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Reevaluating the use of volatility factor in crop insurance premium rating

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Abstract

This article reevaluates the use of volatility factors in federal crop insurance rate setting. The analysis focuses on price risk for corn and soybeans over the period 1990–2021. The sensitivity of insurance premiums to changes in volatility is comparable to the sensitivity resulting from changes in crop prices. Risk Management Agency's (RMA) volatility factor is generally supported to be an unbiased and efficient estimator of the realized volatility, although this support is found to be marginal in the case of soybeans. The out-of-sample forecasting analysis indicates that RMA's current approach can be modified to better reflect price risk over the insurance period.

KEYWORDS

crop insurance, options, price risk, volatility

JEL CLASSIFICATION

G13, G14, G22, C52, D81, Q18

1 | INTRODUCTION

Revenue protection plans for crop insurance have been popular with farmers, protecting $100.95 billion in liability within the standard (mostly crops) book of business and an additional $14.3 billion in liability based on livestock book of business in 2021.[1] Setting insurance premiums for revenue products requires measuring price risk in addition to yield risk. The USDA's Risk Management Agency (RMA), which manages the federal crop insurance program, has been using a market-based methodology to set price guarantees as well as measure price risk over the insurance

[1]For livestock, products that protect solely against price declines are also included.

period since 2011.[2] For insured commodities that have active futures markets, RMA uses futures prices with delivery months closest to, but after, harvest in setting insurance prices. This estimation is made before planting (February for most corn and soybean producers), and 7–8 months before harvest.

To measure price risk over the insurance period, RMA uses implied volatility (IV) values embedded in options associated with the futures contracts of interest. RMA time-adjusts (discounts) the implied volatility values, which are reported as annualized values by an outside vendor. The time adjustment is made to reflect the risk over the insurance period (less than a year) and in line with the treatment of time in the Black- Scholes option pricing model (Figlewski, 1997; Hull, 2009). For typical crop insurance policies on corn and soybeans, the December and November futures contracts, respectively, are used. A time-adjustment to the observed option IV is made to account for two factors: (i) the IV measure reported reflects an annualized measure of price risk and at the time of discovery (February) there is less than a year to contract expiration (suggesting price risk through futures contract expiration is less than the observed IV), and (ii) the actual insured harvest date for most corn and soybean farmers is typically the month of October, not December or November.[3]

The December corn and November soybean futures contracts are used to determine insured prices and measure price risk because there are no October futures contracts for corn or soybeans. However, the extent to which the respective futures delivery months (December and November) and the insured month (October) reflect identical risk profiles (as assumed in the RMA risk adjustment procedure) has not been addressed by RMA or any other market analysts to our knowledge. An independent contractor reviewed RMA's methodology in 2014 (Goodwin et al., 2014a, 2018) and concluded that the use of option-based implied volatilities in measuring realized price risk is valid and should be continued. However, the study only looked at whether the IV observed in a December option, for example, was the most efficient forecast of price risk for December delivery. They did not address whether that same volatility is also an appropriate measure of risk for other dates; in other words, whether the observed December IV just as efficiently measures risk for December futures observed in October as it does December futures in December.

Other research has found that the IV associated with a specific options contract does not efficiently measure price risk for a futures contract before its actual expiration (in other words, the price risk for the December futures contract from February through October exhibits a different risk profile than the risk between February and December). This suggests that using the December (or November) IV from futures options may not efficiently measure the price risk for a mid-October harvest price. This point is implied in Egelkraut et al. (2007, p. 6, their fig. 2),[4] and later confirmed in Fortenbery (2017). In fact, Fortenbery argued that if the risk profiles were invariant to delivery dates serial options would never trade (serial options were not trading over most of the time frame considered in the Egelkraut, Garcia, and Sherrick study).[5] Because the nonconstant volatility factor finding violates the main assumption in the Black–Scholes model,

[2]This was implemented as part the Common Crop Insurance Policy (Combo Policy) initiative as discussed in detail in Supplementary Appendix 1 (SA1).

[3]Given the futures contracts used, soybean IV's should be in a better position than corn IV's in approximating harvest period price risk. In the Midwest, soybeans are typically harvested first, followed by the corn harvest. The latter may extend into the first 2 weeks of November if there is snow. According to a USDA NASS publication (NASS, 2010), most active harvest dates for soybeans in Iowa and Illinois are September 28-October 20 with an ending date of October 31; and September 26–October 26 with an ending date of November 7, respectively. On the other hand, most active harvest dates for corn in Iowa, Illinois, and Minnesota are October 5–November 9 with an ending date of November 21; September 23–November 5 with an ending date of November 20; and October 8–November 8 with an ending date of November 23, respectively.

