WIFO ■ WORKING PAPERS
601/2020

The Potential Capital Requirement for a Minimum Prices Insurance Scheme for Wheat, Maize, and Rape Seed

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WIFO Working Papers 601/2020

May 2020

Abstract

In 2005 the EU lowered the guaranteed minimum prices for crops in its Common Agricultural Policy and stopped market interventions. Consequently, prices started to fluctuate more intensively, and farmers' incomes are now subject to higher price volatility. A crop price insurance scheme could provide an interesting instrument to stabilise the income of European farmers. We analyse the premium level and capital requirement of a hypothetical insurance contract covering several combinations of minimum prices for a bundle of wheat, maize, and rape seed. The premium level is based on the Black option pricing model and a Bayesian autoregressive stochastic volatility model. Monte Carlo simulated forecasts provide estimates for expected variances and a profit-loss distribution for various combinations of minimum prices. The required solvency capital to keep the insurance business afloat at the 1 percent ruin probability creates capital costs exceeding the expected profit.

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2020/099/W/5918

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Verlags- und Herstellungsort: Wien

TABLE OF CONTENTS

Executive Summary

We present a novel instrument for addressing price risk in agricultural commodity markets. Many farmers are financially harmed when product prices are too low to cover variable costs of production and therefore, they are interested in guaranteed minimum prices. In Austria 78 percent of farmers who were asked about their attitudes towards price risk showed an interest in an insurance scheme or a similar instrument to prevent such damage. We analyse a financial instrument that guarantees a minimum price for the crops wheat, maize, and rape seed on European markets.

The details of the insurance product are that a minimum price is selected at the end of January, the contract duration for wheat and maize is nine months, and for rape seed it is six months in the same year. After this period claims are paid if the minimum price selected in January is above the spot price prevailing at contract maturity. The claims payment corresponds to the difference between the insured minimum price and the observed spot price.

We use Bayesian linear normal stochastic variance (SV) models with stochastic autoregressive volatility to compute time varying volatilities for insurance premiums based on commodity option pricing model. We use these models also to simulate spot prices at the maturity date of insurance contracts for the crops of interest. For the estimation, we approximate daily spot prices by prices of futures contracts close to their expiration date from Euronext (nearby). Using Monte-Carlo methods we compute the probabilities of how often the insured minimum prices of a contract would be undercut and the associated expected loss.

For a hypothetical bundle of crops, that represents the Austrian harvest in 2019, we compute the profit and loss distribution for various sets of potential minimum prices (e. g. 130 €/t for milling wheat, 110 €/t for maize, 240 €/t for rape seed). The profit and loss distribution shows that, given the price set mentioned before, a solvency capital of 267 € per bundle is necessary to keep the insurance business afloat at the 100-year ruin probability. Under the prevailing market conditions in the Austrian insurance market this would create costs of capital of 25.4 € per bundle. The estimated market volume of this minimum price insurance product – based on the net premium (net of taxes, costs of capital, administration, and distribution costs) – is € 9.5 mn for Austria.

1. Introduction

The Common Agricultural Policy (CAP) of the European Union introduced administrative prices for major agricultural commodities prior to abolishing custom duties between Member States from 1 July 1967 (*EEC*, 1965). The administrative price is a guaranteed minimum price for a crop or livestock product. Administrative prices were lowered in 1992, and this decline accelerated in 2002; since 2005 they are well below the world market price (*Sinabell*, 2020). In the same year, the EU introduced a minimum blending requirement of biofuel to conventional fossil carbon-based fuels. Because other major producers like the USA introduced similar regulations at the same time, an immediate increase of spot prices for wheat, maize, and rape seed occurred. This induced an expansion of supply in response to higher profitability. Throughout the following years, agricultural commodity prices began to fluctuate more widely, and consequently the operating income of EU farmers is now more exposed to price variation.

US farmers, on the other hand, have been exposed to higher price volatility since the early 1970s. The US financial markets offer several commodity derivatives that allow US farmers to fix prices in advance, or to secure a price floor by buying put options. Both financial instruments allow fixing ex-ante a minimum revenue from selling the harvest. In addition, the US government introduced margin insurance schemes for several commodities in the 2014 Farm Bill (*Cordier*, 2014). Although, agricultural futures and options are also available on Euronext, most EU farmers operate small-scale family farms and do not use financial derivatives.

Given the restrained usage of financial market instruments by EU farmers, the pressure to abolish administrative prices for agricultural products (due to the wish of inclusion in international trade agreements), and higher fluctuations of agricultural prices since 2005, insurance-based instruments are an attractive means of protecting farmers from price volatility. *Meuwissen et al.* (2018) provide a recent survey. Insurance-based instruments offer a minimum price level in exchange for a premium payment by the farmer. The main goal of an insurance scheme is to provide short-term assistance when prices are falling rapidly. They are not designed to protect farm income against permanent reductions in the price level, because premium levels would have to be adjusted accordingly if the price of a crop remains low. Consequently, such a system reduces the risk of low returns to producers, increases the expected price and hence also the level of output.

Based on the demand for price insurance surveyed among Austrian farmers (*keyQUEST*, 2019), we consider an insurance contract that offers a minimum price for wheat and maize on the first trading day in November, and a contract offering a minimum price for rape seed on the first trading day in August. This insurance contract must be signed not later than on the last working day of January the same year. Therefore, the contract duration for wheat and maize is nine months, and for rape seed it is six months. The conditional claims payment is the difference between the insured minimum price and the spot price, should the spot price be below the agreed minimum price. A spot price at or above the minimum price results in a zero claim. This set-up corresponds to a European put option, but contrary to an option, the insurance contract is non-tradeable. It lacks a safety system provided by margin calls, and a settlement system provided by a clearing house.

Alternatively, we compute the amount of solvency capital necessary to run this insurance scheme at various safety levels for a representative insurance contract. The representative contract covers 11 metric tons of wheat, 18 metric tons of maize and 1 metric ton of rape seed. The 11-18-1 relation matches the composition of the Austrian harvest of 2019 (*Statistik Austria*, 2020). The shares roughly scale up to the total harvest if multiplied by 119,000.

While government minimum price guarantees are a widely-used instrument of agricultural policy, price insurance contracts for agricultural crops are rarely applied, presumably because financial markets offer instruments for hedging. Price insurance contracts, however, can offer some advantages over options and futures. The minimum price can be set close to the marginal costs of production, while financial market-based instruments usually offer strike prices close to the current spot price. For example, the spot price for wheat on the 12th of February 2020 on the Euronext exchange was 186 €, while strike prices of the traded options ranged between 181 € and 191 € depending on duration. This indicates that an insurance contract offering a minimum wheat price as low as, say, 130 € protects against extremely bad outcomes, e. g. if the spot price falls below marginal costs. An insurance contract can do so at low premiums, without incurring the cost of permanent spot market tracking and hedging.

Bardsley – Cashin (1990) first described the similarity between the value of a public minimum price guarantee and the price of a put option on the example of the Australian government's minimum price guarantees for the 1979/1980 through 1988/1989 growing seasons. We broadly follow *Bardsley – Cashin* (1990) and compute the price for the proposed insurance contracts by using the formula for a European put options for commodities (*Black*, 1976), adjusted for the time variable volatility of crop prices (*Myers – Hanson*, 1993). The main difference is that the above papers estimate a conventional GARCH model of returns, whereas we estimate a stochastic volatility model (SV) using Bayesian techniques. For the estimation we approximate spot prices by nearby futures prices for wheat, maize and rape seed on Euronext. The SV model allows us to forecast the distribution of log returns on a commodity over a horizon of nine months for wheat and maize and six months for rape seed. Forecasting the distribution of log returns allows us to forecast the distribution of future prices. In addition, the model is used to forecast the distribution of the daily standard deviation of a price at the nine- and six-months horizons. We use this estimate to compute the option value at the end of January, i. e. the insurance premium for a bundle of minimum prices. It is assumed that the premia yield a risk-free return over the duration of the contract. Combining the present value of the premia at maturity with the distribution of future prices allows us to compute the shortfall distribution, i. e. the probabilities of claims payouts and their amounts. The difference between premium intakes and claims payments corresponds to the expected loss/profit of the insured bundle or if one is willing to define a specific solvency level, the estimates for the minimum solvency capital needed for underwriting price insurance contracts.

