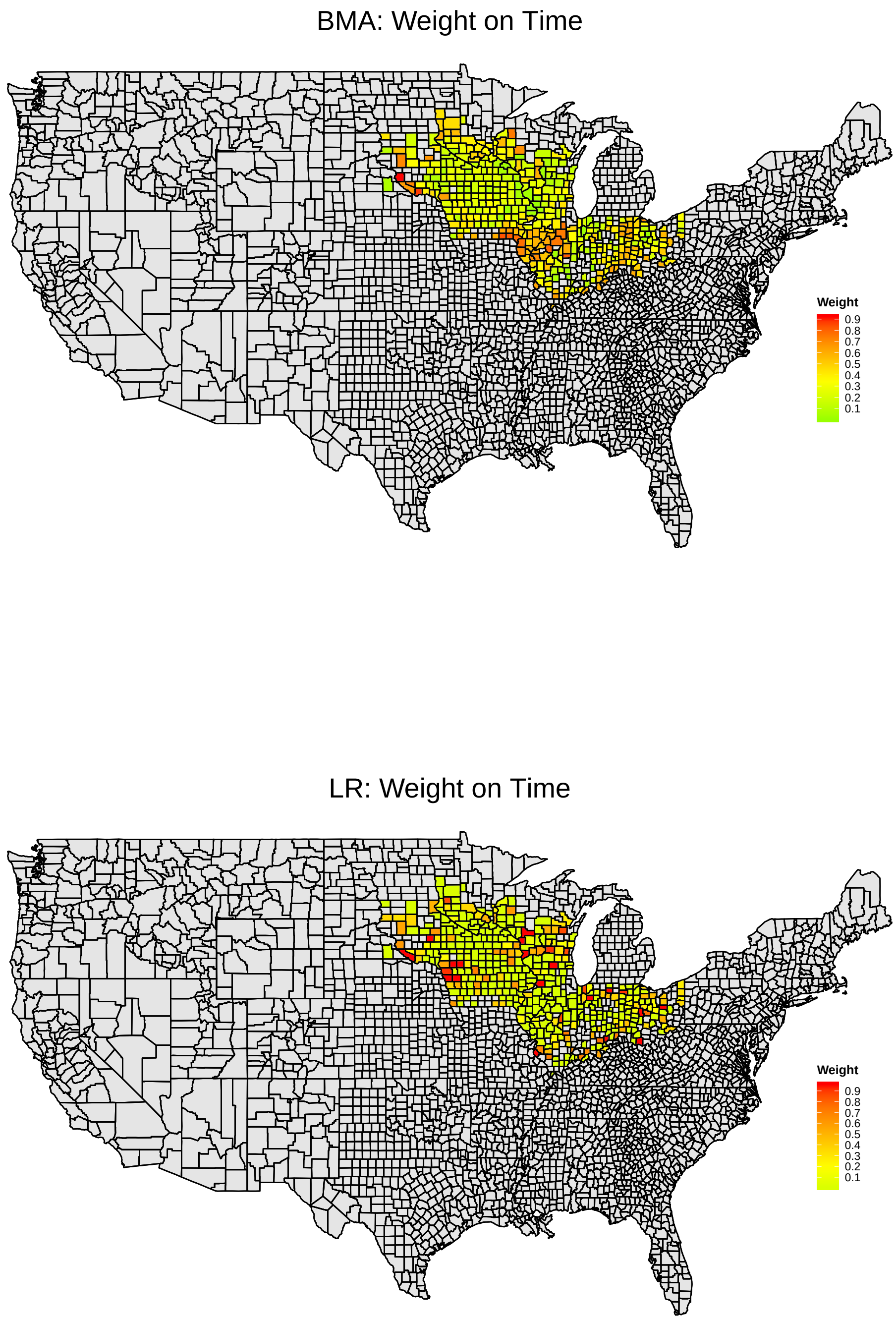


FIGURE 2. BMA and LR Temporal Weights for Corn