[4]Goodwin et al. (2018) cite the work of Egelkraut, Garcia and Sherrick, and note that they find futures-based IV's are systematically different for different delivery periods, but they never address the implications of this in the context of the RMA procedures for determining price risk for October prices using option IV's for later delivery periods.

[5]Serial options are those options that trade on specific futures contracts but trade for months in which the futures contract is not expiring, and they typically cover shorter-periods than the standard options. A serial option for October delivery of a December corn futures contract, for example, will trade from late June through late September, and is essentially offering the right to buy or sell a December futures contract in October.

time-adjustments used by RMA may not yield an accurate estimate of price volatility over the insurance period.

Furthermore, the contractor's review did not examine the direct relationship between implied and realized volatilities. The latter is partially based on the work of Egelkraut et al. (2007); and Christensen and Prabhala (1998). Thus, the contractor did not establish whether implied volatilities are in fact unbiased and efficient estimators of realized volatility over the insurance period. Both issues addressed in this paper raise legitimate concerns as to the actuarial accuracy of premiums for revenue crop insurance plans. Since we find that premium sensitivity to measures of price volatility is comparable to that of insured crop prices, any inaccuracy therein could have material significance. In this paper, we reevaluate the use of volatility factors in federal crop insurance rate-setting as a follow-up to the contractor's review.

2 | DATA AND ESTIMATION RESULTS

We begin by examining the direct relationship between implied and realized volatilities over the period 1990–2021 for corn and soybeans. Subsequently, we evaluate alternative measures of volatility factors through their out-of-sample forecast performance. Finally, we carry out an impact analysis in adjusting the current volatility factor measure.

Realized volatility is measured as the square root of the sum of the squared daily logarithmic returns to the futures prices over the insurance period. The detailed steps in arriving at this formula and its relationship to alternative measures in the literature are relegated to Supplementary Appendix 2 (SA2). Recall that Goodwin et al. (2018) did not take the approach of examining the direct relationship between implied volatility and realized volatility. Egelkraut et al. (2007, p. 5, eq. 6) as well as Christensen and Prabhala (1998, p. 134) looked at such a relationship in a regression analysis. In line with these studies, we estimate regression models by considering realized volatility in each year as the dependent variable and the corresponding volatility factor values as the explanatory variable.

2.1 | Regression analysis

One begins with the assumed relationship between Realized Volatility (RV) and Implied Volatility (IV)

$$\mathrm{RV}_t = \alpha_0 + \alpha_1 \times \mathrm{IV}_t + \varepsilon_t, \tag{1}$$

where α_0 and α_1 are the intercept and slope coefficients, and ε_t is the white-noise disturbance term. The observations are in time-series and $t = 1, 2, \ldots, T$. Note that the RV values are per annum as they are constructed in line with the formula given in Equation (9) in SA2, and the IV values are also per annum and obtained from Barchart.com.[6]

A related assumed relationship is between the time-adjusted realized volatility (denoted with RV^δ, where the superscript δ refers to Equation (3) in SA2) and volatility factor (VF)

$$\mathrm{RV}_t^\delta = \beta_0 + \beta_1 \times \mathrm{VF}_t + \xi_t, \tag{2}$$

[6]The RV per annum measure is extrapolated based on the return observations over the post-insurance price discovery period up until the end date of the life of the underlying futures contract. In 2000, the expiry dates for the December corn and November soybean contracts were changed from being on or about the the 21st of the month to the last business day before the 15th of each month. These extrapolation periods are consistent with the fact that the IV values are observed in the last 5 days of the insurance price discovery period (February) and hence accounts for the information update between the beginning of the year and before March 1.

where β_0 and β_1 are the intercept and slope coefficients, and ξ_t is the white-noise disturbance term. Note that RV^δ is calculated from Equation (11) in SA2 in a manner consistent with the fact that VF is a time-adjusted version of IV.

The regression models from Equations (1) and (2) are estimated for corn and soybeans. The estimation results are presented in Table 1: panel A in the case of Equation (1) and panel B in the case of Equation (2), respectively. In each panel, Models 1 and 2 represent the versions with and without the intercept term. Based on the fit performances between Models 1 and 2 (and lower *Root Mean Square* values), Model 2 is selected for corn, and Model 1 is selected for soybeans. Diagnostic tests on the residuals of the selected models as recommended in Enders (2010) provide considerable support for the assumption that residuals from each regression model follow a white noise process. The support is stronger in the case of corn compared to soybeans. Detailed information on diagnostics are relegated to Supplementary Appendix 4 (SA4).