The next section provides an overview of price developments at the spot and future markets for wheat, maize and rape seed. We continue with a description of the premium calculation followed by a description of the SV models used for the forecasting of commodity prices and the volatility of returns. We present the solvency capital requirement for different ruin probabilities and close with conclusions.

2. Data

Prices for agricultural commodities in the EU have been administrated since 1968, with a lowering of administrated prices after 1992 and a distinct reduction below world market levels since the year 2005. It is remarkable that prices for wheat, maize, and rape seed are recorded at monthly frequencies only, i. e. there is no daily market spot price for these crops available, although official statistics for agricultural products tend to be very detailed. The low frequency of price data reflects no need for daily price information on the side of farmers as well as officials. In Figure 2.1 we show, as an example, the development of wheat, maize, and rape seed producer prices in Austria, a country not participating in the Common Agricultural Policy of the EU until the end of 1994. Before 1994, the producer prices for wheat at times have been stable for several years. Since 1993, gaps emerge in the time series for wheat prices, for months when no price at all has been recorded; such gaps are in the months before harvest. The producer price for maize shows a distinct seasonal variation even after 1995, but after 2005 this pattern disappears completely, giving way for a more volatile fluctuation. On the other hand, producer prices for rape seed appear to have been always subject to high volatility in Austria. After a doubling of prices between 1974 and 1982, they dropped towards their starting level from 1973. Again, after 2005 prices fluctuated widely between 175 € and 470 €.

Figure 2.1 illustrates that farmers are subject to pronounced price swings. Although farmers in the survey conducted by keyQUEST (2019) show a surprisingly high degree of risk tolerance, there is a group of farmers willing to buy insurance and possibly those with a large investment program (compared to their current level of revenues) will get easier access to bank credit if they can buy a price insurance.

The *Black* (1976) option pricing model needs daily futures prices for the computation of the option price. The prices at which Austrian farmers sell their harvest are, however, the monthly prices given in Figure 2.1. Therefore, it is important that fluctuations of daily future prices on the MATIF exchange reflect the development of monthly prices for wheat, maize and rape seed in Austria. Figures 2.2 through Figures 2.4 compare daily prices of futures close nearby their maturity date (nearby) with prices at the maturity date (end) and monthly producer prices in Austria for each crop. We conclude that after joining the European Union in 1995 crop prices in Austria moved in tandem with their counterparts at the MATIF exchange in Paris.

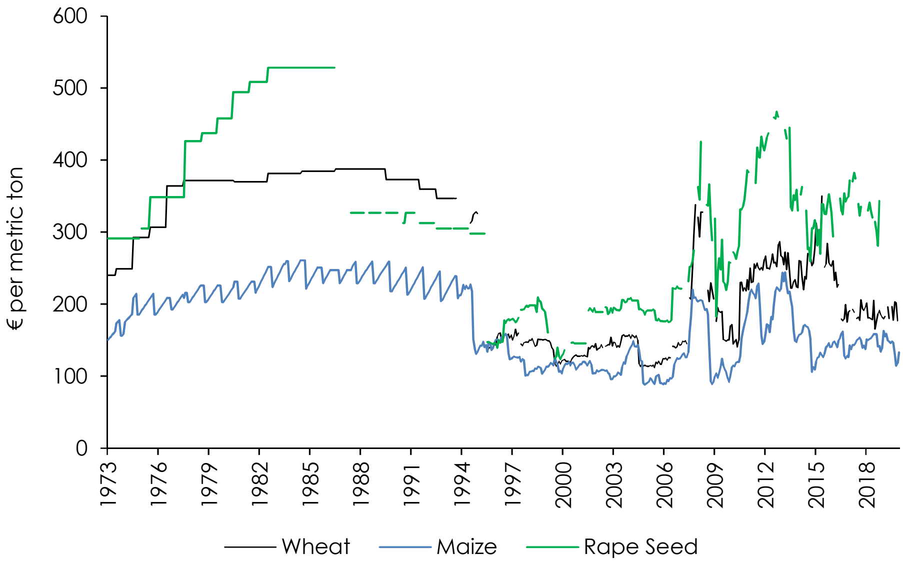
The pricing formula of commodity options by *Black* (1976) deviates slightly from the conventional *Black – Scholes* (1973) model. The reason is that the changes in the log of nearby futures prices (log returns) do not follow a log-normal distribution, rather they feature seasonal patterns caused by planting and harvest cycles, and they tend to be mean-reverting because higher crop prices provide an incentive to expand cultivation. Furthermore, the costs of storage for agricultural commodities are high compared to corporate stocks which reduces the profitability of arbitrage trading. Figure 2.5 shows the substantial seasonality of crop prices based on nearby futures prices. For example, wheat prices tend to be about 7-9 percent above the annual mean during November and December, while maize prices are 3.5 percent below their annual mean in the mid of February and in July 3.5 percent above their annual mean. Table 2.1 show the characteristics of log returns from nearby futures prices. Tests do not reject the zero mean assumptions for log returns of all crops. On the other hand, the presence of frequent outliers leads to a rejection of the normality assumption for log returns. Moreover, Figure 2.6 shows the standard deviation of monthly log returns for US-commodity prices (wheat and maize) back to 1963 measured by a rolling window with a length of 36 months. There are clearly signs of elevated volatility during the oil crisis 1973 through 1975 and during the financial market crisis after 2007. This suggests a degree of heteroscedasticity in the data. The descriptive analysis of prices and log returns suggest using the modified version of the *Black* (1976) option formula suggested by *Myers – Hanson* (1993), *Fofana – Brorsen* (2001) or *Koekebakker – Lien* (2004).

Table 2.1: Summary statistics of daily log returns for nearby futures prices, 2000 to 2019

	Wheat	Maize	Rape seed
Minimum	-0.240	-0.356	-0.166
Median	0.000	0.000	0.000
Maximum	0.164	0.122	0.100
Mean	0.000	0.000	0.000
Standard deviation	0.015	0.014	0.012
Skewness	-0.941	-4.566	-1.363
t-test	0.617	0.723	0.383
Shapiro-Wilk test	0.000	0.000	0.000

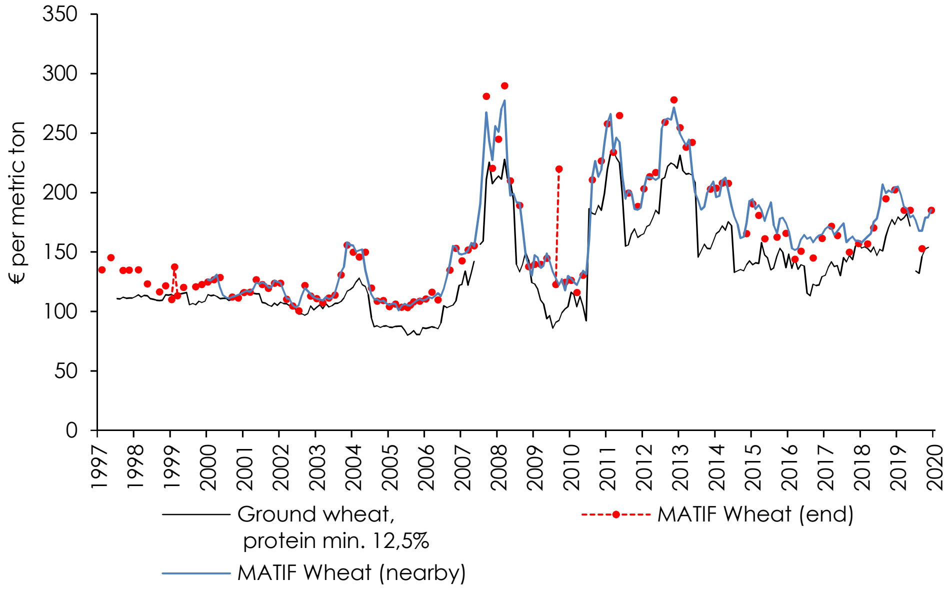
S: MATIF, own computations. P-Value for t-test on zero mean for daily log returns and p-value for Shapiro-Wilk test of normality for daily log returns.