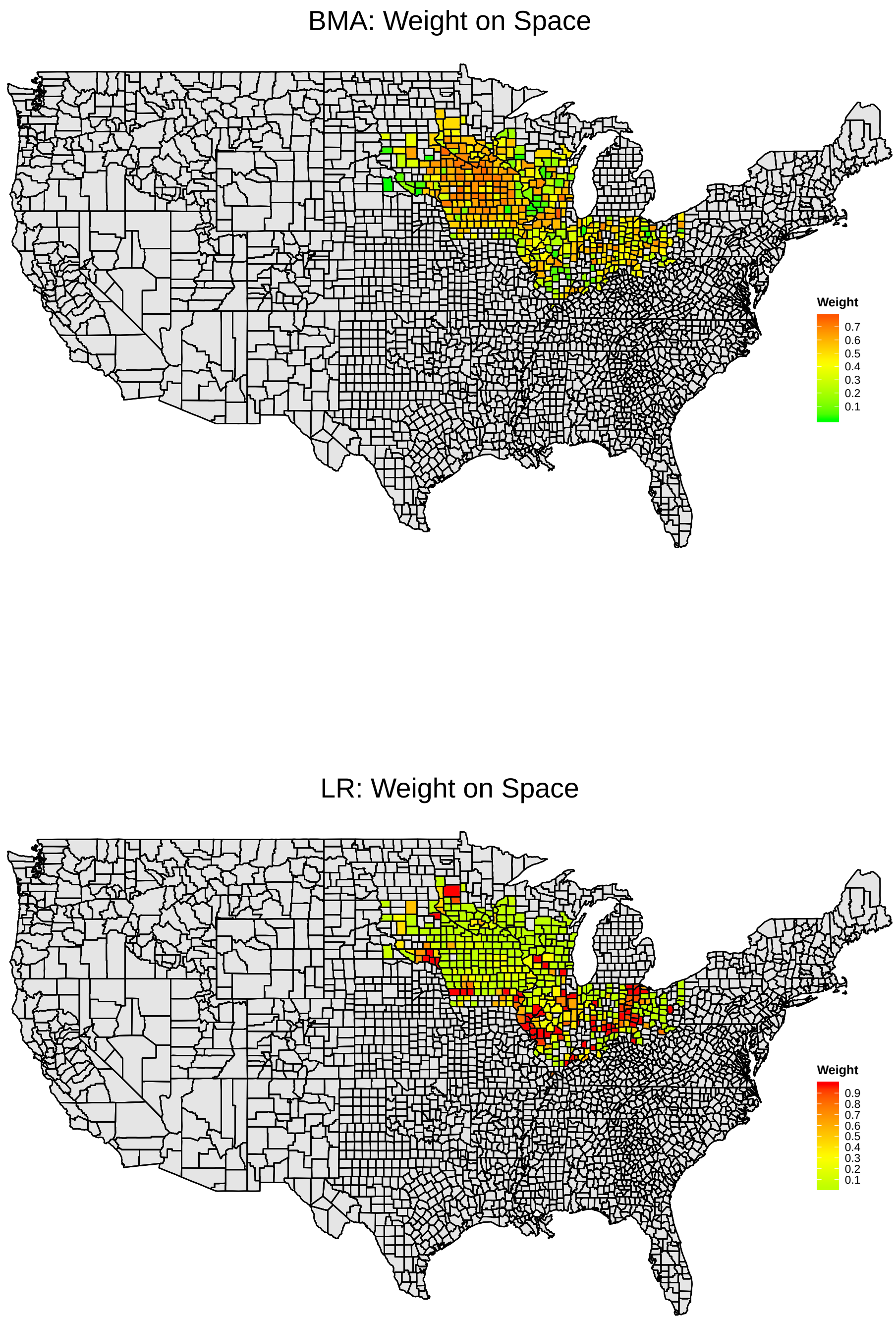
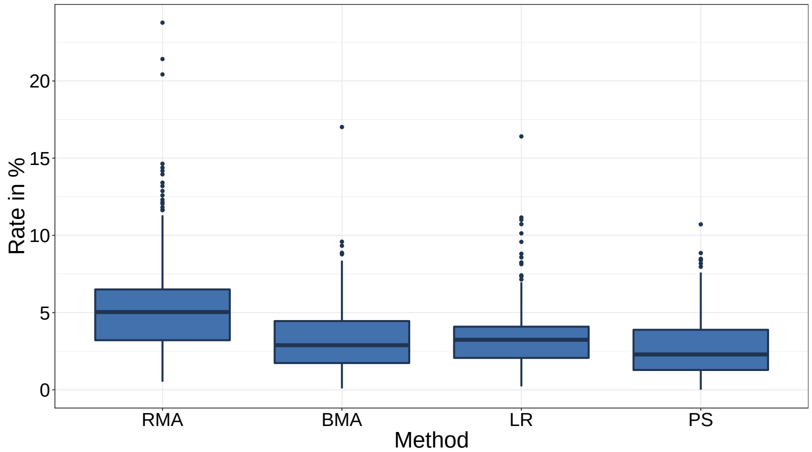
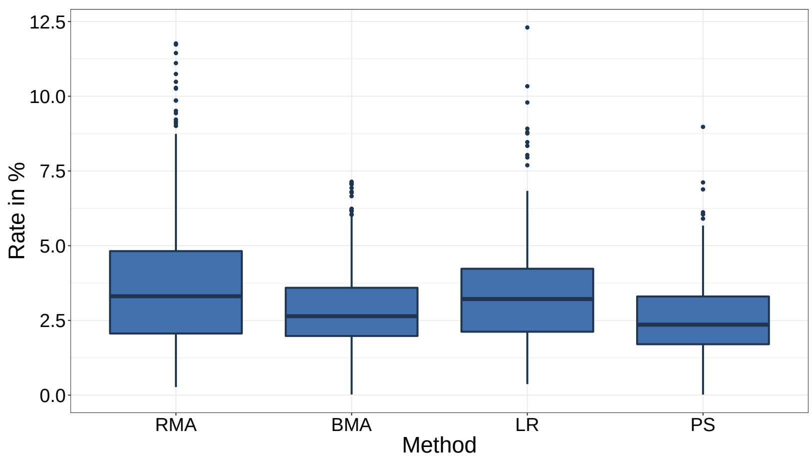