Figures A6 and A7 in SA4, for corn and soybeans, respectively, display implied and realized volatility values as well as the fitted values for the realized volatility from the selected regression models. The regression analysis indicates that implied volatility values are a significant predictor of realized volatilities. It is apparent in the figures that the fit performance is better in the case of corn than soybeans. A similar pattern can be observed in Goodwin et al. (2018, tab. 1, p. 469). One possible explanation is that corn is more heavily traded than soybeans, which may improve the accuracy of implied volatilities as forecasts. Another possible explanation has to do with the shape of realized volatility distributions over the sample period. The mean, median, and standard deviation of realized volatility were smaller in the case of soybeans than corn. On the other hand, realized volatilities have a slightly wider range in the case of soybeans (0.1211–0.3517) compared with corn (0.1318–0.3501). Consistent with this observation, the value of the kurtosis measure was elevated more in soybeans than corn (7.997 and 4.104, respectively). Finally, in line with these observations, we note in SA4 that the normality assumption on the residuals is better supported in the case of corn than soybeans. We now turn to the econometric testing of the estimated parameters.

As noted in Egelkraut et al. (2007); and Christensen and Prabhala (1998), if volatility factor is an efficient and unbiased estimator of realized volatility—as RMA believes—one should not be able to reject the null hypothesis of $H_0: \alpha_0 = 0$ and $\alpha_1 = 1$ in favor of an alternative hypothesis $H_1: \alpha_0 \neq 0$ or $\alpha_1 \neq 1$ in Equation (1). Similarly, $H_0: \beta_0 = 0$ and $\beta_1 = 1$ should not be rejected in favor of an alternative hypothesis in Equation (2). We conduct tests of this by comparing the *p* value

TABLE 1 Parameter estimates where the dependent variable is the realized volatility (RV) for the December corn and November soybean futures prices

	Panel A: RV Per annum[a]				Panel B: RV Over the insurance period[b]			
	Corn		Soybeans		Corn		Soybeans	
Parameter	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Intercept	0.109 (0.04)		6.42** (2.34)		0.73 (0.362)		5.157** (2.245)	
Volatility Measure	0.952*** (9.2)	0.956*** (43.2)	0.704*** (5.86)	0.976*** (30.1)	0.973*** (9.9)	1.008*** (47.8)	0.7295*** (5.8)	1.004*** (29.6)
$\bar{R}^2$	0.732		0.518		0.759		0.511	
RMSE	3.28	3.23	3.92	4.19	2.49	2.45	3.28	3.49

Note: The number of observations is $N = 32$; t -values are inside the parentheses. ***, **, * indicate significance at 1%, 5%, and 10%, respectively, based on the t -statistics. The notation $\bar{R}^2$ and *RMSE* refer to the adjusted-R^2 and root-mean-squared errors.

Abbreviation: RMA, Risk Management Agency.

[a]Volatility measure is Implied Volatility (IV). Both RV and IV are in percent form.

[b]Volatility measure is RMA's volatility factor (VF). Both RV Over the Insurance Period (RV^δ) and VF are in percent form.

associated with the critical value of an F test-statistic (denoted by F_c) with the standard levels of significance at 1%, 5%, and 10%. The number of parameter restrictions equals 2, and the degrees of freedom from the unrestricted model equals 30. Note that Model 1 from earlier constitutes the unrestricted model, while a separate model—not Model 2—reflects the restricted model. Using the Sum of Squared Errors from the unrestricted and restricted models and combining them with the appropriate degrees of freedom for each in the F test-statistics, the F_c values are calculated. These values turn out to be, for corn and soybeans respectively, 1.8865 and 3.0516 in the per annum case in Equation (1); and 0.129 and 2.525 in Equation (2).

The conclusions are subtly different across both crops. For corn, the null hypothesis of efficient and unbiased estimators cannot be rejected when the relationship between realized volatility and the volatility factor is examined over the insurance period (as the critical value of 0.129 has a p value of 0.8795 which is comfortably higher than the standard levels of significance). A similar result applies to the per annum relationship between the two variables (as the critical value of 1.8865 has a p value of 0.1691). For soybeans, when both the realized volatility and implied volatility values are time adjusted, the null hypothesis of an efficient and unbiased estimator can be rejected at the 10% level (the critical value of 2.5254 has a p value of 0.0969) but not at lower levels of significance. A similar result applies to the per annum relationship between the two variables (as the critical value of 3.0516 has a p value of 0.0622).

