Value of Incorporating ENSO Forecast in Crop Insurance Programs

Fujin Yi, Mengfei Zhou, and Yu Yvette Zhang

Agricultural production is substantially affected by the variations in global weather patterns, particularly by the El Niño–Southern Oscillation (ENSO). Thus, incorporating the forecast of imminent ENSO phases can enhance the effectiveness of crop insurance and mitigate the adverse impacts of weather on agriculture. Given the probabilistic nature of the ENSO phase forecast, we employ a Bayesian framework to estimate the value of ENSO information on various aspects of crop insurance. Our results indicate potential benefits of ENSO forecast to insurance rate setting and policy selection. At the same time, we caution against overoptimism in this assessment as economic benefits may diminish as the accuracy of ENSO forecast decreases. Simulations and numerical experiments demonstrate the practical usefulness of the proposed method for various stakeholders of the US crop insurance industry. Implications to various crop insurance policies are also discussed.

Key words: Crop insurance, ENSO, forecast uncertainty, information value, risk.

JEL codes: Q18, Q54.

Agricultural production is subject to natural forces, particularly climatic disturbances, despite the advances of agricultural technology and management practices. El Niño–Southern Oscillation (ENSO) has significant impacts on crop yields due to its climatic effects (Adams et al. 2003). The ENSO phenomenon comprises three phases, namely, El Niño, La Niña, and Neutral.[1] A categorical ENSO classification of an upcoming year is typically made available in late fall before planting and purchasing insurance contracts (Nadolnyak, Vedenov, and Novak 2008). However, ENSO forecast is subject to considerable uncertainty (Barrett 1998; Nadolnyak, Vedenov, and Novak 2008). In particular, the "spring predictability barrier" hinders accurate ENSO forecasting (Lau and Yang 1996; McPhaden 2003; Duan and Wei 2013) and may lead to various inaccuracies in decision making (Barrett 1998). In the absence of a perfect ENSO forecast, it is imperative that incorporating ENSO forecasts into agricultural insurance must take the influence of forecast uncertainty into account.

Existing studies have also suggested that ENSO fluctuations may have a wide range of socioeconomic impacts. Given that ENSO is accepted as the most potent source of annual climatic variability (Berry and Okulicz-Kozaryn 2008), it has been shown to influence variations in agricultural productivity (Dilley 1997), crop yields (Legler, Bryant, and O'brien 1999; Naylor et al. 2001), crop prices (Keppenne 1995; Letson and McCullough 2001), and short-term movements of the world's primary commodity prices (Brunner 2002). Moreover, ENSO alternations have been linked to famines in India (Davis 2002), variations in cholera risk in Bangladesh, malaria epidemics in South Asia and South America (Kovats et al. 2003), and civil conflicts (Hsiang, Meng, and Cane 2011; Scheffran et al. 2012; Klomp and Bulte 2013; Hsiang and Burke 2014).

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[1] Mixed results exist in the literature regarding the frequency and intensity of ENSO anomalies, ranging from slight decreases or little change (Tett 1995; Knutson, Manabe, and Gu 1997; Collins 2000) to increase as a result of climatic change (Timmermann et al. 1999).

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In this study, we explore the potential benefits of incorporating ENSO information into crop insurance programs. Weather events that affect crop yields are often spatially correlated, resulting in the systematic risk for traditional private insurance. Area yield smoothens the idiosyncrasies of individual farm productivity. In addition, it is deemed a better indicator of the systemic risk caused by climate variability. Therefore, we focus on area yield protection (ARP) in our investigation. ARP is an index insurance based on observed yield for an area that encompasses numerous producers and is less susceptible to individual actions of market participants (Harri et al. 2011).

Existing literature on the impacts of ENSO phases on crop insurance is scarce. Ker and McGowan (2000); Nadolnyak, Vedenov, and Novak (2008); and Tack and Ubilava (2015) have investigated the effects of ENSO phases on yield distributions and their implications on the rating of crop yield insurance. Goodwin (2008) has identified some common challenges found in this literature. First, the lack of adequate yield data presents, by far, the most fundamental obstacle to reliable insurance rate making (Ker and Goodwin 2000). The estimation of yield distributions typically relies on a relatively small sample. Conventional parametric approaches and flexible nonparametric estimations suffer from large sampling variations due to a small sample size.

Second, most of the existing studies focus on measuring ENSO's impacts on observed historical yield data. Naturally, these studies are not concerned with the uncertainty of the ENSO phase forecast. However, ENSO is a complicated phenomenon and is difficult to predict. Skillful prediction of ENSO is possible up to a lead time of approximately one year (Latif et al. 1994; Barnston 2015). Although interannual climate prediction has improved in the past decades (Solow et al. 1998; Tippett and Barnston 2008; Tseng et al. 2017; Hu et al. 2019), the ENSO forecast remains challenging because of model and observation errors, as well as the intrinsically volatile nature of the ocean–atmosphere system (Tippett and Barnston 2008). Recognizing that ENSO forecast is highly probabilistic, the uncertainty of such forecast should be incorporated into the evaluation process.

The current study adds to the literature by undertaking a thorough evaluation of the ENSO forecast that takes into account its inherent uncertainty using the Bayesian decision framework. Our investigation, which is based on the top five corn and soybean producing states in the US, corroborates the existing findings that perfect ENSO forecast improves the efficacy of crop insurance programs. At the same time, benefits decrease as the accuracy of ENSO forecast deteriorates. Thus, insurance rate setting and policy selection under poor ENSO forecast do not necessarily outperform those without ENSO information. Our results suggest that the probabilistic nature of the ENSO forecast should be considered when the ENSO information is used in crop insurance rating, particularly against the backdrop of evolving global climate.

In addition to the findings of our empirical investigation, this study also makes the following methodological contributions. First, perfect foresight on ENSO phases does not automatically lead to improved insurance programs. In principle, one can tease out the most relevant yield distribution by utilizing only yield data associated with a given ENSO phase. However, this inevitably reduces the number of observations, which is often quite small to start with. In this study, we adopt an effective estimator in pooling cross-sectional information to show that we can reliably estimate ENSO phase-specific yield distributions in practice. We further demonstrate the economic benefits that stemmed from the improved yield estimation. Second, we recognize the probabilistic nature of the ENSO forecast and accordingly develop a scientifically sound procedure to incorporate potentially erroneous ENSO forecast into assessment and decision making concerning crop insurance.

The remainder of this paper is organized as follows. The second section presents a theoretical framework to evaluate the ENSO forecast in crop insurance. The third section introduces the methodology used in our estimation of yield distribution, crop insurance premium rates, and sources of data. The subsequent sections present the empirical results and conclusions. Given the increasing importance of revenue-based insurance, we conduct a similar investigation on revenue insurance.[2] For brevity, results on revenue insurance, together with some supplementary materials and additional results, are gathered in the Appendix S1.

Theoretical Framework

The Risk Management Agency (RMA) of the USDA is in charge of federal crop insurance

[2] Revenue based insurance accounts for more than 75% of total crop insurance liability in 2018; see https://www.rma.usda.gov/en/Information-Tools/Summary-of-Business. We are grateful to the reviewers for this suggestion.

policies. The RMA typically announces premium rates for the upcoming year by November 30. Given that the ENSO classification forecast of an upcoming year is typically made available in late fall, all crop insurance participants face the same uncertainty before planting and purchasing insurance contracts. The in-depth analysis of real-time seasonal ENSO prediction by Barnston et al. (2015) indicates that the skill of a 6-month lead ENSO prediction has improved to 70%, and the three-month lead prediction skill has reached 80%. Given that they are not required to make the policy allocation under the Standard Reinsurance Agreement (SRA) thirty - days after the sales closing date, private insurance companies may reap more rents by taking advantage of the possibly more accurate ENSO information that is not available to the RMA at the time of its rate setting.