Figure 2.1: Monthly producer prices of premium wheat, maize and rape seed in Austria, 1973 to 2019



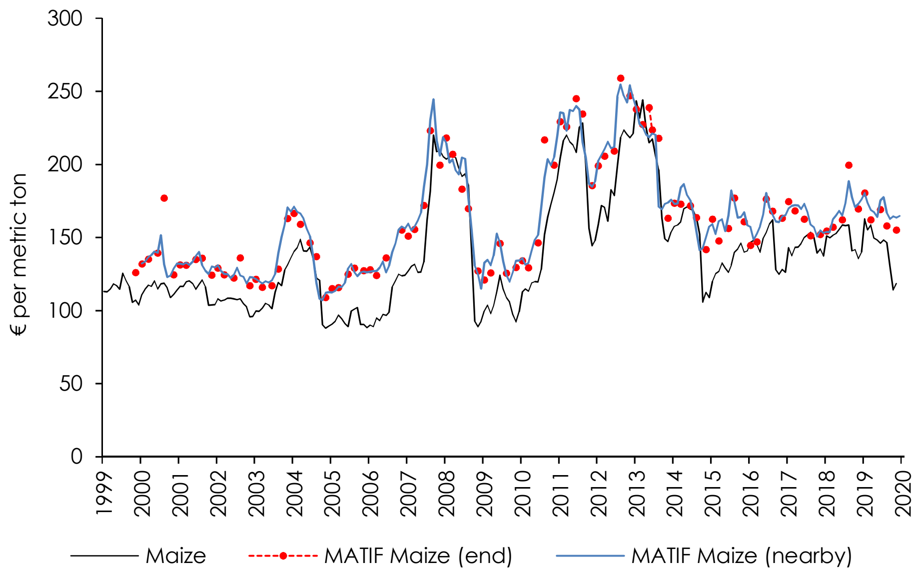
S: Statistik Austria.

Figure 2.2: Monthly producer price for wheat in Austria and Euronext (MATIF) futures prices



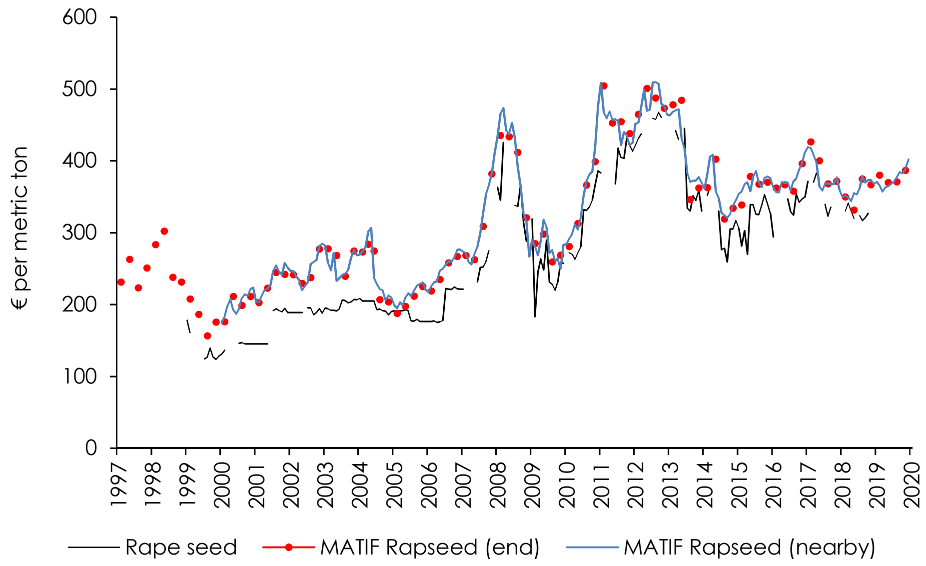
S: MATIF, Statistik Austria.

Figure 2.3: Monthly producer prices for maize in Austria and Euronext (MATIF) futures prices



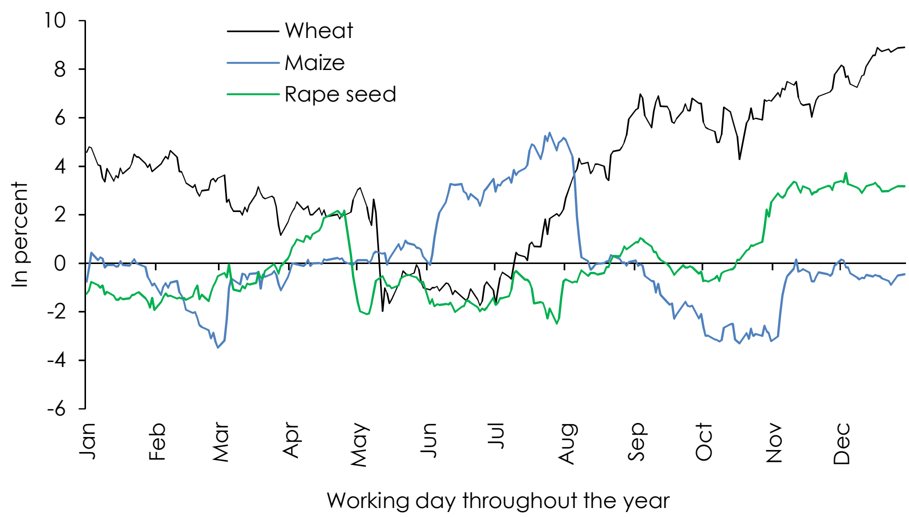
S: MATIF, Statistik Austria.

Figure 2.4: Monthly producer price for rape seed in Austria and Euronext (MATIF) futures prices



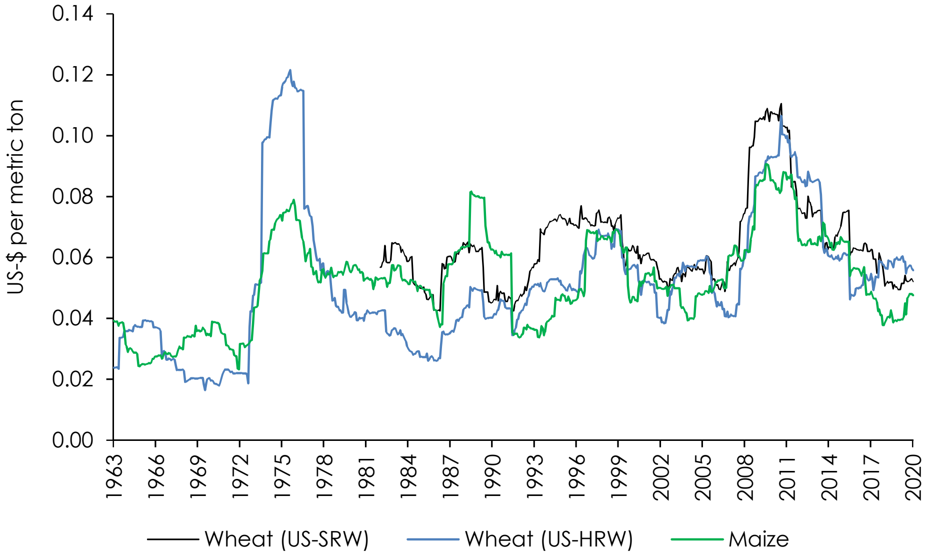
S: MATIF, Statistik Austria.

Figure 2.5: Average daily deviation from annual mean (nearby futures price), 2000 to 2019



S: MATIF, WIFO computations.

Figure 2.6: Time varying standard deviation of log returns for US-commodity prices (36 months rolling window)



S: World Bank Pinksheet. WIFO computations.