The analysis thus far has been all in-sample. The next section compares RMA's volatility factor values against alternative out-of-sample forecast models. This provides validation to the findings based on the regression analysis.

2.2 | Forecast analysis

To further investigate the soundness of the current volatility factor methodology in an out-of-sample comparison, we consider the following adjustments: (i) using the month-long discovery period instead of the 5-day, while both are similarly time adjusted; (ii) eliminating the time-adjustment in volatility factors to account for the fact that the discovery period uses options pricing with a different delivery time than is actually being insured; (iii) using the October serial options; and (iv) using estimated regression model parameters from models focused on the relationship between implied and an alternative measure of realized volatilities. All four adjustments are transparent, simple, and forward-looking as preferred by RMA.

2.2.1 | Adjustment 1: Using the month-long discovery period instead of the last 5 days

Goodwin et al. (2014b, p. 8) recognizes that there is an inherent inconsistency in using crop prices over the entire month of discovery to establish base insurance prices while using only the last 5 days in the same month to estimate the volatility factor. To see the effect of extending the discovery period for the volatility factor, implied volatility values over the entire discovery month are time-adjusted and averaged per RMA's methods. Figure 2 presents the resulting volatility factor values in comparison to those currently used for corn and soybeans, respectively. It is apparent from the figure that the use of a longer period to calculate volatility factor results in a minor change, no more than two percentage points in either direction. For the entire 32-year sample, the month-long measure coincided with the last 5-day measure 13 and 17 times—while the former exceeded the latter only nine and seven times—for corn and soybeans, respectively. Whether the remaining differences between the two measures result in improved out-of-sample forecast performance is investigated below.

2.2.2 | Adjustment 2: Eliminating the time-adjustment in volatility factor calculations

It is critical to understand whether RMA's approach—in which annualized implied volatility values are monotonically discounted based on time—is appropriately modeling the actual decay pattern in estimating price risk before the expiration of a specific futures contract.[7] This can be verified in the time-path of implied volatilities from the futures contracts that are used by RMA and those from October serial options from 2011 to 2021 when these contracts do overlap (see Figures A8 and A9 in Supplementary Appendix 5 [SA5]). When traded over the summer, implied volatilities from the October serial options are consistently higher than implied volatilities from the options underlying the December and November contracts (less than three percentage points in the former and less than two percentage points in the latter). This is despite the fact that the latter options have more time to expiration, and all else equal should translate to greater risk. Thus, discounting the observed annualized implied volatilities from December and November futures before planting (back in February) likely understates the market's perception of price risk over the insurance period; particularly in October.

Eliminating the time-adjustment factor currently used by RMA may ameliorate the observed downward bias. In the absence of the time-adjustment, the discovered last 5-day average of implied volatilities from the futures contract of interest is directly used as a measure of price risk. Since the time-adjustment results in about a 20% discount in implied volatilities from Equation (3) in SA2, eliminating it translates to about a 25% increase in volatility factor value. Premiums naturally would increase in that case, yet the magnitude of the increase varies by level of coverage, unit structure, and policy type in line with the sensitivity analysis in Supplementary Appendix 3 (SA3). An application illustrating the role of base premium rates in this context is provided in SA3 (see Tables A3 and A4).

2.2.3 | Adjustment 3: Using the October serial options

The adjustment described here is based on empirically estimating the relationship between serial options traded for delivery during the insured harvest month compared to the options currently used for discovery, and adjusting the option volatility measures observed during the discovery period based on the historical relationship between serial and standard options when both trade. Note that the serial options are not trading during the discovery period.

As a first step, we develop models for forecasting options-based IVs during the discovery period using information gleaned from the relationships between December or November options and the October serial options that trade for each commodity over the summer months.[8] From these models, an October IV for the next February discovery period is forecast based on the actual harvest contract option IV observed in February adjusted for the empirically identified relationship between the October and harvest contract options from previous years. The estimated October IV from the models is then used to forecast, out-of-sample, the realized volatility over the ensuing insurance period. This implicitly assumes the relationship between the serial and harvest options is stable across crop years—we are using the relationship from the previous crop years to “forecast” October

[7] A basic rule of thumb is that an option loses 1/3 of its time value in the first half of its life and 2/3 in the second half.