This study estimates the value of utilizing ENSO prediction under the framework of Bayesian decision theory. This approach has been used in several previous ENSO valuation endeavors (e.g., Solow et al. (1998) and Adams et al. (2003)). In particular, we evaluate effects of incorporating the ENSO forecast with the estimation of insurance premium rate and loss ratio. Given an ENSO forecast, insurance companies can use historical yield data under the forecasted ENSO phase to estimate the relevant yield distributions and calculate premium rates and loss ratios. Then, they can compare these ENSO phase-specific outcomes with those obtained from pooled data without using the ENSO forecast.

Although incorporating ENSO information in agricultural insurance can be potentially beneficial, we caution about the potential risk associated with the erroneous forecast of the ENSO phase under the current technology. In the absence of perfect foresight on the imminent ENSO phase, its forecast is customarily used to predict various aspects of insurance policies. The predicted outcomes, such as premium rates or loss ratios, are then be used by private insurance companies as a guide for their decisions.

Let a random variable $s \in [E, L, N]$ represent one of three ENSO phases: E for El Niño, L for La Niña, and N for Neutral. For a given ENSO phase s, $T(s)$ is an indicator used to compare quantities of interest estimated with or without ENSO information. Commonly used indices include premium rate efficacy and loss ratio. If an ENSO forecast is used, the expected value of this index is constructed as follows:

$$(1) \qquad \Pi_0 = \Sigma_s T(s) p(s),$$

where $p(s)$ is a prior probability of phase s, and $T(s)$ is calculated based on historical yield data associated with phase s. In the absence of ENSO phase prediction, equal weights are given to all historical observations.

Typically, the annual ENSO phase forecast is released before decisions regarding crop insurance are made by various stakeholders (including insurance companies and farmers). Furnished with an ENSO forecast, private insurance companies can utilize this information to update their expectation on an insurance contract. Let the random variable $x \in [E, L, N]$ represent a particular prediction of an ENSO phase. Under Bayes' Law, the posterior probability $p(s|\, x)$ is formulated as follows:

$$(2) \qquad p(s|x) = \frac{p(x|s)p(s)}{p(x)},$$

where $p(x)$ is the probability of forecasted phase x, and $p(x|\, s)$ is a measure of forecast skill. In this study we consider several hypothetical levels of forecast skill ranging from 50% to 100% without loss of generality. Under perfect forecast, $p(x|\, s) = 1$ if $x = s$, and $p(x|\, s) = 0$ if $x \neq s$, implying that $p(s|\, x) = 1$ if $x = s$, and $p(s|\, x) = 0$ if otherwise. In contrast, a completely uninformative forecast assigns $p(x|\, s) = 1/3$ to each s, effectively rendering $p(s|\, x) = p(s)$. The denominator $p(x)$ is the forecasted probability of the ENSO phase x for a given year, which is computed as $p(x) = \sum_s p(x|\, s)p(s)$. In this fashion, insurance companies can evaluate all possible outcomes $(T(x|\, s))$ given a prediction x of the ENSO phases for each possible state s. The expected outcome using ENSO prediction is then given by:

$$(3) \qquad \Pi_1 = \sum_x \sum_s [T(x|s)p(s|x)]p(x).$$

Here the inner aggregation reflects a conditional outcome associated with a certain prediction x, and the outer aggregation forms its expectation as a convex combination of all possible outcomes weighted by their respective probabilities. The value of ENSO phase prediction is then given by the difference in the expectations with and without ENSO information as follows:

$$(4) \qquad V = \Pi_1 - \Pi_0.$$

The formula provides a straightforward method of measuring the value of utilizing ENSO forecast on insurance contracts.

Empirical Strategies and Data

A common approach to crop yield distribution estimation is to use historical yields for the area of interest and estimate the conditional yield density based on the trend-adjusted residuals (Ker, Tolhurst, and Liu 2015). Crop yield data for individual areas are typically available for relatively short time periods, posing a challenge in separating estimations of individual distributions. Because crop yield distributions from geographically proximate areas tend to resemble one another due to common environmental and climatic conditions, pooling data from adjacent areas can often improve yield estimation. The benefit of pooling information from multiple units has been well established in the literature (Goodwin and Ker 1998; Goodwin and Mahul 2004; Annan et al. 2013; Ker, Tolhurst, and Liu 2015; Zhang 2017). In this study, we adopt the flexible semiparametric density ratio approach developed by Zhang (2017). This approach starts with a common baseline density from the pooled data and proceeds to estimate individual densities as deviations from the baseline density.

Time Trend and Heteroskedasticity

The effect of technology advancement should be removed before the estimation of yield distribution as crop yields have been gradually trending up during the past few decades. Therefore, we apply a flexible model to account for this trend to estimate county-level yield. In particular, the yield for county i in period t, denoted by w_{it}, is modeled as follows:

$$(5) \quad w_{it} = \alpha_0 + \alpha_1 t + \sum\nolimits_j \alpha_{2j} D_j \left(t - knot_j\right) + c_i + e_{it},$$

$$D_j = 1 \; if \; t \geq knot_j, \text{and } 0 \text{ if otherwise},$$

where c_i represents county-specific effect, e_{it} is an error term with mean zero and finite variance, and (α_0, α_1, α_{2j}) is a vector of parameters to be estimated. D_j is an indicator for comparing period t with $knot_j$.

Following a common practice in the literature of crop yield modeling, we use a two-knot linear spline model in our estimation (e.g., Harri et al. 2011 and Zhang 2017), wherein the two knots divide the sample period into three equal subperiods. This specification is also used by the RMA to model the time trend.

Following Goodwin and Mahul (2004) and Zhang (2017), we tackle potential yield heteroskedasticity under the assumption that the yield deviation from the trend is proportional to the level of yields. Harri et al. (2011) have suggested allowing data to determine the form of heteroskedasticity. By contrast, Coble et al. (2010) have shown that in the context of simulation-based rating, reliable estimates of heteroskedasticity will require careful case-specific examination. Typical short time series of crop yields may not be adequate for reliable heteroskedasticity estimation. Thus, we opt for a more tractable specification, which normalizes the estimated error term $\widehat{e}_{it}$ with the trend-predicted yield $\widehat{w}_{it}$, yielding the normalized $\tilde{e}_{it} = \frac{\widehat{e_{it}}}{\widehat{w_{it}}}$.

Density Ratio (DR) Model for Yield Distribution

We provide a brief description of the DR estimator used in this study. First, we estimate the baseline density function, denoted by $\widehat{f}_0$, of the normalized residuals ($\tilde{e}_{it}$) from yield regression based on the pooled sample of all counties. We use a flexible nonparametric log spline density estimator in this step (see Zhang [2017] and references therein).

Second, we estimate densities for individual counties as deviation from the baseline using a Poisson regression approach. Density estimation can be recast as a Poisson regression (Efron and Tibshirani 1996; Simonoff 1998), which is readily available in numerous statistical and econometric computer programs. The general idea is to divide the range of continuous data into a number of equally spaced intervals. Then, we treat the frequency of observations in those intervals as the dependent variable in a Poisson regression using the interval center points as the explanatory variable. In particular, we transform the normalized residuals $\tilde{e}_{it}$ to probabilities $\widehat{U}_{it}$ for each county/year using probability integration transformation with respect to the estimated baseline density, namely, $\widehat{U}_{it} = \widehat{F}_0(\tilde{e}_{it}), t = 1, \ldots, T$, where $\widehat{F}_0$ is the distribution function corresponding to $\widehat{f}_0$. We further divide these values into J equally spaced sub-intervals. Because $\widehat{U}_{it}$ is nearly uniformly distributed, the number of observations in each sub-interval is approximately T/J. We apply a simple rule of thumb to select J, such that T/J is equal to 2. The rationale behind this transformation is that the empirical frequency across these sub-intervals, which are small probability events, can be conveniently estimated via the Poisson regression. Poisson regression is generally an easier statistical task than density estimation and is thus advantageous. In addition, a wide range of model checking tools is readily available for Poisson regression, which can facilitate our model specification and diagnosis.