FIGURE 3. BMA and LR Spatial Weights for Corn



(A) Corn



(B) Soybean

Figure 4. Box Plots of 90% Coverage Premium Rates in 2019

genetically modified seeds. The smaller interquartile range and less outliers is a result of smoothing.

Out-of-sample Rating Games

The above results do not empirically justify the use of the proposed methods; they only show that the results are different from the current RMA approach.[10] To evaluate whether the proposed estimators are more efficient than the current RMA methodology, we conduct an out-of-sample retain-cede rating game, where two players using different methodologies

[10]The proposed methodologies use extraneous information across both space and time in an attempt to recover more efficient 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.

estimate premium rates and adverse select against one another. The game was first proposed by Ker and McGowan (2000) and has since been employed by Ker and Coble (2003), Racine and Ker (2006), Harri et al. (2011), Annan et al. (2014), Tack and Ubilava (2015), Tolhurst and Ker (2015), Yvette Zhang (2017), Shen, Odening, and Okhrin (2018), Park, Brorsen, and Harri (2018), and Ramsey (2019) to justify alternative rating methodologies. The game was modified with an additional test of rating efficiency in Ker, Tolhurst, and Liu (2016). The game was inspired by the retain-cede decision of private insurance companies in regards to the crop insurance contracts they sell. Private insurers allocate policies across different risk sharing schemes, exposing themselves to either greater or less risk and in essence, retaining or ceding the risk of any given policy. Therefore, private insurers determine which policies to retain and which to cede; policies which insurers believe are over-priced and expect an underwriting gain are retained versus policies which insurers believe are under-priced and expect an underwriting loss are ceded. As a result, private insurers necessarily develop their own rates in attempts to strategically averse select against RMA and recover excess rents. Mimicking this allows one to hypothetically compare two sets of premium rates.

In the out-of-sample rating game, we assume that RMA pools all historical yield data as they currently do; that is, yield data from 1951-1997 is used to estimate the RMA premium rates for 1998. Conversely, the private insurer estimates their rates using one of the three methodologies that borrow extraneous yield data across both space and time. We again consider periods of 20 years; that is, the current set would consist of yields from 1978-1997, historical set 1 would consist of yields from 1958-1977, and historical set 2 would consist of yields from 1951-1958.[11] As the rating game moves forward, more and more data will be in the historical set 2. The spatial reference sets come from the group of all other counties' current sets. Based on the two sets of rates from the RMA and private insurer, the private insurer identifies which contracts to retain and which to cede. The underwriting gains or losses for the set of retained and ceded contracts are calculated using the actual yields in 1998. This process is repeated for 20 years, and the loss ratios (defined as the ratio of total underwriting losses to total premiums) for both the retained and ceded sets of contracts are calculated. We conduct the game for each crop at 90% coverage levels.

[11]We considered alternative schemes whereby the historical yield data is split into equal periods (1951-1964, 1964-1977) and results were not qualitatively different.

As in the above cited literature, we undertake two hypothesis tests. The first tests whether the loss ratio from the retained contracts is less than the loss ratio from randomly retaining contracts; choosing which contracts to retain randomly is equivalent to the private insurer being indifferent between the two sets of competing rates. Randomization methods are used to recover the null distribution of the test statistic and a p-value. Game 1 mimics the current reality of the U.S. crop insurance program. However, in the program, the private insurer has an advantage because they react to the RMA premium rates. As such, whichever of the two competing rates the private insurer uses has an inherent competitive advantage in game 1. This advantage is nullified in game 2 by contrasting the changes in loss ratios under both sets of the competing rates (see Ker, Tolhurst, and Liu (2016) for details). The number of contracts considered is the number of counties multiplied by 20 years: 6,210 contracts for corn and 5,595 contracts for soybean. The results, which include the percent retained by the private insurer, the government or ceded contracts loss ratio, the insurer or retained loss ratio, p-value of game 1, and p-value of game 2, are presented in Tables 2-3.