3. Premium calculation for the minimum price insurance

The application of option pricing models for the evaluation of guaranteed minimum prices has already been used by *Bardsley – Cashin* (1990). We transfer this concept to the case of a minimum price insurance contract for wheat, maize, and rape seed. The *Black – Scholes* (1973) option pricing formula gives the equilibrium price of a European put option (P_t) at a given time t as a function of its strike price (K), the current spot price of the underlying asset (S_t), the one-period variance of the proportional price changes in the underlying asset (σ^2), the risk-free interest rate (r), and the time to maturity ($T-t$):

$$P_t = S_t(\Phi(I_1) - 1) - Ke^{-r(T-t)}(\Phi(I_2) - 1),$$

with

$$I_1 = log\left(\frac{S_t}{Ke^{-r(T-t)}}\right)\frac{1}{\sigma\sqrt{(T-t)}} + 0.5\sigma^2\sqrt{(T-t)},$$

$$I_2 = I_1 - \sigma\sqrt{(T-t)},$$

where $\Phi(\cdot)$ denotes the cumulative normal distribution function. The price changes are defined as the log returns on the underlying asset $\log(S_t) - \log(S_{t-1})$. The option pricing formula can be motivated by permanent arbitrage trading between a risk-free asset with rate of return r and the return on a portfolio including the option and its underlying asset. By continuously adjusting the portfolio structure, its return can be made riskless and consequently the equilibrium portfolio return must be equal to the risk-free rate of return.

Because the log returns of commodity prices do not fulfil the normality assumption used in the Black – Scholes model, *Black* (1976) suggested to replace the current spot price (S_t) in the formula above by the futures price of the underlying asset at the maturity date T of the option (F_T). This modification removes problems related to the seasonality of commodity prices, mean-reversion, and storage costs, because these aspects are reflected in the futures price. Additionally, *Myers – Hanson* (1993) argue that the standard deviation of commodity prices log returns is time variable (cf. Figure 2.6) and that conventional estimates of the variance, based on a moving window of 30 days of historic log returns (*Jarrow – Rudd,* 1983), do not adequately reflect the expected variance at maturity in T. *Myers – Hanson* (1993) use the expected standard deviation for date T, computed from Monte Carlo simulated forecasts of a GARCH(1,1) model to compute option prices, and conclude that – compared to models based on historic volatilities – this procedure provides significantly better estimates for observed market prices of soy bean options traded on the Chicago Board of Exchange. *Fofana – Brorsen* (2001) provide further evidence that for maturities between 21 and 50 days, a GARCH based option pricing model is not dominated by option pricing models based on the implied volatility.

We apply a Bayesian normal linear stochastic volatility (SV) model with autoregressive stochastic volatility (*Kastner*, 2016) to demeaned log returns of nearby futures prices $y_t = \log(F_t) - \log(F_{t-1})$. The stochastic volatility model assumes that each observation y_t has its own contemporaneous variance $exp(h_t)$ and consequently allows for heteroscedasticity. By assuming that the log of the variance follows an autoregressive process of order one, the fluctuation of the variance over time is restricted and the model is made estimable. Stochastic volatility models are fundamentally different from GARCH models because the variance follows a stochastic evolution rather than a deterministic process (*Kastner*, 2016).

The model for zero-mean log returns of commodity prices with autoregressive volatility of order one is:

$$y_t \sim N(0, e^{h_t}),$$
$$h_t | h_{t-1}, \mu, \phi, \sigma_\eta \sim N\left(\mu + \phi(h_{t-1} - \mu), \sigma_\eta^2\right),$$
$$h_0 | \mu, \phi, \sigma_\eta \sim N\left(\mu, {\sigma_\eta^2}\big/{(1 - \phi^2)}\right),$$

where $N(\mu, \sigma_\eta^2)$ denotes the normal distribution with mean μ and variance σ_η^2, and h_t represents the unobserved time-varying autoregressive process of order one for the volatility of log returns (variance process). The assumption of a zero mean for the log returns is well supported by t-tests presented in Table 2.1.

The parameters of this process are the level of the log-variance (μ), the persistence of the log-variance (ϕ), and the volatility of the log-variance (σ_η). The initial value for the volatility (h_0) is distributed according to the stationary distribution of an autoregressive process of order one. In the estimation we use slightly informative priors for the level of the log-variance $\mu \sim N(-10{,}10)$ which corresponds to an unconditional variance of log returns of $log(0.0001) \sim -10$. The prior of the persistence parameter follows a Beta-distribution, such that a stable autoregressive variance process is assured. *Kim et al.* (1998) suggest the following values for the hyper parameters of this distribution: a_0=20 and b_0=1.5, implying a mean persistence of 0.86 with the variance of 0.11. Finally, the prior distribution of the volatility of the log-variance is $\sigma_\eta^2 \sim \mathcal{G}\left(0.5{,}0.5B_{\sigma_\eta}\right)$, and we choose the value $B_{\sigma_\eta} = 0.1$ suggested by *Kastner* (2016). We use R-package "stochvol" to estimate this model.

Table 3.1 presents the estimation results of the Bayesian normal linear SV model with autoregressive stochastic volatility for daily log returns of wheat, maize, and rape seed using daily data for nearby futures prices from 1999 through 2019 giving a sample size of roughly 5,150 observations. The time series for nearby futures prices contains several missing observations. For these trading days, we also delete the price information for the other crops from the sample. With one exception, the estimation results are close to our a priori values and they indicate substantial persistence in the volatility variance. Only for rape seed we find a value of the persistency parameter below 0.8 which lies within the 90 percent confidence interval spanned between 0.73 and 0.80. The estimates for the volatility variance are substantially above our a priori assumptions.

Table 3.1: Estimation results for Bayesian Student-t linear models with stochastic volatility for log returns of wheat, maize, and rape seed nearby futures

Parameter	Mean	Standard deviation	Quantiles 0.05	0.5	0.95	ESS
			Wheat			
μ	-9.66	0.10	-9.82	-9.66	-9.50	3,726
φ	0.87	0.01	0.85	0.87	0.89	246
σ	0.84	0.05	0.77	0.84	0.92	141
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	3,726
σ^2	0.71	0.08	0.59	0.70	0.84	141
			Maize			
μ	-9.95	0.10	-10.10	-9.95	-9.79	4,175
φ	0.86	0.01	0.84	0.87	0.88	454
σ	0.85	0.04	0.78	0.85	0.91	271
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	4,175
σ^2	0.72	0.07	0.61	0.71	0.83	271
			Rape seed			
μ	-9.66	0.05	-9.75	-9.66	-9.58	2,992
φ	0.77	0.02	0.73	0.77	0.80	317
σ	0.69	0.03	0.64	0.69	0.75	289
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	2,992
σ^2	0.48	0.05	0.41	0.48	0.56	289

S: Estimation based on Bayesian Student-t linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2015). ESS shows the effective sample size.

4. Computation of the premium level

There is no closed form solution to the GARCH option pricing problem, but GARCH based option pricing can be implemented using Monte Carlo methods and a simulation model. *Myers – Hanson* (1993) derive a closed form approximation to the simulation model. We follow their approach and compute the one-period standard deviation for the Black option pricing model from a Monte Carlo simulation of the latent volatility $h_{i,t}$, where i represents one of the 10,000 simulated volatility forecasts between $t = 0$ and maturity $t = T$. In view of the conditional independence of $h_{i,t}$ for all t and all i, the variance at maturity T is given by $\sum_{t=0}^{t=T} \exp(h_{i,t})$. We plug the square root of the median of the above expression over the 10,000 simulated forecasts as the volatility parameter in the *Black* (1976) option price model and compute option prices for several sets of strike prices. Figures 4.1 to 4.3 show our estimates for the latent historic volatility series from 1999 through January 2019 and for the forecast period from February 1st 2019 until T for each crop. The models expect an increasing variance for wheat and rape seed, while the variance for maize will decline over the lifetime of the option.