Let Y_{ij}, $j = 1, \ldots, J$ be the number of transformed data $\widehat{U}_{it}$ in the j-th interval. Under the assumption that $Y_{ij} \sim \text{Poisson}(\mu_{ij})$, the Poisson regression function is given by:

$$(6) \quad \ln E\left(Y_{ij}\right) = \ln(T) + \ln f_0\left(j^*\right) + \alpha_i + \beta_i' \phi\left(j^*\right),$$

where the first two terms on the right-hand side are offset parameters that do not enter the estimation. α_i is a county-specific intercept. We define $j^* = (j - 1/2)/J$ as the mid-point of the j-th interval to form a vector of Legendre polynomials, ϕ, which are orthonormal with respect to the standard uniform distribution.

The function of the county-specific crop yield density is then given by

$$(7) \quad \widehat{f}_i(x) = \widehat{f}_0(x) \exp\left\{\widehat{\alpha}_i + \widehat{\beta}_i' \phi\left(\widehat{F}_0(x)\right)\right\},$$

where the normalizing $\widehat{\alpha}_i$ is calculated as:

$$(8) \quad \alpha_i = \ln\left\{\int \widehat{f}_0(x) \exp\left(\widehat{\beta}_i' \phi\left(\widehat{F}_0(x)\right)\right) dx\right\}^{-1}.$$

The second factor in the final density estimate, $\exp\left\{\widehat{\alpha}_i + \widehat{\beta}_i' \phi\left(\widehat{F}_0(x)\right)\right\}$, captures the deviations of the individual density from the baseline density. The factor reflects the density ratio $\widehat{f}_i(x)/\widehat{f}_0(x)$, hence the name "density-ratio" estimator.

Crop Insurance

The expected indemnity paid by an insurance company is calculated as:

$$(9) \quad \text{Expected Indemnity} = \Pr\left(y < \alpha Y^*\right) \cdot \left[\alpha P Y^* - P E\left(y | y < \alpha Y^*\right)\right],$$

where y is the realized yield, Y^* is the expected yield, P is the unit price, and $\alpha \in [0, 1]$ is the contract coverage level. In this study, we focus on $\alpha = 0.9$, which is the most commonly selected coverage level. It accounts for 95% of the recent policies (Ker, Tolhurst, and Liu 2015). An actuarially fair premium rate is given by:

$$(10) \quad \text{Premium Rate} = \frac{\text{Expected Indemnity}}{\alpha P Y^*}.$$

In the US, the RMA sets the premiums for agricultural insurance programs. However, private insurance companies are the delivery agents to farmers. The loss ratio is a key consideration in these companies' selection of insurance policies in the reinsurance context. Given a set of insurance policies Ω, the loss ratio is calculated as follows:

$$(11) \quad \text{Loss ratio} = \frac{\Sigma_{k \in \Omega} \max\left(0, \alpha \widehat{Y}_k^* - y_k\right)}{\Sigma_{k \in \Omega} \widehat{\pi}_k},$$

where $\widehat{\pi}_k$ is the estimated premium for policy k, $\alpha \widehat{Y}_k^*$ is the guaranteed yield, and y_k is the realized yield. Clearly, an accurate estimation of premiums is critical in insurance companies' policy selection decision with the RMA.

Estimation and Simulation Design

This section describes how to utilize ENSO information to estimate yield densities and subsequent economic derivatives, such as premium rate and loss ratio. Three possibilities are considered in using ENSO forecasts based on the observed area yields: (*a*) ignore the forecast and estimate the yield distribution based on pooled data of all years, (*b*) assume a perfect ENSO forecast and estimate an ENSO phase-specific yield distribution based on observations under the forecasted ENSO phase, and (*c*) use the proposed Bayesian framework to combine multiple ENSO phase-specific yield distributions.

The first case assigns equal weights to all observations, as is used in most studies such as Ker and Goodwin (2000) and Zhang (2017). The second case relies solely on a subset of observations based on the ENSO phase classification, ignoring potential classification errors. This approach is adopted by Nadolnyak, Vedenov, and Novak (2008) and Tack and Ubilava (2015). The third case allows the possibility of ENSO misclassification and constructs a Bayesian averaging of all possible outcomes, taking into account their probabilities and forecast uncertainty. This strategy retains all observations while assigning them different weights based on their predicted ENSO phases.

Then, we investigate a rating game between private insurance companies and the government to explore how insurance companies, through strategic policy selection, can reap the benefits of improved premium estimation by utilizing ENSO information. To encourage the provision of crop insurance to all eligible producers, the federal government shares risks with private insurance companies through the SRA (Coble et al., 2007). Under the SRA, a private insurance company can exploit information asymmetry to its advantage (e.g., Ker and McGowan (2000), and Ker and Coble (2011)). Insurers can transfer a portion of losses to RMA, which can occur with widespread yield shortfalls in exchange for ceding their right to a portion of the gains when premiums are greater than indemnities. In addition, insurance companies can base their policy selection on the comparison between their own premium estimates and the RMA rates. They will retain policies they deem profitable and cede unprofitable ones.

Data

We focus on the top five corn- and soybean-producing states in the US in our empirical evaluation of the value of ENSO forecast in crop insurance. These states (Iowa, Illinois, Nebraska, Minnesota, and Indiana) account for 62% and 52% of national corn and soybean productions during the last decade, respectively. Handler (1984) has reported a strong relationship between the US corn yields and ENSO events using data dating back to 1868. Cadson, Todey, and Taylor (1996) have shown that monthly precipitation and temperature are significantly related to the ENSO events that occurred in the Corn Belt. Similarly, Midwestern US soybean yields are shown to be affected by ENSO conditions (Hollinger, Ehler, and Carlson 2001). These findings corroborate the influence of ENSO phases on corn and soybean production. Moreover, these findings imply the potential benefits of using ENSO forecast in crop insurance rate setting and agricultural risk management.

In this study, we use seventy-year corn and soybean yield data for all counties in the five states from 1947 to 2016 provided by the National Agricultural Statistics Service. We use the standards of the Japan Meteorological Agency to classify the seventy years into the El Niño phase (1951, 1957, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1987, 1991, 1997, 2002, 2006, 2009, 2014, and 2015), the La Niña phase (1949, 1954, 1955, 1956, 1964, 1967, 1970, 1971, 1973, 1974, 1975, 1988, 1998, 1999, 2007, and 2010), and the Neutral phase (the rest of the years).

To implement the Bayesian method outlined in the previous section, we need to specify the prior probability $p(s)$, likelihood function $p(x|\, s)$, and posterior probabilities $p(s|\, x)$. Previous studies, including those of Solow et al. (1998) and Adams et al. (2003), have adopted a long-run perspective and used the historical frequency of s as the prior probabilities. Alternatively, Timmermann et al. (1999) have constructed simulated probabilities, which is calculated based on the projected levels of greenhouse gases provided by the Intergovernmental Panel on Climate Change (IPCC). These frequencies show a trend of increased occurrence of the El Niño and La Niña phases, such that each ENSO phase occurs with nearly equal frequency. In this study, we consider both specifications of prior probability. The historical frequency of ENSO phases is calculated based on a seventy-year period (1947–2016). The results are reported in table 1.

The likelihood function $p(x|\, s)$ signifies prediction skill. This study considers perfect (100%) and various less-than-perfect forecast skills (50–90%). In particular, this likelihood function is configured as follows. For a given period, the realized ENSO phase matches its prediction with probability $p(x|\, s)$; otherwise, the other two phases occur with equal probability $[1 - p(x|\, s)]/2$. For example, if the El Niño phase is forecasted with 70% forecast skill, the probability of its realization is 70%, whereas the La Niña and Neutral phases each have a 15% probability of occurrence. Tables A1 and A2 in the online supplementary Appendix S1 report the posterior probabilities under varying prediction skills.