Table 2 presents the rating game results for corn. When the private insurer uses the BMA estimator, they realize a loss ratio less than RMA in six of total seven states. With respect to game 1, the p-value is significant for five of seven states. This suggests that economically and statistically significant rents can be recovered by private insurers using the BMA method. With respect to game 2, the p-value is significant in four of seven states. This suggests that the proposed BMA method leads to statistically significantly more accurate premium rates than the current RMA methodology. When using LR method, similar to the BMA estimator, the private insurer realizes a loss ratio less than the RMA in all seven states except Illinois. With respect to game 1, the p-value is significant in five of seven states. With respect to game 2, the p-value is significant in three of seven states. Finally, when using the PS estimator, the private insurer realizes a lower loss ratio than the RMA in all seven states except Illinois. With respect to the p-value in game 1, we find significance in five of seven states. With respect to the p-value in game 2, we find significance in three of seven states. In summary, we find statistically significant monies can be earned by the private insurers employing these estimators which simultaneously smooth across space and time by adverse selecting against the government (RMA) in 15 of the 21 games. Moreover, we find that the rates produced by these proposed estimators are statistically more accurate than the RMA rates in 10 of the 21 games. In no games is the RMA estimator found to be statistically more accurate than the three proposed estimators.

Table 3 shows the results for soybean. When the private insurer uses the BMA estimator, they realize a loss ratio less than RMA in all six states. With respect to game 1, the p-value is significant for five of six states. With respect to game 2, the p-value is significant in three of six states. When the private insurer uses the LR method, they realize a loss ratio less than the RMA in all six states. With respect to game 1, the p-value is significant in all six states. With respect to game 2, the p-value is significant in two of six states. Finally, when using the PS estimator, the private insurer realizes a lower loss ratio than the RMA in all six states. With respect to the p-value in game 1, we find significance in five of six states. With respect to the p-value in game 2, we find significance in two of six states. In summary, we find statistically significant monies can be earned by the private insurers employing these estimators which simultaneously smooth across space and time by adverse selecting against the government (RMA) in 15 of the 18 games. Moreover, we find that the rates produced by these proposed estimators are statistically more accurate than the RMA rates in 7 of the 18 games. In no games is the RMA estimator found to be statistically more accurate than the three proposed estimators.

The above games assume that the RMA uses all available historical yield data in estimating their premium rates. However, as mentioned, literature is showing that yield data greater than 25 years in the past should be discarded in the rating process. Therefore, we repeat the above analysis assuming RMA discards yields greater than 25 years. The above games compared the proposed smoothing across space and time to no smoothing and using all historical yield data. We also wish to compare the proposed smoothing across space and time to no smoothing and using only trimmed yield data or the most current 25 years of yield data. The results are presented in Tables 4-5 in appendix. The results are very consistent with the above game results. The proposed smoothing across space and time is preferred to no smoothing and historically trimming yields.

Conclusions

Recent literature (Ker, Tolhurst, and Liu (2016); Park, Brorsen, and Harri (2018); and Ramsey (2019)) find that estimating premium rates by incorporating spatial information can

Table 2. Rating Game Results of Corn: RMA with Full Sample

Method-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	Game 1 p-value	Game 2 p-value
BMA vs RMA						
Illinois	73	59.9	0.406	0.589	0.0577	0.1316
Indiana	60	68.9	0.633	0.568	0.0013	0.0002
Iowa	91	51.6	0.340	0.300	0.1316	0.2517
Minnesota	57	76.7	0.370	0.169	0.0000	0.0059
Ohio	58	55.8	0.907	0.458	0.0013	0.0013
Wisconsin	48	62.0	0.445	0.389	0.0059	0.8684
South Dakota	27	79.3	1.370	0.494	0.0002	0.0000
LR vs RMA						
Illinois	73	53.6	0.417	0.602	0.0577	0.0207
Indiana	60	54.9	0.680	0.529	0.0000	0.0577
Iowa	91	41.4	0.386	0.258	0.0059	0.1316
Minnesota	57	60.2	0.310	0.153	0.0002	0.0207
Ohio	58	46.4	0.748	0.510	0.4119	0.2517
Wisconsin	48	49.0	0.443	0.380	0.0207	0.7483
South Dakota	27	70.7	1.408	0.434	0.0000	0.0000
PS vs RMA						
Illinois	73	68.1	0.277	0.618	0.0577	0.0577
Indiana	60	77.2	0.614	0.576	0.0059	0.0059
Iowa	91	55.4	0.355	0.292	0.0577	0.2517
Minnesota	57	77.1	0.329	0.176	0.0000	0.1316
Ohio	58	69.2	1.030	0.479	0.0000	0.0013
Wisconsin	48	77.5	0.437	0.399	0.0059	0.9423
South Dakota	27	92.0	1.422	0.546	0.0002	0.0002

increase efficiency and accuracy. To date, no one has proposed estimating premium rates by incorporating extraneous yield information across both space and time. This is particularly important, as recent literature (Shen, Odening, and Okhrin (2018); and Liu and Ker (2019)) has shown that, given the significant changes in seed and farm technology, incorporating historical losses (as is currently done) increases estimation error.