We plug the median volatility at maturity T from the 10,000 forecasts into the *Black* (1976) formula and compute insurance premiums for given sets of minimum prices. We use the minimum prices for which a survey among Austrian farmers by *keyQUEST* (2019) indicates some demand for a wheat price insurance among Austrian farmers. For maize and rape seed we rescale the minimum prices for wheat accordingly to achieve comparable minimum prices. Table 4.1 shows the premiums for various minimum (strike) prices per metric ton. The last row in Table 4.1 shows that the premium level is highest for minimum prices close to the prevailing spot prices (S_t)[1]. In this case, the premium ranges between 5.5 percent (rape seed) and 8.3 percent (wheat) of S_t, i. e. at the date of buying insurance. The reason for high premium levels is the higher probability of realised spot price at maturity T (S_T) below the insured minimum price K. Consequently, lower insured minimum prices require a lower premium level because the probability of a very low spot price at maturity that would trigger a claims payment ($K > S_T$) becomes smaller. For minimum prices far below the current spot price S_t, the premium level falls below one euro per metric ton, i. e. in a range between 0.03 (maize) and 0.27 percent (wheat) of the spot price at that date of buying insurance (S_t).

Hull – White (1987) and *Johnson – Shanno* (1987) point to the fact that stochastic volatility adds an additional source of risk to the valuation of options which is not generally diversifiable, and the arbitrage argument, on which *Black's* (1976) option pricing formula is build, breaks down. *Myers – Hanson* (1993), however, argue that equivalent restrictions can be imposed on the preferences and/or the correlation properties of the stochastic process resulting in risk-neutral

[1] We do not have access to daily spot prices for wheat, maize, and rape seed and therefore, we approximate spot prices by the corresponding daily nearby futures prices from MATIF/Euronext in all our computations. Theoretically and in practice, futures prices converge to the spot price as the maturity date approaches. To keep our arguments consistent with our notation of the Black option pricing model, we will refer to nearby futures prices as spot prices in the following.

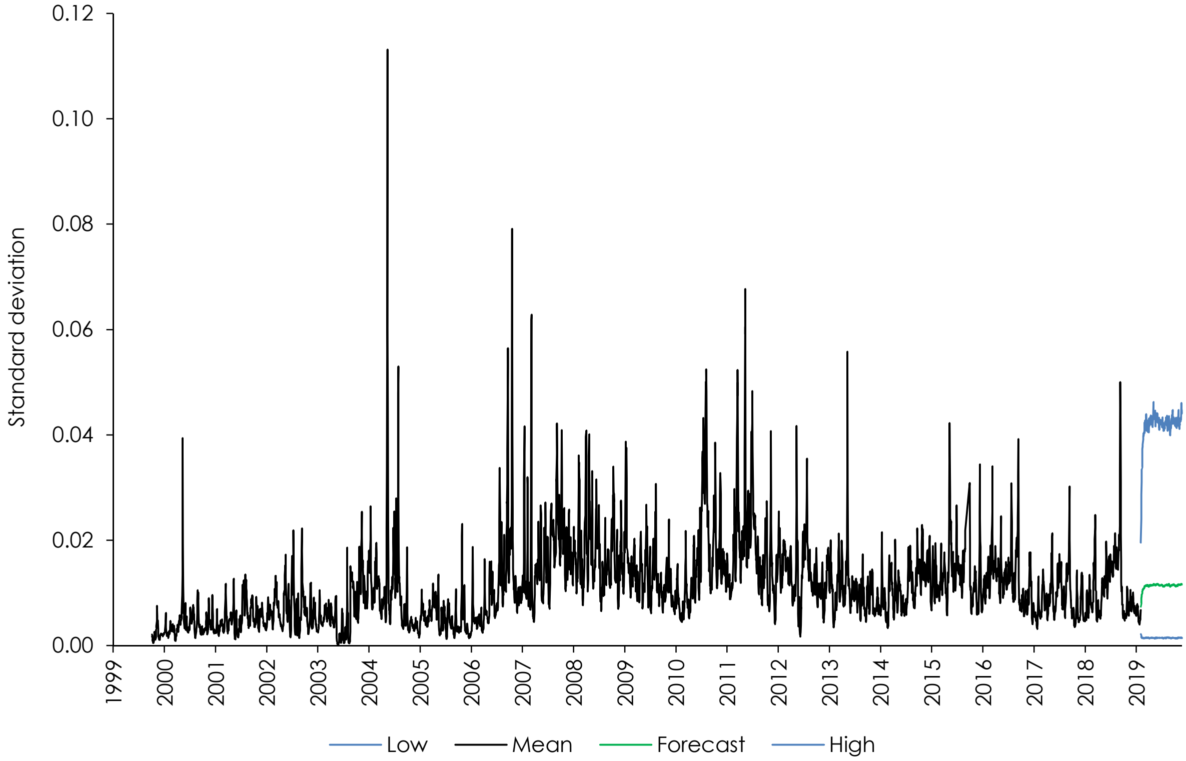
valuation. Alternatively, risk-neutral valuation may be an adequate approximation if many risk-neutral agents are active in the market. Finally, because the risk preferences of all market participants are not known, option pricing formulas requiring information on individual preference are of limited use.

Table 4.1: Level of insurance premium using the Black option price formula for selected insured minimum prices

Wheat	Maize	Rape seed	Wheat	Maize	Rape seed
Insured minimum prices € per metric ton			Premium level € per metric ton		
130	110	240	0.55	0.05	0.00
140	120	260	1.28	0.22	0.04
150	130	290	2.59	0.67	0.53
160	140	310	4.69	1.70	1.87
170	150	330	7.73	3.58	5.05
180	160	350	11.78	6.60	11.01
190	170	370	16.87	10.89	20.33

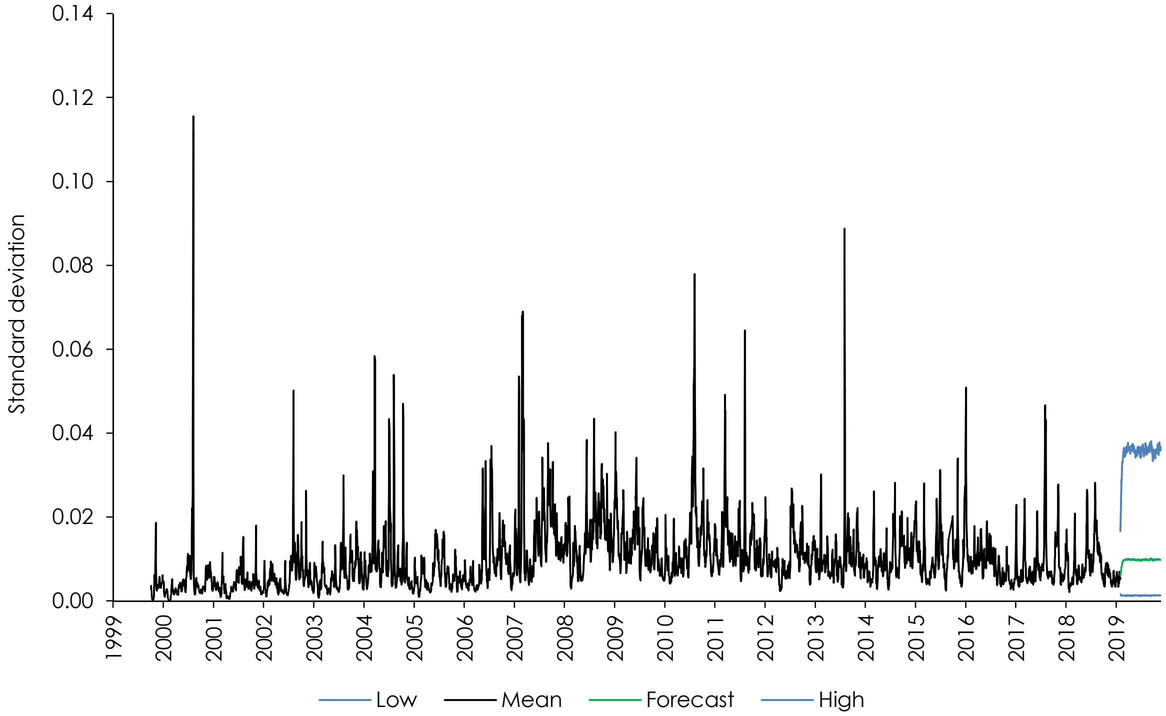
S: *Black* (1976) option price formula using the median forecasted standard deviation at maturity T based on 10,000 forecasts of the volatility from a Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). Insured period for wheat and maize 9 months, and 6 months for rape seed starting with February 1st 2019 with the following realised nearby futures price for wheat (€ 204.25), maize (€ 177.75), and rape seed(€ 372) on January 31st 2019.