Table 1. ENSO Phase Prior Probabilities $p(s)$ under Different Assumptions

	ENSO probability (%)		
	El Niño	La Niña	Neutral
Seventy-year period (1947–2016)	24.2	22.9	52.9
IPCC projection	33.9	31.0	35.1

Notes: The first row uses historical ENSO phase frequencies from 1947 to 2016 as prior probabilities. The second row uses the forecast by Timmermann et al. (1999) that accounts for climate change.

Verification of Yield Distribution Variations across ENSO Phases

For brevity, we have chosen not to report the estimated densities for individual counties. However, we report the estimated average yield distributions for corn and soybean in each of the five states in figures 1 and 2. As the yield levels vary substantially among different areas, we centralize the yield density by removing the average yields in each region in these displays. The solid line depicts the yield distribution over the entire period, whereas the three broken lines correspond to various ENSO phases. We observe evident deviations of ENSO phase-specific densities based on the pooled data. Consistent with existing literature (e.g., Gallagher 1987), and Goodwin and Ker 1998), all densities exhibit negative skewness based on the pooled sample or different ENSO phases.

Closer inspection suggests that the El Niño corn/soybean yield densities in Iowa and Illinois are visually different from the other two phase-specific densities that bear close resemblance. In particular, those in Iowa and Illinois feature the thinnest left tail among the three, implying a low probability of poor yields. Generally, one would expect that a low expected loss and premium for yield insurance is associated with such yield distribution. This conjecture is consistent with the findings of Cadson, Todey, and Taylor (1996) and Phillips et al. (1999), who have explored the preferred weather patterns for yield improvement under the El Niño phase. This argument is also corroborated by our investigation into ENSO influence on crop insurance, which is reported in the following sections.

In addition to visual comparison of the estimated densities, we formally test the hypothesis in which crop yield distributions are identical across different ENSO phases during our sample period. In particular, we use a nonparametric entropy test for this purpose. Unlike CDF-based tests, such as the Kolmogorov–Smirnov (KS) test (e.g., Nadolnyak, Vedenov, and Novak 2008), the entropy test is a PDF-based test that may have better power under moderate sample sizes. This method also addresses the critiques of Goodwin (2008) on the KS test. In addition, we use a bootstrap method for inference, which is more reliable than asymptotic critical values. Readers are referred to Maasoumi

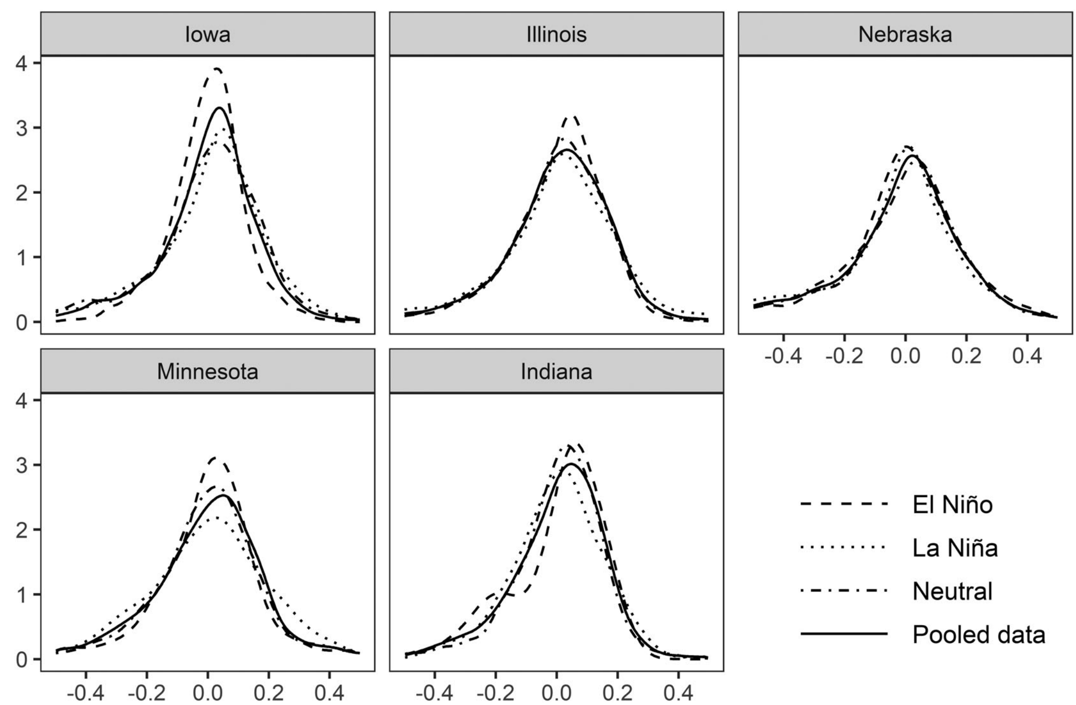

Figure 1. Estimated ENSO phase-specific corn yield densities

Note: These graphs show the estimated average corn yield distributions (with mean subtracted) for corn in the five states.

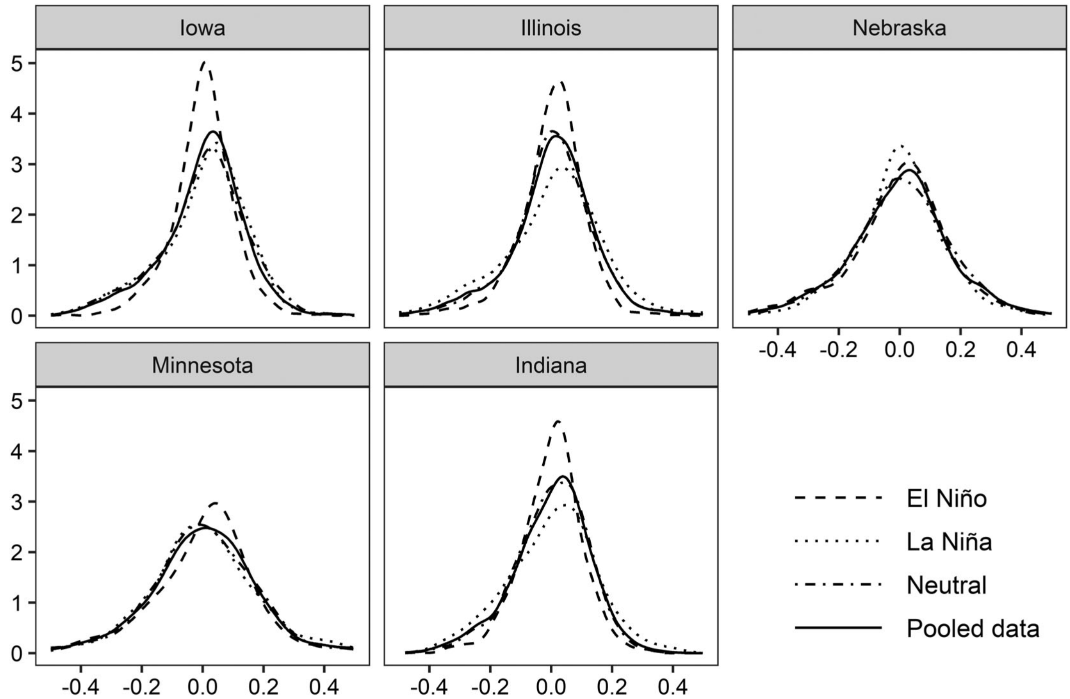

Figure 2. Estimated ENSO phase-specific soybean yield densities

Note: These graphs show the estimated average soybean yield distributions (with mean subtracted) in the five states.

and Racine (2002) for further details on this test and its implementation.