In this manuscript, we generalize three methods, which have been previously used to spatially smooth yields, to perform smoothing across both time and space simultaneously. Our results illustrate significant borrowing of information across both time and space. Not surprisingly, the premium rates are less variable across space. Finally, we evaluate the three

Table 3. Rating Game Results of Soybean: RMA with Full Sample

Method-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	Game 1 p-value	Game 2 p-value
BMA vs RMA						
Illinois	82	36.6	0.858	0.368	0.0207	0.2517
Indiana	59	44.7	0.872	0.463	0.0002	0.0207
Iowa	93	38.4	1.015	0.314	0.1316	0.0577
Minnesota	55	71.5	1.034	0.430	0.0000	0.0207
Ohio	51	62.9	1.186	0.462	0.0000	0.0207
Wisconsin	33	86.4	1.437	0.711	0.0013	0.1316
LR vs RMA						
Illinois	82	29.7	0.767	0.408	0.0059	0.2517
Indiana	59	32.5	0.764	0.457	0.0207	0.1316
Iowa	93	22.5	0.802	0.337	0.0013	0.0207
Minnesota	55	58.9	0.932	0.380	0.0013	0.0059
Ohio	51	46.5	0.901	0.467	0.0013	0.0577
Wisconsin	33	72.7	1.142	0.683	0.0059	0.5881
PS vs RMA						
Illinois	82	52.0	0.951	0.426	0.0207	0.0577
Indiana	59	62.6	1.041	0.494	0.0013	0.0207
Iowa	93	46.6	1.101	0.341	0.1316	0.2517
Minnesota	55	71.9	0.937	0.436	0.0013	0.1316
Ohio	51	71.9	1.201	0.513	0.0013	0.1316
Wisconsin	33	91.4	2.199	0.698	0.0000	0.1316

proposed methods using an out-of-sample simulated game -- representative of the structure of the U.S. crop insurance program -- and find very strong evidence that smoothing across time and space can garner significant rents through adverse selection activities by the private insurers and is more efficient than the current RMA methodology. Specifically, we find statistically significant monies can be earned by the private insurers in 15 of the 21 games for corn and 15 of the 18 games for soybean. Furthermore, we find that the rates produced by these proposed estimators are statistically more accurate than the RMA rates in 10 of the 21 games for corn and 7 of the 18 games for soybean. In none of the 39 games is the RMA estimator found to be statistically more accurate than the three estimators which smooth across space and time.

References

Annan, F., J. Tack, A. Harri, and K. Coble. 2014. "Spatial pattern of yield distributions: Implications for crop insurance." *American Journal of Agricultural Economics* 96:253–268.

Atwood, J., S. Shaik, and M. Watts. 2003. "Are crop yields normally distributed? A reexamination." *American Journal of Agricultural Economics* 85(4):888–901.

Gallagher, P. 1987. "US soybean yields: Estimation and forecasting with nonsymmetric disturbances." *American Journal of Agricultural Economics* 69:796–803.

Goodwin, B.K., and A. Hungerford. 2015. "Copula-based models of systemic risk in US agriculture: Implications for crop insurance and reinsurance contracts." *American Journal of Agricultural Economics* 97:879–896.

Goodwin, B.K., and A.P. Ker. 1998. "Nonparametric estimation of crop yield distributions: Implications for rating group-risk crop insurance contracts." *American Journal of Agricultural Economics* 80:139–153.

Goodwin, B.K., and N.E. Piggott. 2019. "Has Technology Increased Agricultural Yield Risk? Evidence From the Crop Insurance Biotech Endorsement." Unpublished, Working paper.

Harri, A., K.H. Coble, A.P. Ker, and B.J. Goodwin. 2011. "Relaxing heteroscedasticity assumptions in area-yield crop insurance rating." *American Journal of Agricultural Economics* 93:707–717.

Hoeting, J.A., D. Madigan, A.E. Raftery, and C.T. Volinsky. 1999. "Bayesian model averaging: A tutorial." *Statistical science* 14(4):382–401.

Just, R.E., and Q. Weninger. 1999. "Are crop yields normally distributed?" *American Journal of Agricultural Economics* 81(2):287–304.

Kaylen, M.S., and S.S. Koroma. 1991. "Trend, weather variables, and the distribution of U.S. corn yields." *Review of Agricultural Economics* 13(2):249–258.

Ker, A.P. 2016. "Nonparametric estimation of possibly similar densities." *Statistics & Probability Letters* 117:23–30.

Ker, A.P., and K. Coble. 2003. "Modeling conditional yield densities." *American Journal of Agricultural Economics* 85:291–304.

Ker, A.P., and B.K. Goodwin. 2000. "Nonparametric estimation of crop insurance rates revisited." *American Journal of Agricultural Economics* 82(2):463–478.

Ker, A.P., and Y. Liu. 2017. "Bayesian model averaging of possibly similar nonparametric densities." *Computational Statistics* 32:349–365.

Ker, A.P., and P. McGowan. 2000. "Weather-based adverse selection and the US crop insurance program: The private insurance company perspective." *Journal of Agricultural and Resource Economics* 25:386–410.