[8] Essentially, this comes from regressing the October serial option IV on the December or November option IV using daily data over the period in which the serial options trade (early June through late September). The data span 2000 through 2021. We examined several iterations, including using all available data to forecast the next year's IV for the insurance period, a rolling timeline based on a10- or 5-year history, and a naïve model that only considered the previous year's relationship between the serial and harvest contract options. The results using the forecast October IV in February to then forecast the realized volatility over the insurance period indicated the relationship from the full information models based on all available data before the February forecast date was preferred. The model specification process is discussed in more detail in SA5, and all results are available from the authors.

IV in February of the next crop year. We then use the identified relationship to forecast, out-of-sample, realized volatility from 2011 through 2021.

2.2.4 | Adjustment 4: Using the estimated regression results between realized and implied volatilities

This adjustment process comes out of the regression models described earlier that relate observed implied volatilities to realized volatility. These models were chosen based on the fit performance of the alternative models considered; hence, they are all data-driven (see panel B in Table 1).

In this procedure, the volatility factor, once established by RMA at the end of the discovery period, is plugged in as the value of an explanatory variable and regressed on historical realized volatility. The regression model then predicts a value for the realized volatility for the next insurance period based on the estimated parameters from the regression. This approach is similar to the forecast approach used in the serial option analysis: next year's realized volatility forecast is based on the empirical relationship identified in previous years. The predicted value is then used as the adjusted volatility factor in the premium rate making procedure.

In the case of the corn model, the intercept term was not found significant and therefore dropped, while the slope term, which was found significant, suggested a near-zero adjustment to the volatility factor values. In the case of the soybean model, both the intercept and slope terms were found significant. Because of the nature of the selected regression models, for corn, the predicted values and the associated adjustment are in proportion to the volatility factor values. For soybeans, the regression method adjusts very high volatility factor values downwards but very low volatility factor values upwards. The latter is driven primarily by the fixed intercept effect.

2.2.5 | Out-of-Sample testing of all adjustments

Beginning with the adjustment via the regression method, recall that t indexes years and $t \in \{1990, \ldots, 2021\}$, $T = 32$ and denotes the total number of observations.[9] Let F denote the number of out-of-sample predictions and f denote forecast years. Now, $F = 5$ refers to the forecast period $f \in \{2017, \ldots, 2021\}$, $F = 7$ corresponds to $f \in \{2015, \ldots, 2021\}$, and $F = 10$ refers to $f \in \{2012, \ldots, 2021\}$. For instance, when $F = 10$, the regressions are initially run using data from 1990 to 2011 and the results are used to forecast realized volatility for 2012. Then 2012 is added to the data and the regressions are run again. As such, a full information forecasting model is used, which assumes old data never loses its relevance in forecasting although its effect will diminish as additional data points are considered. The regressions are then re-run and 2013 is forecast. As an alternative method, forecasts are also generated recursively, that is, the first observation is dropped while adding a new observation to the analysis before running each regression so that the number of observations remains constant.

Note that whether one does the forecasting based on the full information or recursively is only relevant to the forecast performance of the adjustment by the regression method. That is because only the adjustment by the regression method uses the selected estimated regression models for each crop in the out-of-sample analysis. The other three adjustments and the RMA's volatility factor represent the predicted realized volatilities themselves. This would be equivalent to setting the estimated coefficient in front of the explanatory variable (the volatility factor version of interest) to

[9] Although there have been significant changes in the futures market—including delivery dates, expiry dates (footnote 6)—we maintain that 1990 and onward is a reasonable period to include in the analysis. For corn and soybeans, futures prices and implied volatility values going back to 1990 were available from Barchart.com. The revenue insurance was allowed starting in the 1994 Act. The Crop Revenue Coverage (CRC) and Revenue Assurance (RA) plans of insurance (the predecessors of RP) were introduced in 1996 and 1997, respectively (Glauber et al., 2002).