For brevity, we provide a state-level summary of the test results in table 2. In particular, we tabulate the percentage of counties that reject the hypothesis of identical yield densities across two distinct ENSO phases at the 1% statistical significance level. For example, in 76% of counties in Iowa, the corn densities in the Neutral phase differ significantly from those in the La Niña phase. Our results suggest a clear separation of densities under El Niño from the two other phases across all five states and two crops. The hypothesis of identical density is rejected in 75.9% of the counties with a p-value less than 0.01. Phase-specific yield density comparisons can be found in figure A1 in Appendix A in the online supplementary Appendix S1.

Overall, our tests decisively reject the hypothesis of identical yield distributions across different ENSO phases in most counties. These results imply that insurance companies may potentially benefit from exploiting the difference in ENSO phase-specific yield distributions in their insurance contract designation or policy selection in the reinsurance phase.

Table 2. Frequency of County-Level Density Equality Test across ENSO Phases, p-value < 0.01 Is Reported (%)

	Iowa	Illinois	Nebraska	Minnesota	Indiana
Corn					
Neutral vs. El Niño	100	100	73.12	67.50	92.39
Neutral vs. La Niña	75.76	60.78	70.97	86.25	71.74
El Niño vs. La Niña	100	95.10	76.34	95.00	73.91
Soybean					
Neutral vs. El Niño	70.71	85.29	67.14	64.38	98.91
Neutral vs. La Niña	52.53	71.57	78.57	89.04	97.83
El Niño vs. La Niña	68.69	93.14	81.43	95.89	98.91

Note: The table reports the share of counties in each state that report significant difference (at 1% level) in yield densities between different ENSO phases.

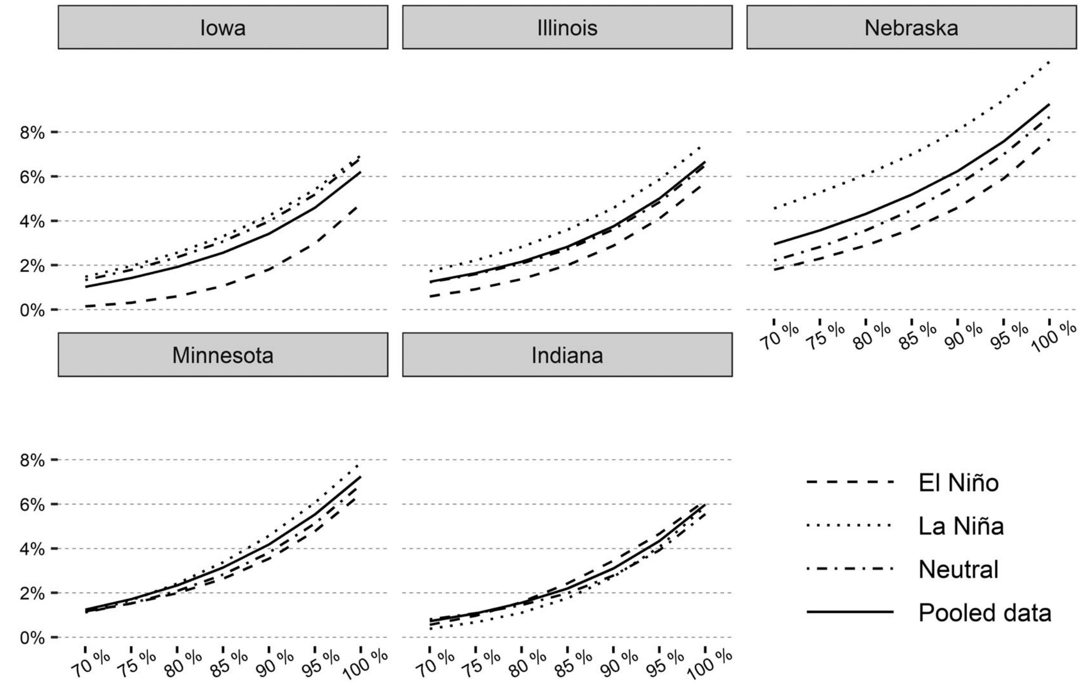

Figure 3. Corn premium rates based on the ENSO phase-dependent distributions

Note: These graphs present the estimated average corn premium rates for various coverage levels in each state.

Premium Rate Effects

Actuarially Fair Premium Rates

We follow Ker, Tolhurst, and Liu (2015) and Zhang (2017) to estimate actuarially fair premium rates using a simulation-based method. First, we apply the DR approach to estimate yield densities from the pooled data and individual ENSO phases. Thereafter, we treat the estimated densities as true yield distributions and draw random samples (with size of 5,000) to calculate the premium rates. Figures 3 and 4 show the estimated rates by coverage level ranging from 70% to 100% under different ENSO phases for corn and soybean.[3] Evidently, the premium rates vary with different ENSO phases, underscoring the importance of incorporating ENSO information into the insurance rate setting. For example, the premium rates for corn in Nebraska and Minnesota without using the ENSO information are higher than the rates derived from the El Niño and Neutral yield densities. Consistent with the thinner left yield distribution tails in Iowa and Illinois in the El Niño years, the corresponding premium rates are lower than those under the two other ENSO phases, as shown in figures 1 and 2. In contrast, the expected losses in the La Niña phase in these states are heavier, thus necessitating higher premium rates.

Efficacy of the ENSO Forecast on Premium Rates

We use a series of simulations to explore the efficacy of insurance rate setting under various ENSO forecast scenarios. In particular, we construct a set of pseudo-observations from the three "true" ENSO phases according to the long-run perspective. We employ historical yield observations from 1947 to 2016. Then, we grouped the normalized residuals according to their ENSO phases and estimate three ENSO phase-specific distributions on the basis of the DR method described above. "True" premium rates are calculated based on these estimated yield distributions.

We measure the efficacy of rate setting by the mean squared error (MSE) in the

[3] Premium rates for individual counties are available upon request.

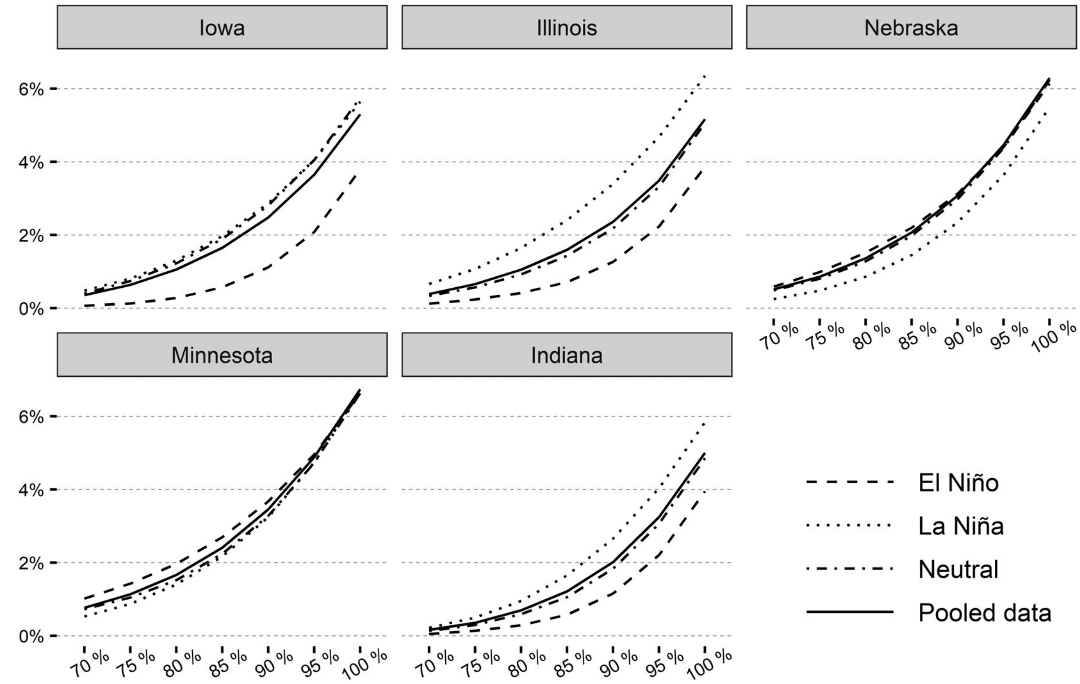

Figure 4. Soybean premium rates based on the ENSO phase-dependent distributions

Note: These graphs present the estimated average soybean premium rates for various coverage levels in each state.