Ker, A.P., and T. Tolhurst. 2019. "On the Treatment of Heteroscedasticity in Crop Yield Data." *American Journal of Agricultural Economics* 101:1247–1261.

Ker, A.P., T.N. Tolhurst, and Y. Liu. 2016. "Bayesian estimation of possibly similar yield densities: Implications for rating crop insurance contracts." *American Journal of Agricultural Economics* 98:360–382.

Li, D., L. Simar, and V. Zelenyuk. 2016. "Generalized nonparametric smoothing with mixed discrete and continuous data." *Computational Statistics & Data Analysis* 100:424–444.

Li, Q., and J. Racine. 2003. "Nonparametric estimation of distributions with categorical and continuous data." *Journal of Multivariate Analysis* 86:266–292.

Liu, Y., and A.P. Ker. 2019. "When Less is More: Historical Yield Data and Rating Area Crop Insurance Products." Unpublished, Working paper.

Norwood, B., M.C. Roberts, and J.L. Lusk. 2004. "Ranking crop yield models using out-of-sample likelihood functions." *American Journal of Agricultural Economics* 86:1032–1043.

Park, E., B.W. Brorsen, and A. Harri. 2018. "Using bayesian kriging for spatial smoothing in crop insurance rating." *American Journal of Agricultural Economics* 101:330–351.

Racine, J., and A.P. Ker. 2006. "Rating crop insurance policies with efficient nonparametric estimators that admit mixed data types." *Journal of Agricultural and Resource Economics* 31(1):27–39.

Racine, J., and Q. Li. 2004. "Nonparametric estimation of regression functions with both categorical and continuous data." *Journal of Econometrics* 119:99–130.

Ramsey, F. 2019. "Probability distributions of crop yields: A bayesian spatial quantile regression approach." *American Journal of Agricultural Economics*, pp. forthcoming.

Shen, Z., M. Odening, and O. Okhrin. 2018. "Adaptive local parametric estimation of crop yields: Implications for crop insurance rate making." *European Review of Agricultural Economics* 45:173–203.

Sherrick, B.J., F.C. Zanini, G.D. Schnitkey, and S.H. Irwin. 2004. "Crop insurance valuation under alternative yield distributions." *American Journal of Agricultural Economics* 86(2):406–419.

Skees, J.R., and M.R. Reed. 1986. "Rate making for farm-level crop insurance: Implications for adverse selection." *American Journal of Agricultural Economics* 68(3):653–659.

Tack, J., A. Harri, and K. Coble. 2012. "More than mean effects: Modeling the effect of climate on the higher order moments of crop yields." *American Journal of Agricultural Economics* 94:1037–1054.

Tack, J.B., and D. Ubilava. 2015. "Climate and agricultural risk: Measuring the effect of ENSO on US crop insurance." *Agricultural Economics* 46:245–257.

Tolhurst, T.N., and A.P. Ker. 2015. "On technological change in crop yields." *American Journal of Agricultural Economics* 97:137–158.

Yvette Zhang, Y. 2017. "A Density-Ratio Model of Crop Yield Distributions." *American Journal of Agricultural Economics* 99:1327–1343.

Zhu, Y., B.K. Goodwin, and S.K. Ghosh. 2011. "Modeling yield risk under technological change: Dynamic yield distributions and the US crop insurance program." *Journal of Agricultural and Resource Economics* 36:192–210.