TABLE 2 Out-of-sample forecasting results

Volatility factor options	Corn F = 5 RMSE	Corn F = 7 RMSE	Corn F = 10 RMSE	Soybeans F = 5 RMSE	Soybeans F = 7 RMSE	Soybeans F = 10 RMSE
RMA's current method	3.57	3.24	2.97	1.83	3.07	2.78
Adjust via using the month-long average	3.57	3.09	2.69	2	2.54	2.38
Adjust by eliminating the time-adjustment	4.48	4.55	4.4	3.77	3.73	3.79
Adjust via the use of October serial options	3.78	3.38	2.92	1.92	2.79	2.57
Adjust via the selected estimated regression model[a]	3.6; 3.56	3.28; 3.24	3.04; 3.01	2.25; 2.22	2.73; 2.67	2.44; 2.45

Abbreviations: RMA, Risk Management Agency; RMSE, root-mean-squared error.

[a]The first RMSE figure reported is based on the full information forecasting method, while the second is based on the recursive forecasting method (see the text). For each crop, based on the in-sample RMSE measure, the model with or without the intercept term (Models 1 or 2) was selected before out-of-sample predictions. The selected model in each iteration of forecasting was mostly in line with the selected model for the respective crop based on the full sample as reported in Table 1 (panel B).

1 within the regression framework. With that clarification, forecast performance across model specifications arising from the four adjustments and the current RMA approach of measuring volatility are evaluated based on comparisons of root-mean-squared errors (RMSE) across forecasts. The RMSE is calculated as the square root of the average of squared deviations between the realized volatility and the predicted realized volatility over the forecast horizon. Table 2 presents the results for corn and soybeans.

It is a well-known result in econometrics that if the conditional mean is correctly specified, the expected value of the dependent variable minimizes the quadratic loss function. The question is then whether the proposed adjustment approximates the expected value of the dependent variable better than the current method in use. The results show that the suggested changes on RMA's volatility factor values lead to improved forecast performance. For corn and soybeans, the adjustment via using the volatility factor based on the month-long average has the lowest RMSE value over the 7- or 10-year forecast horizons considered, and therefore is selected among the options considered.[10] For soybeans, the adjustment based on regression analysis comes a close second over the same forecast horizon. When the forecast horizon is shortened to 5 years, RMA's current method either ties with (corn) or is slightly better (soybeans) than the adjustment using the month-long average. For both crops, eliminating the time-adjustment has the worst performance among all options considered. Finally, while the differences among the RMSE values appear to be small, testing whether these differences are statistically significant in a robust manner requires more observations and will be the subject of future research.

2.3 | Impact analysis

To carry out an impact analysis, we first need a measure of the volatility factor sensitivity of insurance premiums. Here we use a measure in the form of semi-elasticities: the ratio of the percent change in the premium amount to a change in the volatility factor value in percentage points. This measure and its elasticity counterpart are formally defined in Equation (12) in SA3. We look at numerous examples to gain insight into the factors influencing premium sensitivities.

[10]The forecast performance appears to improve for corn as the forecast horizon gets larger, while soybeans do not exhibit the same pattern. The underlying reason may have to do with the better fit observed for corn compared to soybeans in the regression analysis as discussed earlier in the text.

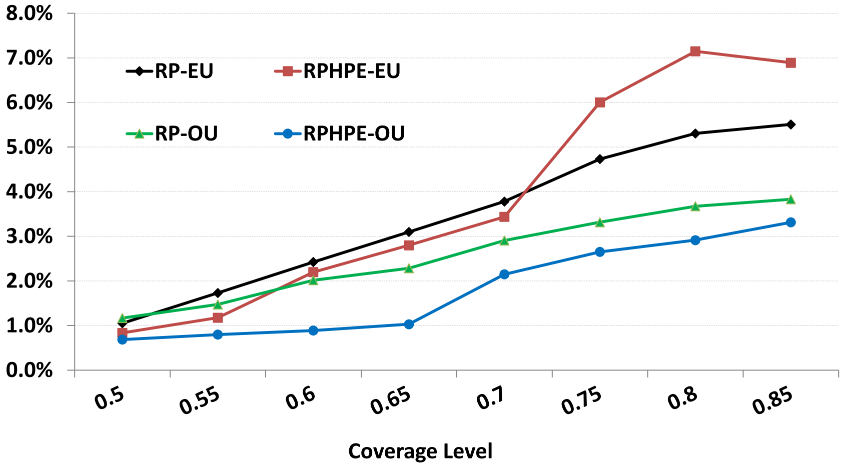

FIGURE 1 2021 Illinois corn example, enterprise or optional units—Percent premium impact of 1-point change in volatility factor. See Example 6 in Table A2 for the parameter values. The legends "RP-EU," "RPHPE-EU," "RP-OU," and "RPHPE-OU" refer to revenue protection (RP) or revenue protection with harvest price exclusion (RPHPE) plans under enterprise Units (EU) or optional units (OU).