estimation of premium rates, relative to the "true" premiums. A total of 500 samples of size $T = 70$ for each county are drawn from the "true" distributions. For each sample, the premiums are calculated based on the estimated densities using the DR approach. For each predicted ENSO phase (x) out of the three possibilities, we calculate the premiums under three different ENSO scenarios (s), yielding a total of nine combinations. Their corresponding MSE is then calculated as follows:

$$\text{(12)} \qquad \text{MSE}(x|s) = 1/500 \sum_{i=1}^{500} \left[\widehat{\pi}_i(x|s) - \pi(s)\right]^2,$$

where π is the "true" premium rate, and $\widehat{\pi}_i$ is the corresponding estimate in the i-th experiment. These nine estimated MSE $(x|s)$s are then plugged into Equation (3) to calculate the expected MSE with ENSO forecast. For MSE without ENSO prediction, we pool all the generated observations across the three ENSO phases to estimate the pooled yield density using the same DR method. The estimated premium rates based on the pooled yield density are compared with the "true" premium rates in each ENSO state s to compute the ENSO phase-dependent MSE as follows:

$$\text{(13)} \qquad \text{MSE}(s) = 1/500 \sum_{i=1}^{500} \left[\widehat{\pi}_i - \pi(s)\right]^2.$$

The three estimated MSE (s)s are plugged into Equation (1) to calculate the expected MSE without ENSO forecast.

For each experiment, we estimate the premium rates based on the prior probabilities $p(s)$ according to the seventy-year (1947–2016) historical frequency or the IPCC projection. Table 3 shows the average MSEs for the premium rate estimation of corn and soybean in various states based on historical ENSO frequency. As expected, in the case of a perfect forecast skill, premium rates based on the identified ENSO phase densities are substantially more accurate than those based on the pooled data. Take the corn yields in Iowa as an example. A perfect ENSO forecast improves MSE relative to that without ENSO forecast by 66% when we use prior probabilities based on

Table 3. MSE (Multiplied by 10^4) of Yield Insurance Premium Rates across Counties Based on a Historical Prior Probability

	Corn				Soybean			
	(1)		(2)		(3)		(4)	
	Mean	Fraction of gain (%)	Median	Fraction of gain (%)	Mean	Fraction of gain (%)	Median	Fraction of gain (%)
Iowa								
No ENSO forecast								
Pooled data	2.3410	-	1.2144	-	1.0832	-	0.7066	-
Utilize ENSO forecast								
Perfect skill forecast	0.7956	66.01	0.6046	50.21	0.3388	68.72	0.2664	62.29
90% skill forecast	1.3055	44.23	0.8831	27.28	0.6034	44.30	0.4265	39.64
80% skill forecast	1.8154	22.45	1.1616	4.35	0.8679	19.88	0.5866	16.98
70% skill forecast	2.3253	0.67	1.4401	−18.59	1.1324	−4.55	0.7466	−5.67
60% skill forecast	2.8352	−21.11	1.7186	−41.52	1.3970	−28.97	0.9067	−28.33
50% skill forecast	3.3451	−42.89	1.9971	−64.45	1.6615	−53.39	1.0668	−50.98
Illinois								
No ENSO forecast								
Pooled data	1.8100	-	0.9734	-	1.1280	-	0.6666	-
Utilize ENSO forecast								
Perfect skill forecast	1.0431	42.37	0.8725	10.36	0.3866	65.72	0.2729	59.06
90% skill forecast	1.2616	30.30	0.9702	0.33	0.6136	45.60	0.3987	40.18
80% skill forecast	1.4801	18.23	1.0678	−9.70	0.8407	25.47	0.5245	21.31
70% skill forecast	1.6986	6.15	1.1654	−19.73	1.0677	5.35	0.6503	2.44
60% skill forecast	1.9171	−5.92	1.2631	−29.76	1.2947	−14.78	0.7761	−16.43
50% skill forecast	2.1356	−17.99	1.3607	−39.79	1.5217	−34.90	0.9019	−35.30
Nebraska								
No ENSO forecast								
Pooled data	3.5100	-	2.2196	-	1.1542	-	0.7234	-
Utilize ENSO forecast								
Perfect skill forecast	1.3998	60.12	1.1156	49.74	0.5432	52.94	0.4125	42.97
90% skill forecast	2.0795	40.75	1.5196	31.54	0.7656	33.67	0.5442	24.77
80% skill forecast	2.7592	21.39	1.9236	13.34	0.9880	14.40	0.6759	6.57
70% skill forecast	3.4389	2.02	2.3276	−4.86	1.2103	−4.86	0.8076	−11.64
60% skill forecast	4.1186	−17.34	2.7316	−23.07	1.4327	−24.13	0.9393	−29.84
50% skill forecast	4.7983	−36.71	3.1356	−41.27	1.6551	−43.40	1.0710	−48.04
Minnesota								

(Continues)

Table 3. Continued

	Corn				Soybean			
	(1)		(2)		(3)		(4)	
	Mean	Fraction of gain (%)	Median	Fraction of gain (%)	Mean	Fraction of gain (%)	Median	Fraction of gain (%)
No ENSO forecast								
Pooled data	1.8427	-	1.1220	-	0.8502	-	0.4114	-
Utilize ENSO forecast								
Perfect skill forecast	0.9596	47.93	0.7743	30.99	0.5871	30.95	0.3440	16.39
90% skill forecast	1.2105	34.31	0.8880	20.86	0.6585	22.55	0.4005	2.65
80% skill forecast	1.4614	20.69	1.0017	10.73	0.7299	14.15	0.4770	−15.94
70% skill forecast	1.7123	7.08	1.1153	0.60	0.8012	5.75	0.4935	−19.95
60% skill forecast	1.9632	−6.54	1.2290	−9.53	0.8726	−2.64	0.5100	−23.96
50% skill forecast	2.2141	−20.16	1.3427	−19.66	0.9440	−11.04	0.5264	−27.97
Indiana								
No ENSO forecast								
Pooled data	0.9651	-	0.6030	-	0.6241	-	0.4481	-
Utilize ENSO forecast								
Perfect skill forecast	0.5790	40.00	0.5028	16.61	0.2178	65.10	0.1733	61.34
90% skill forecast	0.6854	28.98	0.5468	9.31	0.3440	44.88	0.2643	41.02
80% skill forecast	0.7918	17.96	0.5908	2.02	0.4702	24.67	0.3554	20.70
70% skill forecast	0.8981	6.94	0.6348	−5.27	0.5963	4.45	0.4464	0.39
60% skill forecast	1.0045	−4.08	0.6787	−12.56	0.7225	−15.76	0.5375	−19.93
50% skill forecast	1.1109	−15.10	0.7227	−19.86	0.8486	−35.98	0.6285	−40.25

Notes: The table reports the average and median estimation MSEs across all counties in a state at different forecast skills. The fraction of gain is computed relative to the result without ENSO forecast.

historical ENSO frequency. Similarly, a 69% improvement is observed when we use prior probabilities based on the IPCC projection reported in table A3 in the online supplementary Appendix S1.

Equally, if not more, important are the findings that the benefits of ENSO forecast crucially depend on forecast skills. Evidently, with the decline of forecast skills, ENSO phase predictions are increasingly plagued by prediction errors. As a result, the subsequent premium estimations that incorporate the possibly erroneous predictions are compromised. In the case of Iowa, the 66% improvement under perfect forecast is reduced to 44% under 90% forecast skills. This decline continues steadily along with forecast skills such that when forecast skills fall below 60%, the estimation based on the pooled data outperforms the one with ENSO forecast. In the other four states in table 3, we observe a similar decrease in benefits of incorporating ENSO forecast when forecast skills deteriorate. The finding based on IPCC projection from table A3 exhibits a similar overall pattern.