Appendix

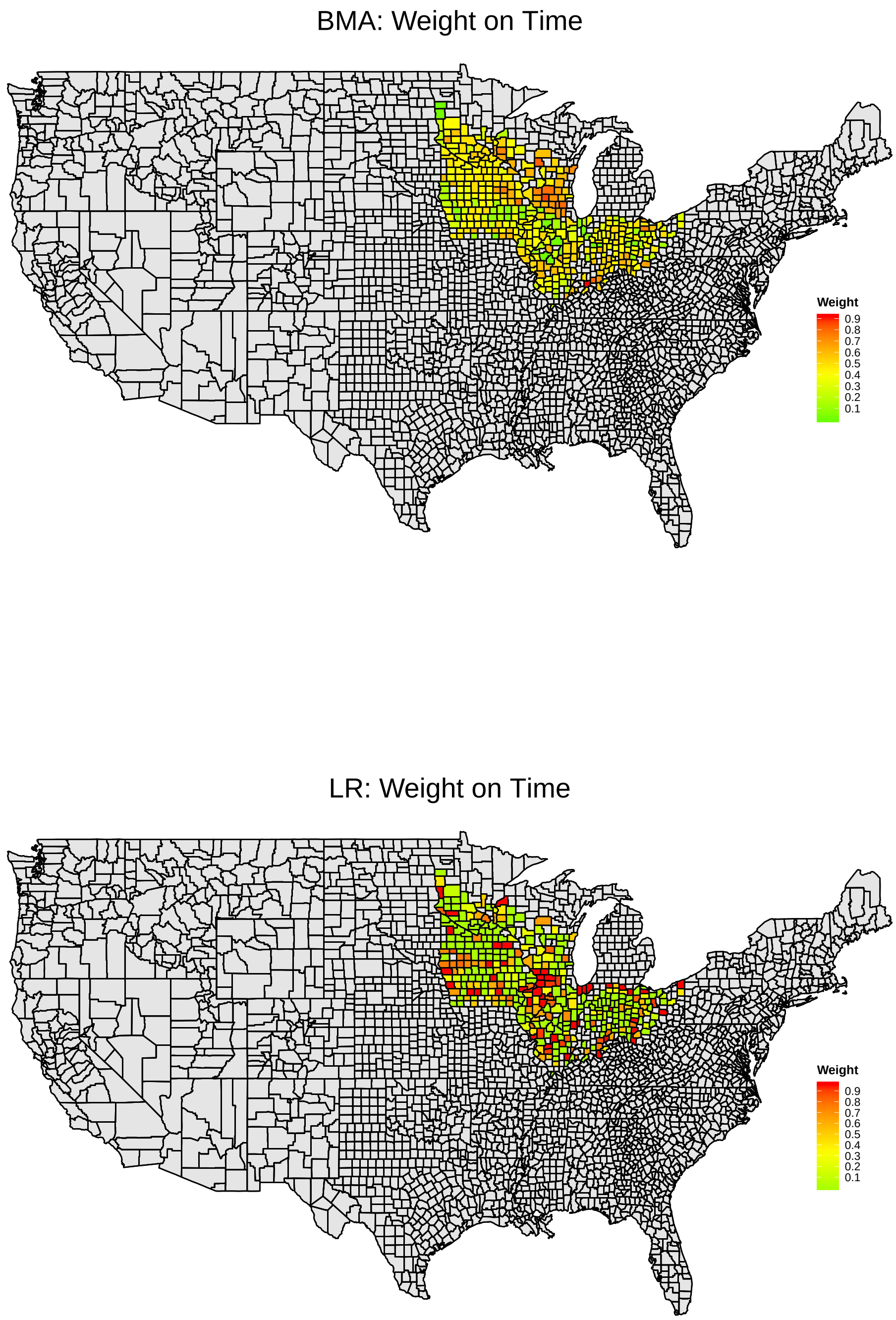


FIGURE 5. BMA and LR Temporal Weights for Soybean

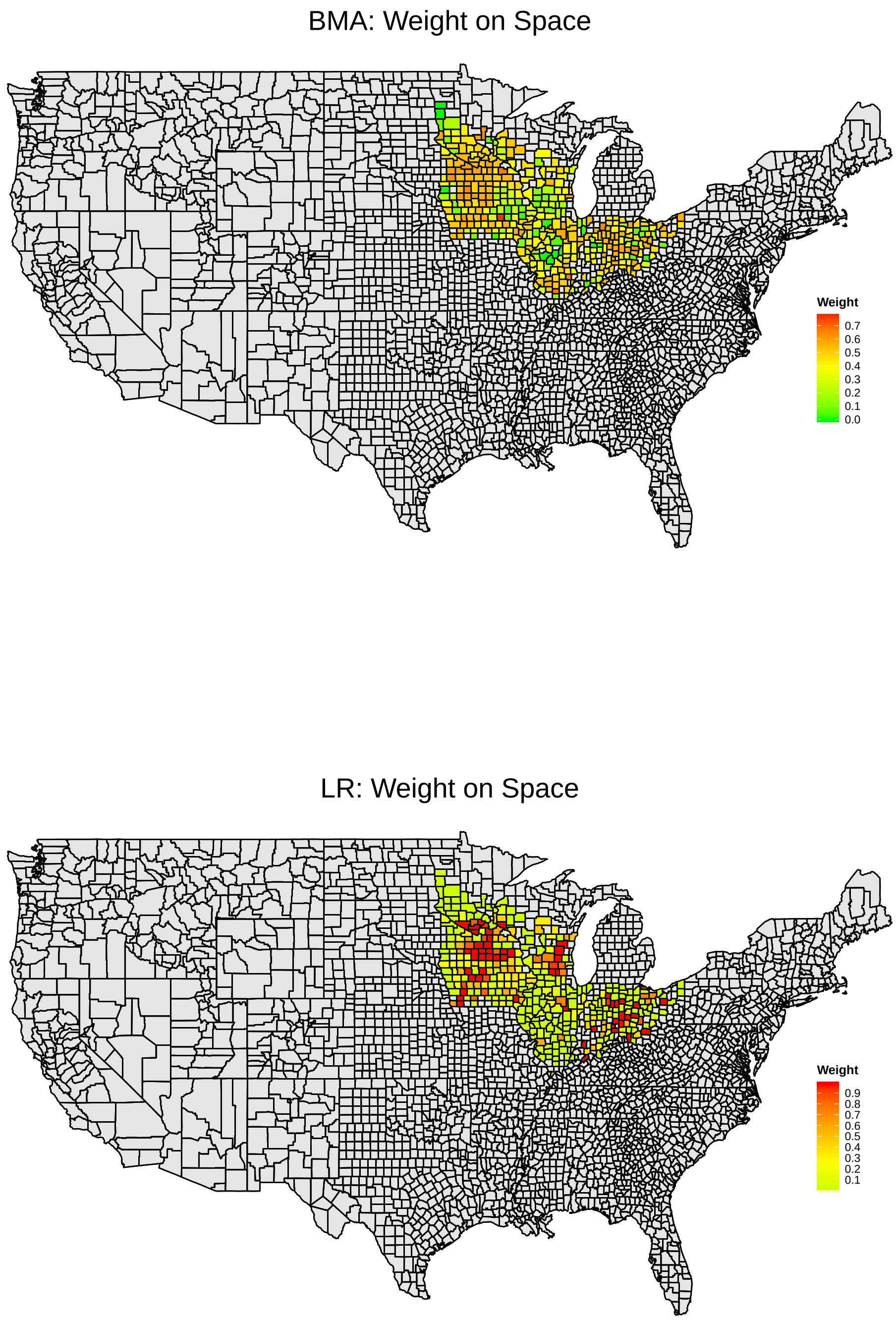


FIGURE 6. BMA and LR Spatial Weights for Soybean

On-line Appendix

Table 4. Rating Game Results of Corn: RMA with Restricted Sample

Method-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	Game 1 p-value	Game 2 p-value
BMA vs RMA						
Illinois	73	26.6	0.699	0.769	0.0013	0.0207
Indiana	60	33.1	0.851	0.628	0.0000	0.0013
Iowa	91	29.7	0.422	0.336	0.0577	0.0577
Minnesota	57	29.8	0.367	0.177	0.0000	0.0013
Ohio	58	24.9	0.913	0.315	0.0002	0.0059
Wisconsin	48	20.1	0.715	0.206	0.0002	0.7483
South Dakota	27	32.8	1.140	0.645	0.0013	0.0207
LR vs RMA						
Illinois	73	25.3	0.772	0.611	0.0059	0.1316
Indiana	60	28.5	0.805	0.672	0.0002	0.0577
Iowa	91	28.0	0.412	0.349	0.1316	0.1316
Minnesota	57	22.9	0.305	0.291	0.0059	0.1316
Ohio	58	35.2	0.845	0.560	0.0577	0.4119
Wisconsin	48	19.2	0.702	0.207	0.0002	0.0577
South Dakota	27	26.7	1.176	0.496	0.0000	0.2517
PS vs RMA						
Illinois	73	39.5	0.610	0.867	0.0577	0.2517
Indiana	60	35.9	0.622	0.971	0.0000	0.0577
Iowa	91	32.6	0.384	0.393	0.0577	0.7483
