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Developing a Moving Average Crossover Strategy as an Alternative Hedging Strategy for the South Africa Maize Market

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Abstract: Grain marketing is complex because important decisions are made on the timing of sales and the quantities sold at every trading activity. The literature suggest various grain-hedging strategies, however these strategies are not adaptable to changing market conditions or are difficult for a producer to implement. To address these limitations, our study developed tailor-made moving average crossover (MAC) strategies that are adaptable to changing market conditions and can be easily followed by risk neutral and risk averse grain producers. The study used daily closing prices for the white maize May futures contract for the period 2009/2010 to 2019/2020. An optimization model was solved using the evolutionary algorithm embedded in Excel® to identify the optimal MAC strategy that maximizes the margin above marketing cost for a risk aversion level. The results showed that optimal MAC strategies differ amongst producers with different levels of risk aversion. Furthermore, it was found that the risk-averse producers perform best by marketing their grain early in the marketing season. Meanwhile, the risk-neutral producers perform better by spreading their marketing activities throughout the season. The results further showed that the optimal MAC strategies performed better than the previously proposed routine strategies. The conclusion is therefore that an optimal MAC strategy outperforms routine strategies because of its ability to adapt to changing market conditions, while still being easy to implement.

Keywords: technical analysis; maize; South Africa; marketing strategies; agricultural derivatives market

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1. Introduction

South Africa is the 10th largest maize producer in the world and the largest in Africa (calculated based on data obtained from the United States Department of Agriculture (USDA)). Within an African context, South Africa plays an important role in ensuring food security in the Southern African Development Community (SADC). On average, about 53% of the SADC's total maize imports originate from South Africa, with the imports for 2020 and 2021 amounting to 67% and 64%, respectively [1]. The profitable production of maize in South Africa is perceived as important to ensure that South Africa remains a net exporter of maize to the SADC.

Since the deregulation of the South African agricultural markets in 1996, the producers are operating in a free-market system where prices are determined by local and international demand and supply. The commodity prices can vary widely in the free market, and producers must select the best marketing strategy for price risk management. Derivative instruments, such as options and futures, were developed to manage the price risk in the commodity markets, such as precious metals [2], energy commodities [3,4] and agricultural commodities [5,6]. Grain marketing strategies that use derivative contracts can assist grain producers in receiving the best possible prices for their crops, while reducing price risk [7]. Optimal grain marketing is also crucial for producers' financial sustainability, since one wrong marketing decision can counteract the good production decisions made throughout the production season. Jordaan [8] found that most of the producers in South Africa do not use pre-harvesting marketing strategies, which is consistent with recent research by Michels et al. [9], who found a limited adoption of futures contracts by agricultural producers to manage price risk. Meanwhile, Venter et al. [10] argued that complex strategies discourage producers from using pre-harvest marketing strategies, since producers do not know how to apply these complex strategies. More straightforward strategies, such as routine and portfolio hedging, have been proposed as an alternative to these complex marketing strategies.

The literature on the routine hedging strategies in the grain crop market has shown contradictory results. Some of the researchers found that the grain hedging strategies result in significant economic returns. An example of such profitable strategies include routinely shorting with a put option at plant [10,11], strategies that use options and futures combined [12], pre-harvest futures contracting [13,14] and pre-harvest options contracting [15]. The pre-harvest hedging portfolios, consisting of futures and options, have also been found to be favorable [16]. On the other hand, Zulauf et al. [17] found that routine hedging strategies have a limited ability to enhance returns, while Hunter [18] showed that the futures prices often yield lower prices than daily spot prices after adjusting for an arbitrage bound. The contradicting results suggest that the effectiveness of pricing strategies to increase the expected returns and reduce the variability of these returns are location, commodity and marketing-year specific.