Figure 4.1: Historic and forecasted volatility of log returns for wheat nearby future prices, 9 months horizon



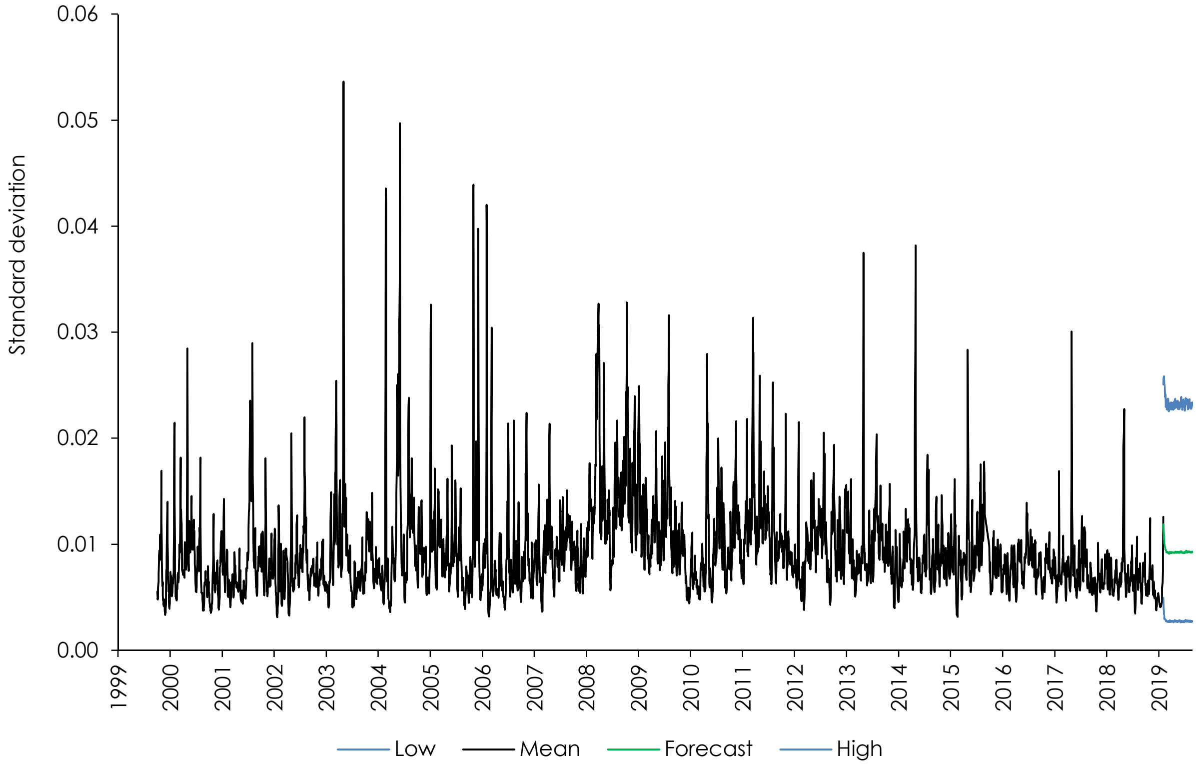
S: MATIF. Standard deviation estimated from 10,000 forecasts of the volatility based on Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). Low and High provide 5 and 95 percent confidence intervals from 10,000 draws.

Figure 4.2: Historic and forecasted volatility of log returns for maize nearby future prices from Bayesian normal linear model with autoregressive stochastic volatility, 9 months horizon



S: MATIF. Standard deviation estimated from 10,000 forecasts of the volatility based on Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). Low and High provide 5 and 95 percent confidence intervals from 10,000 draws.

Figure 4.3: Historic and forecasted volatility of log returns for rape seed nearby future prices from Bayesian normal linear model with autoregressive stochastic volatility, 6 months horizon



S: MATIF. Standard deviation estimated from 10,000 forecasts of the volatility based on Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). Low and High provide 5 and 95 percent confidence intervals from 10,000 draws.

5. The potential capital requirement for a minimum price insurance scheme

Options are traded on derivative markets and buying and selling activities are administrated by dedicated clearing houses, who document trades, do the book keeping and organise margin calls if the option is in or out of the money. Insurance contracts, on the other hand, are not traded on an exchange and have no system of margin calls to back them up. Instead insurance companies provide solvency capital in line with a predefined ruin probability. In this section we suggest a method to compute the solvency capital necessary for a crop price insurance.

The Bayesian linear normal SV model with stochastic autoregressive volatility produces also stochastic forecasts of the nearby futures price at maturity (F_T). Because F_t converges towards S_T when $t \to T$ the forecasts for F_T must be close to S_T (*Kolb*, 1997), cf. also Figures 2.2 to 2.4. Based on Monte Carlo simulated forecasts for each crop price, we can compare the distribution of historic nearby futures prices F_t with the distribution of 10,000 simulated nearby futures prices at maturity T (F_t) in Table 5.1. If we assume that $F_T \sim S_T$, we can interpret the numbers in Table 5.1 as forecasts for S_T. The median forecast from the Monte Carlo simulation is higher than the historic median. This is a direct consequence of the mean zero assumption for log-returns in the stochastic volatility model and high starting values at the end of January 2019, cf. the nearby prices listed in the note to Table 4.1 and Figures 2.2 through 2.4), respectively. A view on the maximum values for simulated nearby futures prices at *T* shows that the Bayesian linear normal model generates substantial outliers lying above the historically observed range. For wheat and maize, the minimum values for simulated spot price (S_T) are also substantially below their historic counterparts indicating that the model can produce extremely low prices as well. Only the simulated minimum values for the nearby futures price of rape seed is substantially above the corresponding historic minimum. The other quantiles for low prices also suggest that the Monte Carlo simulation produces comparatively optimistic prices for rape seed.

Let the index j indicate the respective crop j = (wheat, maize, rape seed), and let an insured bundle cover 11 metric tons of wheat, 18 metric tons of maize and 1 metric ton of rape seed $\alpha = (11{,}18{,}1)$. This relation reflects the relative quantities of each crop in the Austrian harvest from 2019 normalised such that a minimum of one metric ton of rape seed is insured and the quantities for wheat and maize are rounded to full metric tons. The profit/loss distribution of an insurance contract covering such a bundle results from a comparison of each simulated forecast for the spot price at T (S_{ijT}) with the corresponding insured minimum prices K_j as given in the first three columns of Tables 4.1 and 5.2. The insurance for crop *j*'s price produces a profit corresponding to the premium payment P_{jt} given in Table 4.1 if $K_j < S_{ijT}$, i. e. if the spot price of j in draw i at maturity T is above the insured minimum price. On the other hand, crop j's price insurance triggers a claims payout of size $K_j - S_{ijT}$ if $K_j > S_{ijT}$. Furthermore, if $K_j - S_{ijT} > P_{jt}$, the price insurance for crop *j* will bring a loss for the insurer. Given our 10,000 simulated forecasts of the spot prices S_{ijT} for each crop we compute the profit/loss (PL_i) of the insured (11, 18, 1)-bundle for each draw i as:

$$PL_i = exp(rT)(\sum_{j=1}^{3} \alpha_j P_{jt}) - \sum_{j=1}^{3} \alpha_j max\left((K_j - S_{ijT}), 0\right) \qquad \text{i=1, 2,..., 10,000.}$$

Here the first term represents the present value of the premia at maturity. Given 10,000 simulations for the spot price at maturity T of each crop, this produces 10,000 expected profit/loss numbers for the insured bundle at each set of minimum prices K_j shown in the rows of Table 5.2. The lower quantiles of the profit/loss distribution show the ruin probability for the crop price insurance, given our sets of minimum prices. For example, the first row in Table 5.2 shows the quantiles for minimum prices of 130 € for wheat, 110 € for maize, and 240 € for rape seed given an insured bundle covering 11 metric tons of wheat, 18 metric tons of maize, and 1 metric ton of rape seed. The 1 percent quantile in the first row implies that a loss of 267 € or bigger occurs for such a bundle once every 100 years. The 0.1 percent quantile in the first row implies that a loss of 753 € or bigger occurs for such a bundle once every 1,000 years, and the 0.01 percent quantile shows that a loss of 1,003 € or bigger occurs for such a bundle once every 10,000 years. The last column in Table 5.2 shows that underwriting the lowest price bundle has a negative expected profit of $E(PL)$ = -0.83 € because the premium level is low for minimum prices K_j far below the initial spot price S_t.