Minnesota	57	32.0	0.317	0.271	0.0207	0.1316
Ohio	58	35.7	0.921	0.446	0.0000	0.0207
Wisconsin	48	32.0	0.745	0.316	0.0207	0.8684
South Dakota	27	63.9	1.236	0.811	0.0059	0.0577

TABLE 5. Rating Game Results of Soybean: RMA with Restricted Sample

Method-State	Number of Counties	Retained by Private (%)	Loss Ratio Government	Loss Ratio Private	Game 1 p-value	Game 2 p-value
BMA vs RMA						
Illinois	82	18.4	0.860	0.305	0.0002	0.1316
Indiana	59	13.7	0.981	0.269	0.0013	0.0577
Iowa	93	22.3	0.920	0.240	0.0207	0.2517
Minnesota	55	32.5	0.885	0.567	0.0059	0.0577
Ohio	51	30.0	1.010	0.464	0.0000	0.0207
Wisconsin	33	41.4	1.524	0.856	0.0013	0.0577
LR vs RMA						
Illinois	82	28.5	0.807	0.554	0.1316	0.1316
Indiana	59	18.1	0.834	0.811	0.0577	0.2517
Iowa	93	22.9	0.823	0.409	0.0013	0.2517
Minnesota	55	23.5	0.832	0.554	0.0577	0.1316
Ohio	51	26.0	0.881	0.617	0.0207	0.0577
Wisconsin	33	31.4	1.326	0.962	0.0207	0.4119
PS vs RMA						
Illinois	82	28.3	0.859	0.477	0.0207	0.4119
Indiana	59	23.9	1.013	0.461	0.0207	0.2517
Iowa	93	29.0	0.938	0.328	0.1316	0.7483
Minnesota	55	38.3	0.882	0.591	0.0577	0.9423
Ohio	51	37.8	1.052	0.477	0.0002	0.0207
Wisconsin	33	55.0	1.727	0.865	0.0059	0.0577