A common drawback of the above routine hedging strategies is that the unfolding market information is not considered in the decision to sell during the marketing year. Technical analyses of unfolding market information are frequently used by the marketing experts to inform marketing decisions. Geldenhuys [19] and Dreyer [20] used composite technical indicators to compile a technical indicator system, where a marketing decision is made when all of the underlying indicators generate the same trading signal. The technical indicators included by Geldenhuys [19] and Dreyer [20] include the Relative Strength Index, Stochastic Oscillator, Commodity Channel Index, Moving Average Convergence Divergence and Exponentially Weighted Moving Average. However, it can be argued that the pricing strategies based on these sophisticated technical indicators are too complex for producers to understand, and therefore will not be adopted by producers. The moving average crossover (MAC) pricing strategy is a less complex strategy that is easily understood by decision-makers, since it uses the activity of two simple moving averages to inform buying or selling decisions during the marketing year [21–25]. Furthermore, several researchers have demonstrated the potential of the MAC pricing strategy to dominate other strategies [23–25]. The MAC pricing strategy is, however, seldom applied by grain producers to inform the grain marketing decisions.

Applying the MAC pricing strategy within your marketing plan can be difficult, since the producer does not know how many trading signals will be generated within a specific marketing year. Not knowing the number of trading signals further complicates the decisions regarding the quantity sold. Knowing the optimal distribution of crop sales during the marketing year is important, since it has a significant bearing on the variability of the profit margins of a marketing strategy.

The main objective of this research is to develop an effective marketing strategy (both in terms of quantity of produce sold and timing of sales) that could be routinely implemented to produce consistent results in relation to the decision-makers' risk tolerance, while considering the dynamic environment within a marketing year. The objective is achieved using evolutionary optimization to determine the optimal MAC combination that defines the timing of sales and the optimal quantity of produce sold at each trading signal for a utility-maximizing producer with a specific risk-aversion level. The research is unique because the MAC combination and the quantity of produce sold at each trading signal are uniquely defined for a decision-maker with a specific risk tolerance for the MAC marketing strategy. The superiority of the MAC marketing strategy is demonstrated by comparing the strategy with several other marketing strategies.

The rest of the paper is organized as follows: Section 2 describes the data and methodology used in the study; Section 3 presents the results, Section 4 the discussion and Section 5 concludes the research.

2. Data and Methods

2.1. Data

The data used in the analysis are the daily closing prices for white maize May futures' contract prices that were obtained from the Johannesburg Stock Exchange (JSE) and the South African Grain Information Service (SAGIS). The first trading day in a given marketing year is assumed to be the first business day in October, whereas the last trading is on the sixth last business day in May in the following year. The authors initially intended to investigate 24 marketing years from 1996/1997 to 2019/2020. However, historical volatility is only available for the last 11 marketing years. Consequently, all of the analyses were completed using the marketing years ranging from 2009/2010 to 2019/2020, to make it a fair comparison between the PUT strategy that uses the historical volatility and the other marketing strategies. Since this study only focuses on the pre-harvest data, June, July, August and September were omitted from every marketing year. The Consumer Price Index obtained from Statistics South Africa [26] was used to deflate the nominal prices, using 2020 as a base year.

Figure 1 shows the octiles for the May futures contract over time, to determine the probability of the distribution of prices for the 11 marketing years. The octiles divide the cumulative probability scale into eight equal subsets. A specific octile indicates the probability of sampling a price that is less than the price associated with the octile. For example, in Figure 1, O50 fluctuates around R2900/ton, indicating that 50% of the prices lie below the R2900/ton level. O87.5 fluctuates around R3500/ton. Therefore, there is only a 12.5% chance that the prices will be above the R3500/ton price level. The extremely high prices above R5250/ton are the direct result of a short supply of maize, caused by one of the worst droughts ever recorded in South Africa during the 2015/2016 marketing year. Interestingly, the maximum prices of the low octiles (O25 and below) reach their maximum before the 10th of December. A downward trend is observed, with small differences between the upswings and downswings in the prices for the rest of the marketing season.