A likely reason for too small premiums at low minimum prices is the uniform application of the median volatility at maturity T from the 10,000 forecasts in the *Black* (1976) formula at all price levels, independent of their distance to the current spot price. *Ghysels et al.* (1996) hint at the fact that in practice the implied volatility of option heavily depends on calendar time t, the time to maturity and the moneyness of an option. These factors may create various biases in option pricing or hedging when the Black-Scholes implied volatilities are used to evaluate new options at different strike prices and maturities. This phenomenon is usually called "volatility smile" as the difference between implied Black-Scholes volatilities and the constant volatility at maturity T resembles a U-shaped pattern centred around the current spot price, cf. *Rubinstein* (1985) for an early empirical application showing the smile. Besides stochastic volatility, *Ghysels et al.* (1996) mention price jumps, transactions costs, bid-ask spreads, non-synchronous trading, and liquidity problems as possible sources for the volatility smile. In our case this implies that insurers will have to derive factors inflating the volatility at maturity T, resulting from the stochastic forecasts, in a non-linear way, depending on the distance of the insured minimum price from the current spot price. The derivation of such factors depends on the trade-off between price competitiveness and solvency and is a practical decision which we leave open to a potential insurer.

If the insurer underwrites higher minimum prices it will run a higher default risk. The quantile at which the crop price insurance remains profitable increases as we move down the rows of Table 5.2 until the last row, where the ruin probability reaches more than 25 percent. As can be seen in the last column, underwriting a riskier minimum price creates positive expected profits as the bias from the volatility smile becomes smaller, but it requires far bigger amounts of solvency capital to keep the insurance business afloat.

The relevance of the required solvency capital presented in Table 5.2 can be illustrated by combining the necessary equity capital with the rate of return of Austrian insurance companies in the property-liability business. *Url* (2019) shows that the rate of return on equity was 10 percent in 2019, over the last five years the average was 9.5 percent. This implies that the provision of solvency capital of 267 €, necessary to keep the business afloat at the 100-year ruin probability (the 1 percent quantile in the first row), creates costs of capital of 25.4 € (= 267 x 0.095). Given that the cost of capital can be distributed over 30 metric tons of crops in the bundle this results in a surcharge of 0.85 € to the premium levels presented in the first row of Table 4.1 which covers the cost of providing solvency capital for the insurer. An institutional set-up of the insurer as a mutual could reduce the need to generate a constantly high rate of return on equity. Alternatively, continuous hedging strategies can reduce the ruin probability effectively, but at the cost of buying and selling options and continuously watching the derivatives market.

The representative survey among Austrian farmers by *keyQUEST* (2019) revealed another interesting detail about their potential demand for crop price insurance. Out of the interviewed group of crop-growing farmers 13 percent had a clear interest for crop price insurance and another 65 percent were interested if conditions would be suitable, in total 78 percent articulated an interest in such a product. Given a combined harvest of 3.53 mn metric tons of wheat, maize and rape seed, respectively, this gives a potential insured quantity of 2.75 mn metric tons, i. e. 78 percent of the combined harvest.

The conjoint analysis by *keyQUEST* (2019) also revealed the distribution of the demand for wheat price insurance over the minimum prices given in the first column of Table 4.1, for insurance premiums without government subsidies. In this case, 11.8 percent of wheat farmers preferred the minimum price bundle in the first row of Table 4.1 i. e. 130 €; 14.7 percent preferred 140 €, most farmers (29.4 percent) opted for 150 €, and 17.6 percent mentioned 160 € as their preferred price. Each of the upper three minimum prices received support by 8.8 percent of farmers, respectively. Given these results from market research we estimate the potential annual net premium volume (net of taxes, costs of capital, administration, and distribution costs) for crop insurance in Austria at € 9.5 mn (78 percent of the harvest insured). This compares well to the gross premium income of the main agricultural insurer (Österreichische Hagelversicherung) in 2018 of € 156.2 mn (*FMA*, 2019).

Table 5.1: Comparison of historic and simulated daily nearby futures prices, 2000-2019

	Historical			Forecasted		
	Wheat	Maize	Rape seed	Wheat	Maize	Rape seed
Minimum	99	105	171	38	54	215
0.1 percent quantile	100	106	172	83	75	246
1 percent quantile	104	111	181	114	108	273
5 percent quantile	108	118	201	140	129	301
Median	156	157	324	204	178	372
95 percent quantile	252	236	474	298	246	461
99 percent quantile	270	254	508	362	296	507
99.9 percent quantile	290	261	520	489	404	576
Maximum	293	265	525	634	539	743

S: MATIF, estimated from 10,000 Monte Carlo forecasts of the volatility based on Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). The forecast horizons are 6 months for rape seed and 9 months for wheat and maize.

Table 5.2: Profit and loss distribution for bundles of crops at selected insured minimum prices (Normal linear model)

Insured minimum price level			Lower quantiles of the profit/loss distribution						Mean profit of
Wheat	Maize	Rape seed	0.01%	0.10%	1%	5%	10%	25%	insured bundle
€ per metric ton			€ per insured bundle						
130	110	240	-1003.19	-752.58	-266.99	6.94	6.94	6.94	-0.83
140	120	260	-1159.75	-912.33	-401.37	-68.89	17.95	17.95	2.67
150	130	290	-1316.60	-1044.08	-525.05	-182.76	-32.31	41.10	10.92
160	140	310	-1468.14	-1181.42	-634.20	-286.15	-129.03	71.27	26.42
170	150	330	-1577.84	-1291.08	-742.88	-384.12	-217.96	36.58	50.54
180	160	350	-1653.31	-1413.92	-869.66	-467.08	-294.37	-17.55	82.09
190	170	370	-1705.33	-1486.52	-974.31	-564.30	-355.62	-55.80	118.06

S: Own computations based on 10,000 simulated accumulated return paths using the Bayesian linear normal model for each crop. The insured bundle covers 11 metric tons of wheat, 18 metric tons of maize, and 1 metric ton of rape seed at the insured minimum prices per metric ton given in columns 1 to 3. Profits result from the premium income for the insured bundle based on insurance premium shown in Table 4.1 and losses result from payouts for the insured bundle if the forecasted price level at maturity T is below the insured minimum price. The 1 percent quantile of the loss distribution provides the information that a loss of this size or bigger occurs once every 100 years.

6. Robustness

The time series properties of log-returns in Table 2.1 indicate the prevalence of outliers. For this reason, we use an alternative stochastic volatility model with heavy-tailed innovations. The Student-t linear stochastic volatility model is described in *Kastner* (2015) and substitutes the normal distribution in the equation for the log-returns in the stochastic volatility model above by a Student-t distribution:

$$y_t \sim t_v(0, e^{h_t}),$$

with v degrees of freedom. This model has one additional parameter (v) to be estimated from the data. We use a uniform a priori distribution for $v \sim \mathcal{U}(2{,}100)$ providing upper and lower a priori bounds for the degrees of freedom of the t-distribution. The lower bound (2) provides a higher probability of outliers and the upper bound (100) brings about a t-distribution which is already close to the normal distribution (*Kastner*, 2015). Table 6.1 presents the results and shows that the estimates for the degrees of freedom parameter v are very low for wheat and maize, while the estimate of 13 for rape seed still indicates more than usual outliers. This confirms our conclusion that log-returns show excessively many outliers compared to a normal distribution.

The associated profit/loss distribution for this model is documented in Table 6.2 and shows a capital need for the bundle with the lowest minimum prices at the 1 percent ruin probability of 485 €, i. e. some 80 percent above the capital requirement under the normal distribution assumption.