The parameter values that are used in seven such examples are listed in Table A2. The preceding table and the details of the calculations are also relegated to SA3. Figure 1 showcases the premium sensitivities for the 2021 Illinois corn example for RP and RPHPE plans on enterprise or optional units (column 6 in Table A2).[11] Similarly, Figure A1 (which is relegated to SA3) shows the premium sensitivities for the 2021 Iowa soybeans example (column 7 in Table A2). These and other examples based on RMA's cost estimator tool as well as on other simulation models (such as Bulut and Collins, 2014; Sherrick, 2015) provide evidence that the degree of sensitivity is dependent on the policy type, unit type, level of coverage, initial level of the volatility factor, and the direction of change in volatility—although the latter results in a minor difference as expected.

Finally, it is evident that the sensitivity of insurance premiums to changes in volatility factor values can be best quantified as a range rather than a single number. Based on the examples using RMA's cost estimator for corn and soybeans, a 1 percentage point increase in the volatility factor results in a 0.55% to 7.15% increase in total premium at coverage levels 60% and above. That is, the premium sensitivity takes values between 0.55 and 7.15.[12] For a related interpretation of the sensitivity (the elasticity formula in Equation (12) in SA3), the examples suggest a range of premium changes between 0.066% to 1.073% for each 1% change in the volatility factor. To put the results into perspective, a 1% change in the discovered price of a crop generally increases the total premium by about 1%.[13] As such, insurance premiums are materially sensitive to the volatility factor values being used. It is therefore essential to ensure that the underlying methodology generates accurate forecasts of the actual (realized) volatility.

For both corn and soybeans, some hypothetical differences between the current version of the volatility factor (based on the last 5-day average) and the proposed version (based on the month-long

[11] On a crop-by-crop basis, individual crop insurance plans can be obtained in basic,optional, and enterprise units. Basic units include all acreage of the crop in a county held by the insured under identical ownership. Optional units are subdivisions of basic units. The subdivision can be based on location and production practices. Each farm in a section can stand alone for insurance purposes. Enterprise units combine all of a producer's interest for the crop in a county (includes acreage in which the insured has a share). More detailed information on insurance units can be found in Bulut (2020).

[12] We focus on 60% coverage and above because the Cost Estimator webtool delivered some unexpected results at 50% and 55% levels (see Figure A1 in SA3).

[13] For revenue plans, some numerical examples conducted via the RMA's Cost Estimator indicate that the premium sensitivity estimates with respect to the base price for such plans remain less than 1.5% and stay near 1% for most coverage levels.

average) are considered as the adjustments. These values, listed in the first columns of Table 3, vary between −2 to 2 percentage points and they are consistent with the historical range of deviations (see Figure 2). The impacts of foregoing adjustments on total premiums were evaluated by considering the low, medium, and high values: 2, 4, and 6, for the sensitivity. Recall that a sensitivity value being equal to 2, for instance, translates into the following impact: a 1 percentage point increase in the volatility factor increases the premium by 2%. Based on this procedure, the resulting premium impacts at various values of volatility are reported in Table 3 for both crops. Premium impacts move in tandem with the direction of adjustment as higher values of volatility factor translates into a higher premium amount per the sensitivity analysis from earlier. Such adjustment could have premium impacts up to (in either direction) $579.3 million and $367.15 million for corn and soybeans, respectively, depending on the premium sensitivity values considered. In light of the premium sensitivity examples for the 2021 Illinois corn and Iowa soybeans from Figures 1 and A1 and the other examples that are included in Tables A2–A4 in SA3, premium impacts should be expected to vary by plan type, unit structure and

TABLE 3 Premium impact of adjusting RMA's volatility factor (VF) values

	Corn			Soybeans		
	Incremental premium (in million $s) depending on alternative semi-elasticity values			Incremental premium (in million $s) depending on alternative semi-elasticity values		
Adjustment (in percentage points)	Low = 2	Mid = 4	High = 6	Low = 2	Mid = 4	High = 6
2	193.1	386.2	579.3	122.4	244.8	367.2
1	96.5	193.1	289.6	61.2	122.4	183.6
0	0.0	0.0	0.0	0.0	0.0	0.0
−1	−96.5	−193.1	−289.6	−61.2	−122.4	−183.6
−2	−193.1	−386.2	−579.3	−122.4	−244.8	−367.2

Note: In 2021, the parts of countrywide premium that was influenced by the VF values stood at $4.83 billion and $3.06 billion for corn and soybeans, respectively. Those included RP and RPHPE plans among others (see Footnote 5 in SA3) and were obtained from the RMA's Summary of Business tables, which is available at: https://prodwebnlb.rma.usda.gov/apps/SummaryOfBusiness/ReportGenerator. Using the shorthand notation ε for the value of sensitivity, a 1 point increase in VF increases the premium by ε%.