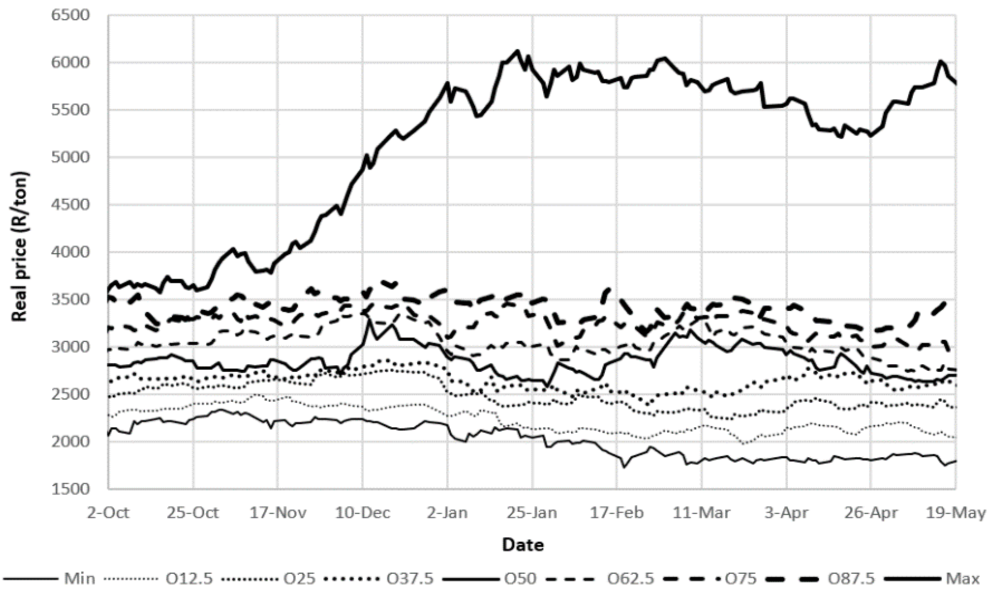

Figure 1. Octiles of the real prices for the May futures contract over the 11 marketing years (base year is 2020). Source: Data adapted from SAGIS data.

2.2. Marketing Strategies and Risk Quantification

A marketing strategy is defined by two decisions. First, a decision needs to be made on the timing and prices of the sales, as determined by the pricing strategy. Secondly, the amount of crop produce that will be sold at the specified time and price needs to be determined. The margin above marketing cost (MAMC) of a marketing strategy is quantified using empirical distributions of the realized prices of a specific pricing strategy multiplied by the quantity of maize sold at the realized prices in each of the marketing years minus the marketing costs. The routine marketing strategies include a PUT option marketing strategy, that requires daily price volatility information. The historical volatility information was only available for the last eleven marketing years. The MAC marketing strategy is compared to all of the other routine strategies, using the last 11 years of data to characterize the MAMC to ensure that all of the strategies' marketing conditions are the same.

Next, the alternative marketing strategies are discussed.

2.2.1. Moving Average Crossover (MAC) Marketing Strategy

A moving average is a standard technical analysis tool that smooths out the price data by creating a moving average price based on a specific number of historical prices. The simple moving average is one of the most widely used technical indicators and is calculated by:

$$SMA_k^n = \frac{1}{n} \sum_{t=k-n+1}^{k} P_t \tag{1}$$

where:

SMA_k^n—n-day simple moving average at position k in the time series;

P_t—price at day t.

A single moving average on its own does not provide a signal to trade. The MAC pricing strategy uses a combination of two simple moving averages to generate the selling signals of futures contracts. The futures contracts are standardized, transferrable, exchange-traded contracts that involve the delivery of the commodity at a specified price and date in the future [27]. Upon the expiration of a futures contract, the producer is required to deliver the agreed amount of quality grain to the agreed location in exchange for the agreed price. The MAC pricing strategy places a short hedge when the shorter-day moving average ($n = short$) crosses the longer-day moving average ($n = long$) from above [15–17]. A selling signal is triggered with the MAC pricing strategy when the following conditions are met:

$$SMA_k^{n=short} > SMA_k^{n=long} \text{ and } SMA_{k+1}^{n=short} < SMA_{k+1}^{n=long} = Sell \tag{2}$$

Figure 2 illustrates the principle behind the MAC pricing strategy, where a trading signal is generated when the shorter-day moving average ($SMA_k^{n=short}$) crosses the longer-day moving average ($SMA_k^{n=long}$) from above.