Loss Ratio Estimation and Policy Selection

Loss ratios reflect return on capital in insurance and reinsurance programs. Therefore, we explore the implications of utilizing ENSO information on the loss ratios of crop insurance policies. First, we consider the estimation of loss ratios for a given set of policies. Then, we examine whether and to what extent private insurance companies can benefit from ENSO information in the strategic selection of crop insurance policies in the reinsurance context with the RMA.

Estimation of Loss Ratios

Because parameter uncertainty can cause difficulty in the insurance rating using yield simulation (Coble et al. 2010), out-of-sample assessment is commonly used to evaluate the rating of crop yield insurance. For the current study, the out-of-sample experiment of Harri et al. (2011) and the sample counterpart approach of Tack and Ubilava (2015) are not applicable because we only obtain one realization for a specific ENSO phase each year. However, we need all potential yields under different ENSO phases to generate the expected loss ratios using ENSO forecast. To overcome the infeasibility of obtaining three realized ENSO specific yields in the same year, 500 samples of yields are randomly drawn from a "true" yield distribution for comparison with the guaranteed yields in the ENSO-specific insurance contracts. The loss ratios are then calculated accordingly.

In particular, we use the following procedure to generate samples from estimated distributions. First, we estimate three county-specific "true" ENSO phase corn/soybean yield distributions on the basis of a period out of twenty sets of samples (1947–2016, 1948–2016,…, 1966–2016) to generate twenty groups of corresponding parameters. These sets of parameters are considered to describe twenty "true" yield distributions. Second, 500 samples of realized crop yields for all the counties in a specific state are randomly drawn from the twenty sets of "true" county yield distribution we have combined. This method is similar to that of Harri et al. (2011), which allows the variation of estimated parameters to be incorporated into different samples.

Third, we estimate the ENSO-dependent loss ratios based on the generated samples. Let $\alpha\widehat{Y}^*(x)$ be the guaranteed yield in a predicted phase x, and $y(s)$ be the yield in a realized phase s. Nine loss ratios are calculated on the basis of simulation between realized phase s and predicted phase x, according to $\mathrm{T}(x|s) = \text{Loss ratio}(x|s) = \frac{\Sigma_{k\in\Omega}\max\left[0, \alpha\widehat{Y}^*_k(x) - y_k(s)\right]}{\Sigma_{k\in\Omega}\widehat{\pi_k}}$. The expected loss ratio with ENSO phase prediction is computed using Equation (3). For loss ratio without ENSO prediction, the preceding yield drawn can be compared with the guaranteed yield based on the density functions estimated using pooled data without ENSO information $\alpha\widehat{Y}^*_{pool}$. Fourth, we plug three possible values of $\mathrm{T}(s) = \text{Loss ratio}(s) = \frac{\Sigma_{k\in\Omega}\max\left[0, \alpha\widehat{Y}^*_{pool,k} - y_k(s)\right]}{\Sigma_{k\in\Omega}\widehat{\pi_k}}$ in Equation (1) to calculate the expected loss ratio. Lastly, the effects of the ENSO forecast on the loss ratio for private insurance companies are calculated according to Equation (4).

The estimation results for corn and soybean based on a historical prior probability are reported in table 4. The loss ratios with perfect ENSO phase forecast are lower than those without ENSO information. For instance, in the case of Iowa corn, the loss ratio with

Table 4. Average Loss Ratios across Counties Based on Historical Prior Probability

	Iowa	Illinois	Nebraska	Minnesota	Indiana
Corn					
No ENSO forecast					
Pooled data	1.1197	1.0693	1.0812	1.0324	1.3849
Utilize ENSO forecast					
Perfect skill forecast	0.9842	0.9857	0.9883	0.9827	0.9842
90% skill forecast	1.0455	1.0097	1.0049	1.0030	1.0951
80% skill forecast	1.1067	1.0337	1.0215	1.0233	1.2060
70% skill forecast	1.1680	1.0577	1.0382	1.0437	1.3169
60% skill forecast	1.2292	1.0817	1.0548	1.0640	1.4278
50% skill forecast	1.2905	1.1057	1.0715	1.0843	1.5387
Soybean[a]					
No ENSO forecast					
Pooled data	1.1485	1.0715	1.1104	1.1682	1.1485
Utilize ENSO forecast					
Perfect skill forecast	0.9823	0.9795	0.9876	0.9834	0.9823
90% skill forecast	1.0375	1.0303	1.0197	1.0455	1.0375
80% skill forecast	1.0928	1.0811	1.0519	1.1076	1.0928
70% skill forecast	1.1480	1.1319	1.0840	1.1696	1.1480
60% skill forecast	1.2033	1.1827	1.1162	1.2317	1.2033
50% skill forecast	1.2585	1.2335	1.1483	1.2938	1.2585

Note: The table presents the weighted average loss ratios across all counties in each state at different levels of forecasting skill.
[a]Nebraska has only 57 historical soybean yield observations.

perfect ENSO forecast is approximately 0.98. The benefit of incorporating ENSO forecast is shown again to decrease with reduced forecast skills, which becomes negative when the forecast skill is less than 70%. This general profile of decreasing benefits with forecast skills is also observed in the other states. Table A4 reports the estimation results using ENSO information based on IPCC projection, which shows a similar overall pattern.

Policy Selection

We follow the standard procedure used by Harri et al. (2011), Annan et al. (2013), and Ker, Tolhurst, and Liu (2015) in our investigation of policy selection. Insurance companies use their own estimates to assess the profitability of insurance policies. In particular, given a predicted ENSO phase, insurance companies make their policy selections based on the comparison between the RMA rates and their ENSO-dependent premium rate estimates. For each forecasted ENSO phase, insurance companies cede the policies with privately estimated rates higher than the RMA rates, as they are likely underpriced. By contrast, policies with rates lower than RMA rates are retained by insurance companies. These policies are plausibly overpriced and are thus profitable. Given the RMA rates, each forecasted phase has three potentially realized yields from the "true" ENSO distribution. Therefore, we obtain nine combinations of conditional loss ratios given the ENSO phase forecast. Accordingly, the expected loss ratios of the retained and ceded policies are computed using the conditional loss ratios in a manner similar to that described in the previous section.

Tables 5 and 6 report the average percentage of the retained and ceded contracts and their respective loss ratios. Across different levels of forecast skills, the loss ratios of the retained policies are consistently lower than those of ceded policies. This finding indicates the potential benefits of policy selection. Column (4) reports the average loss ratios of the ceded policies relative to those of the retained policies. The loss ratios of the ceded policies are at least 20% higher than those of retained polices. Furthermore, we follow Ker, Tolhurst, and Liu (2015) to test whether this strategy of policy selection is effective for insurance companies. We generate 10,000 random contract selections with the same percentage of retained policies. Then, we use the empirical distribution of their corresponding loss ratios to test the null hypothesis that the proposed method is ineffective in identifying profitable policies. The null hypothesis is rejected at the 1% significance level in all our

Table 5. Rating Game Results for Corn Insurance Based on Historical Prior Probability