Abbreviation: RMA, Risk Management Agency.

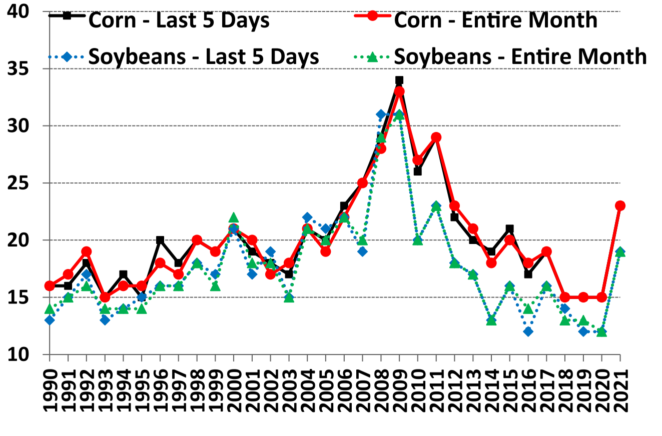

FIGURE 2 Averaging implied volatility values in the last 5 days of February versus over the entire month—Corn and soybeans. The source for implied volatility values is Barchart.com. Time adjustment was applied to implied volatilities per RMA's methods. RMA, Risk Management Agency.

coverage levels, and location. For a given case, a higher premium sensitivity would naturally translate as a higher premium impact arising from a point change in volatility factor value.

3 | CONCLUSION

We have reevaluated the use of volatility factor in premium rate-setting for revenue plans of crop insurance. Our analysis covers corn and soybeans over the period 1990–2021. We verify that the sensitivity of insurance premiums to changes in volatility is comparable to the sensitivity resulting from changes in crop prices. Through the regression analysis of realized volatilities on implied volatilities, we find that the volatility factor as currently measured is supported as an efficient and unbiased estimator of the price risk for corn, while this support requires levels of significance stronger than 10% in the case of soybeans. To further investigate, we analyze the out-of-sample forecast performance of the volatility factor vis-à-vis four possible adjustments: (i) using the month-long average of implied volatilities instead of the last 5-day average in the discovery month, (ii) eliminating time-adjustment in volatility factor calculations, (iii) using the October serial options, and (iv) using the estimated regression models between implied and realized volatilities. The out-of-sample forecast analysis suggests that improvements can be made to RMA's price volatility forecast to make them more actuarily accurate. Specifically, for both crops, the adjustment via using the month-long average delivers the best forecast performance among all options considered over the 10-year forecast horizon. Such an adjustment would be the practical and simple approach to improve upon the existing methodology, and it could have substantial premium impacts (up to 12% in either direction) depending on the premium sensitivity values considered.

The analysis can be extended to other major crops such as spring and winter wheat, cotton, and rice. One complication is that implied volatility values are available for these commodities only starting in 2008 or 2009, which in turn limits the data available for identifying the initial regression model structure. This issue should be resolved as more observations become available each passing year. Our preliminary analysis suggests that livestock insurance product premiums are more volatility factor-sensitive than crop counterparts. Availability of nearly year-round and more frequent sales for livestock products naturally generate more observations than the crop cases, which in turn should be useful in empirically investigating similar research questions in that space as well (Bozic et al., 2012).

Finally, in modeling the dependency relationship between prices and yields RMA, uses the Iman-Conover method which in turn can be closely approximated by a Gaussian copula with a linear correlation coefficient (Coble et al., 2010, p. 96). The impact of alternative copula model choices on simulated rates has been the subject of several papers such as Goodwin and Hungerford (2014) and Ramsey et al. (2019). The latter report some pronounced rate differences under a high price volatility factor value scenario especially when the underlying correlation level between prices and yields is at the higher end (pp. 242–243 in their paper). The premium sensitivity to volatility factor as it relates to the dependency measures between prices and yields is left for future research.

DATA AVAILABILITY STATEMENT

For replication purposes, data used in the study are available from the authors upon request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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