Another possible extension of the stochastic forecasting model would be to add autocorrelation of the log-returns to the normal linear stochastic volatility model. The equation for the log-returns in the stochastic volatility model above changes to

$$y_t \sim N(0 + \beta y_{t-1}, e^{h_t}),$$

with β showing the degree of autocorrelation in log-returns. We use a flat a priori distribution for this parameter $\beta \sim N(0{,}10000)$ with zero mean. Given low autocorrelation coefficients of -0.06 (wheat), -0.03 (maize), and -0.002 (rape seed) this prior fits well with the time series properties of log-returns. Table 6.3 shows the estimates for this model, which are close to the estimates of the normal linear stochastic volatility model. The 1 percent quantile for the first minimum price bundle in Table 6.3 shows a loss of 433 € or more per bundle, i. e. 60 percent of the value generated by the normal linear stochastic volatility model.

Our results for alternative specifications of the mean process show that deviations from a Gaussian log-return process result in higher losses for given levels of the ruin probability. A possible insurer would have to take this margin into account, when computing the premium level and providing the solvency capital. Nevertheless, high solvency capital requirements under non-Gaussian assumption can also be avoided by actively hedging the insurance portfolio on derivatives market.

Table 6.1: Estimation results for Bayesian normal linear models with stochastic volatility for log returns of wheat, maize, and rape seed nearby futures

Parameter	Mean	Standard deviation	Quantiles 0.05	0.5	0.95	ESS
			Wheat			
μ	-10.19	0.26	-10.62	-10.19	-9.77	2699
φ	0.99	0.00	0.98	0.99	0.99	164
σ	0.26	0.03	0.22	0.26	0.31	76
exp(μ/2)	0.01	0.00	0.01	0.01	0.01	2699
σ^2	0.07	0.01	0.05	0.07	0.09	76
ν	2.80	0.15	2.56	2.80	3.07	269
			Maize			
μ	-10.37	0.16	-10.64	-10.37	-10.11	2286
φ	0.97	0.01	0.95	0.97	0.98	105
σ	0.36	0.04	0.30	0.36	0.42	66
exp(μ/2)	0.01	0.00	0.00	0.01	0.01	2286
σ^2	0.13	0.03	0.09	0.13	0.18	66
ν	3.18	0.21	2.86	3.17	3.55	172
			Rape seed			
μ	-9.90	0.13	-10.08	-9.92	-9.67	15.4
φ	0.92	0.07	0.76	0.95	0.98	3.6
σ	0.32	0.19	0.16	0.23	0.70	3.4
exp(μ/2)	0.01	0.00	0.01	0.01	0.01	15.4
σ^2	0.13	0.16	0.02	0.05	0.48	3.4
ν	12.52	20.00	3.81	4.34	67.13	7.5

S: Estimation based on Bayesian normal linear model with AR(1) stochastic volatility using R-package stochvol (*Kastner*, 2016). ESS shows the effective sample size.

Table 6.2: Profit and loss distribution for bundles of crops at selected insured minimum prices (Student-t linear model)

Insured minimum price level: Wheat	Maize	Rape seed	Lower quantiles of the profit/loss distribution: 0.01%	0.10%	1%	5%	10%	25%	Mean profit of insured bundle
€ per metric ton			€ per insured bundle						
130	110	240	-1339.81	-1073.90	-484.92	-0.55	0.01	0.01	-14.77
140	120	260	-1480.86	-1210.92	-616.71	-139.00	0.11	0.11	-23.43
150	130	290	-1606.12	-1421.67	-767.46	-284.65	-70.49	1.14	-37.09
160	140	310	-1743.00	-1564.44	-919.00	-422.71	-210.39	5.48	-55.49
170	150	330	-1990.74	-1751.25	-1070.18	-560.61	-340.53	-39.07	-72.20
180	160	350	-2201.79	-1923.76	-1225.17	-687.19	-451.85	-131.73	-74.93
190	170	370	-2372.91	-2094.89	-1329.33	-780.46	-543.88	-190.10	-53.82

S: Own computations based on 10,000 simulated accumulated return paths using the Bayesian linear normal model for each crop. The insured bundle covers 11 metric tons of wheat, 18 metric tons of maize, and 1 metric ton of rape seed at the insured minimum prices per metric ton given in columns 1 to 3. Profits result from the premium income for the insured bundle based on insurance premium shown in Table 4.1 and losses result from payouts for the insured bundle if the forecasted price level at maturity T is below the insured minimum price. The 1 percent quantile of the loss distribution provides the information that a loss of this size or bigger occurs once every 100 years.

Table 6.3: Estimation results for Bayesian normal linear models with stochastic volatility for log returns of wheat, maize, and rape seed nearby futures

Parameter	Mean	Standard deviation	Quantiles 0.05	0.5	0.95	ESS
			Wheat			
μ	-9.70	0.10	-9.87	-9.70	-9.54	1207
φ	0.86	0.01	0.84	0.86	0.88	286
σ	0.92	0.06	0.83	0.92	1.03	110
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	1207
σ^2	0.85	0.12	0.68	0.84	1.06	110
			Maize			
μ	-9.98	0.10	-10.14	-9.98	-9.82	2813
φ	0.87	0.01	0.85	0.87	0.88	497
σ	0.88	0.04	0.81	0.87	0.94	263
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	2813
σ^2	0.77	0.07	0.66	0.77	0.89	263
			Rape seed			
μ	-9.67	0.05	-9.75	-9.67	-9.59	2811
φ	0.78	0.02	0.74	0.78	0.81	287
σ	0.68	0.03	0.63	0.68	0.74	259
$\exp(\mu/2)$	0.01	0.00	0.01	0.01	0.01	2811
σ^2	0.47	0.05	0.40	0.47	0.55	259

S: Estimation based on Bayesian normal linear model with AR(1) stochastic volatility and AR(1) in log-return equation using R-package stochvol (*Kastner*, 2016). ESS shows the effective sample size.

7. Conclusions

In 2005 the EU lowered the guaranteed minimum prices for crops in its Common Agricultural Policy and stopped market interventions. Consequently, prices started to fluctuate more intensively, and farmers' incomes are now subject to higher price volatility. US-farmers are more familiar with this phenomenon because US-crop prices fluctuate since the beginning of the 1970s and financial markets offer a rich set of agricultural derivatives. Moreover, the US-government provides a margin insurance scheme to US-farmers. Although, agricultural futures and options are also available on Euronext, most European farmers operate small scale family farms and do not use financial derivatives.

A crop insurance scheme could provide an interesting alternative to European farmers by reducing income risk resulting from extremely low prices without requiring financial literacy and continuous market observation. Contrary to derivative markets, insurance contracts may cover minimum prices which are substantially below the current spot price. We develop a hypothetical insurance contract for a bundle of wheat, maize, and rape seed prices that can be bought before the start of the planting season and that matures after the end of the harvesting season. We compute the premium per metric ton by applying a commodity option pricing formula and compute the associated variance measure from Monte Carlo simulated forecasts of a Bayesian normal linear model with autoregressive stochastic volatility. The resulting net premium levels for bundles of low minimum prices are also small in comparison to the spot prices prevailing at the date of buying insurance. The gross insurance premium would have to be recharged by adding costs of capital, administrative and distribution costs as well as taxes.

This model also provides us with the basis to compute the profit/loss distribution for several insurance bundles defined by various bundles of minimum prices. The results show, that even for prices far below the spot price at the time of buying the insurance contract, the required solvency capital to keep the insurance business afloat at the one percent ruin probability is comparatively high and causes capital costs which are considerably above the expected profit of an insured bundle. Another caveat is the cross-correlation among log returns of nearby futures prices in our sample. Our univariate stochastic forecast models do not consider these cross-correlations and therefore our estimates of the required solvency capital may be at the lower bound. Combining our approach with a multivariate stochastic volatility model would be fruitful avenue of future research.

One alternative to holding large amounts of solvency capital is to start hedging the insurance portfolio with options on the derivative market if the spot price approaches the insured minimum price. Nevertheless, the insurer would need some capital if it pursues a hedging strategy; the solvency capital requirement would then be the price of an option with a strike price close to the current spot price.

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