	(1) Percentage of retained policies	(2) Loss ratio (Retained)	(3) Loss ratio (Ceded)	(4) Ceded to retained ratio
Iowa				
No ENSO forecast				
Pooled data	51.47	0.9688	1.2919	1.3335***
Utilize ENSO forecast				
Perfect skill forecast	51.11	0.8465	1.4559	1.7199***
90% skill forecast	51.64	0.8709	1.4281	1.6399***
70% skill forecast	52.68	0.9196	1.3727	1.4926***
50% skill forecast	53.72	0.9684	1.3172	1.3602***
Illinois				
No ENSO forecast				
Pooled data	52.24	0.9571	1.1962	1.2499***
Utilize ENSO forecast				
Perfect skill forecast	56.92	0.8503	1.3415	1.5778***
90% skill forecast	56.79	0.8699	1.3120	1.5082***
70% skill forecast	56.52	0.9090	1.2528	1.3782***
50% skill forecast	56.25	0.9481	1.1936	1.2589***
Nebraska				
No ENSO forecast				
Pooled data	39.74	0.9002	1.3094	1.4546***
Utilize ENSO forecast				
Perfect skill forecast	49.39	0.8330	1.5475	1.8577***
90% skill forecast	49.17	0.8492	1.5196	1.7894***
70% skill forecast	48.73	0.8816	1.4637	1.6603***
50% skill forecast	48.29	0.9140	1.4079	1.5403***
Minnesota				
No ENSO forecast				
Pooled data	53.79	0.9056	1.1418	1.2608***
Utilize ENSO forecast				
Perfect skill forecast	69.68	0.8564	1.3922	1.6257***
90% skill forecast	68.21	0.8742	1.3532	1.5479***
70% skill forecast	65.26	0.9099	1.2752	1.4016***
50% skill forecast	62.31	0.9455	1.1972	1.2662***
Indiana				
No ENSO forecast				
Pooled data	53.42	1.2219	1.5598	1.2766***
Utilize ENSO forecast				
Perfect skill forecast	66.62	1.1918	1.7714	1.4863***
90% skill forecast	66.65	1.2075	1.7364	1.4381***
70% skill forecast	66.70	1.2387	1.6665	1.3454***
50% skill forecast	66.75	1.2699	1.5965	1.2572***

Notes: Column (1) reports the percentage of retained policies for private insurance companies. Columns (2) and (3) report the loss ratios of the retained policies for insurance companies and ceded policies for RMA, respectively. Column (4) is the ratio of column (3) to column (2). Asterisks *, **, and ***denote statistical significance at 10%, 5%, and 1% levels, respectively.

tests, strongly supporting the effectiveness of the policy selection strategy.

When forecasting with ENSO information, insurance companies tend to retain a relatively higher percentage of policies. The loss ratios of the retained policies are smaller than those obtained without ENSO information. For example, the loss ratio of retained corn policies in Iowa under perfect ENSO forecast skill is 0.85, compared with 0.97 without ENSO information (see table 5). At the same time, the loss ratios of the ceded policies are 1.46 and 1.29 with and without ENSO information, respectively. The ratio between the two loss ratios (ceded v.s. retained) is 1.72 with ENSO information, which is considerably higher than 1.33 without ENSO information. These results suggest that private companies can improve their profits by selecting profitable policies from RMA based on their own estimates.

Similar to the previous examination of incorporating ENSO information into the estimation of premium rates and loss ratios, caution should be exercised regarding the

Table 6. Rating Game Results for Soybean Insurance Based on Historical Prior Probability

	(1) Percentage of retained policies	(2) Loss ratio (Retained)	(3) Loss ratio (Ceded)	(4) Ceded to retained ratio
Iowa				
No ENSO forecast				
Pooled data	48.22	1.0311	1.2612	1.2232***
Utilize ENSO forecast				
Perfect skill forecast	64.12	0.9435	1.5015	1.5915***
90% skill forecast	63.45	0.9610	1.4700	1.5298***
70% skill forecast	62.12	0.9959	1.4070	1.4128***
50% skill forecast	60.79	1.0309	1.3440	1.3037***
Illinois				
No ENSO forecast				
Pooled data	47.96	0.9497	1.2242	1.2889***
Utilize ENSO forecast				
Perfect skill forecast	60.83	0.8485	1.4006	1.6507***
90% skill forecast	59.92	0.8677	1.3776	1.5878***
70% skill forecast	58.12	0.9059	1.3316	1.4699***
50% skill forecast	56.31	0.9441	1.2855	1.3616***
Nebraska				
No ENSO forecast				
Pooled data	45.36	0.9547	1.2875	1.3486***
Utilize ENSO forecast				
Perfect skill forecast	55.79	0.8622	1.5321	1.7769***
90% skill forecast	56.62	0.8840	1.4932	1.6892***
70% skill forecast	58.27	0.9274	1.4153	1.5260***
50% skill forecast	59.92	0.9709	1.3373	1.3774***
Minnesota				
No ENSO forecast				
Pooled data	46.25	1.0189	1.3290	1.3043***
Utilize ENSO forecast				
Perfect skill forecast	61.56	0.9641	1.5831	1.6419***
90% skill forecast	61.37	0.9847	1.5414	1.5655***
70% skill forecast	61.00	1.0257	1.4582	1.4216***
50% skill forecast	60.63	1.0668	1.3749	1.2889***
Indiana				
No ENSO forecast				
Pooled data	48.22	1.0311	1.2612	1.2232***
Utilize ENSO forecast				
Perfect skill forecast	64.12	0.9435	1.5015	1.5915***
90% skill forecast	63.45	0.9610	1.4700	1.5298***
70% skill forecast	62.12	0.9959	1.4070	1.4128***
50% skill forecast	60.79	1.0309	1.3440	1.3037***

Notes: Column (1) reports the percentage of retained policies for private insurance companies. Columns (2) and (3) report the loss ratios of the retained policies for insurance companies and ceded policies for RMA, respectively. Column (4) is the ratio of column (3) to column (2). Asterisks *, **, and ***denote statistical significance at 10%, 5%, and 1% levels, respectively.

uncertainty of ENSO forecast. Our results show that the benefits of ENSO information to policy selection decrease with forecast skill. Across the five states and two crops, it appears that ENSO information improves the effectiveness of policy selection in most states with a better than 70% forecast. When the forecast skill is reduced to 50%, little improvement is observed. However, in some cases, deteriorations in performance relative to those without ENSO information are also observed. Similar results based on IPCC projection are reported in tables A5 and A6.

In addition to yield insurance, we also explore the potential benefits of incorporating ENSO information on revenue insurance. For brevity, we delegate discussions of revenue insurance and our estimation results to the online supplementary Appendix S1. It is found that revenue insurance pricing is generally more difficult than that that of yield insurance as revenue insurance combines yield and price risks, whereas yield insurance only contains a single risk. Nonetheless we obtain qualitatively similar effects on insurance rating by incorporating ENSO forecast. A perfect ENSO forecast significantly reduces the estimation error (in terms of MSE) compared with those of the pooled data. However, the benefits decrease with forecast skills, which is consistent with the findings for area yield insurance. From the reinsurers' perspective, private companies have considerable room to garner rent through revenue insurance by exploiting ENSO forecast to their advantage.

Conclusions

This study utilizes county-level data of the top five corn and soybean producing states in the US to assess the value of incorporating ENSO forecast in crop insurance policies. We take into account the uncertainty of ENSO forecast and employ a Bayesian decision theory framework in our evaluation. Our investigation corroborates the benefits of utilizing ENSO information under perfect forecast, as reported in existing literature.

Unlike previous literature, we also demonstrate that the potential benefits of utilizing ENSO forecast depends on its accuracy. Moreover, we caution against over-optimism in assessing the potential benefits of incorporating ENSO information in agricultural insurance. Under a perfect or fairly accurate forecast, we show that incorporating ENSO information is likely to improve the rating efficacy and decrease the loss ratios of private insurance companies. However, the degree of forecast accuracy influences its potential benefits to such an extent that net economic loss can occur due to poor forecast. Our results underscore the importance of accounting for ENSO forecast uncertainty in its benefit evaluation. More importantly, we provide a practical assessment framework that informs various stakeholders in decision making regarding incorporating ENSO forecast into crop insurance.

In this study, we have focused on private insurance companies and demonstrate how they can potentially benefit from incorporating ENSO information. We conclude by noting that the benefits stem from the improved premium estimates that utilize informative ENSO forecast. Therefore, although modification to RMA's programs is presumably a rather involved and complex process, we conjecture that the RMA can improve its program design and economic performance by incorporating ENSO information in a similar manner.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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