The timing of the selling signals is dynamic and dependent on the number of periods (n) included in the calculation of the longer-day and shorter-day moving averages, and the price time-series itself. Consequently, the number and timing of the trading signals generated by a specific MAC pricing strategy will differ between the different marketing years, complicating the decisions regarding the quantity sold at each trading signal. A standard maize futures contract on the Agricultural Products Division of the JSE represents 100 tons of maize. The assumption was made that 1000 tons of maize would be produced in a given marketing year, and therefore a maximum of 10 futures contracts can be sold on the futures market. The assumption was further made that the same number of contracts would be sold consecutively in each marketing year, to produce an implementable marketing strategy. Furthermore, the longer-day and shorter-day moving averages that define the MAC pricing strategy are also the same between the marketing years. The study also assumed that there are only marketing costs when marketing through the futures market and that there are no marketing costs when selling on the spot market. The marketing costs of futures contracts were assumed to be R30/ton, based on R15/ton to open a futures position and R15/ton to close out the same position.

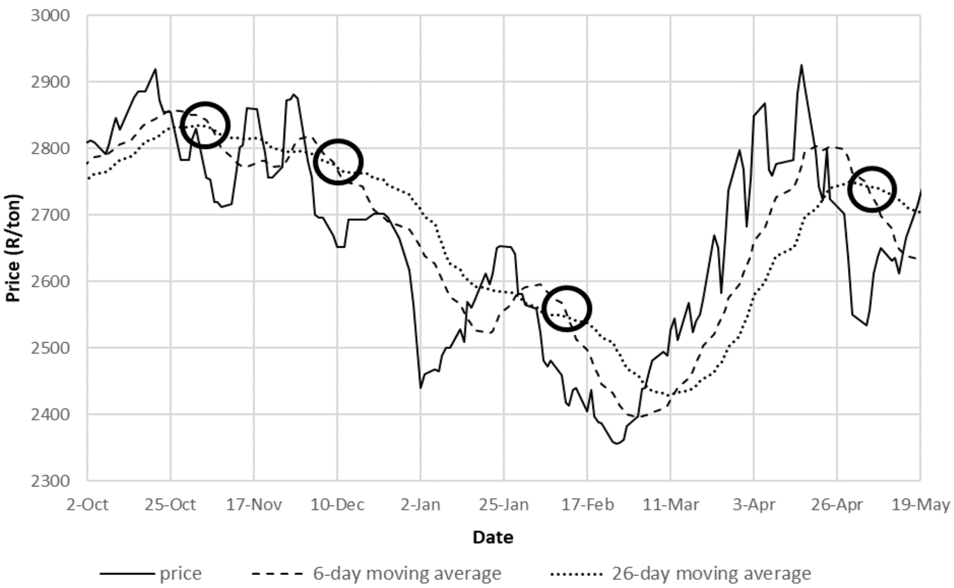

Figure 2. Trading signals generated by a moving average crossover pricing strategy for the 2019–2020 marketing year. Source: Author's compilation.

The MAC marketing strategy allows the producer to decide upon the moving averages that define the timing of the crop sales and the number of maize contracts sold at each signal to maximize the profit margins. Determining the optimal longer-day and shorter-day moving averages and the number of contracts sold for a risk-averse producer that wants to maximize his profit margins is difficult, due to the discontinuous nature of the problem. The optimization problem was simplified by generating selling signals for 435 combinations of 1 to 29-day shorter moving averages and 2 to 30-day longer moving averages for each marketing year. The optimal quantity of the contracts sold for each of the 435 MAC combinations was optimized, with the following risk optimization model:

$$Max\ CE = ln\left\{\left(\frac{1}{R}\sum_{r}^{R} e^{-r_a MAMC_r}\right)^{\frac{1}{-r_a}}\right\} \tag{3}$$

$$MAMC_r = \sum_{m}(p^f_{mr} - mc^f_{mr})C^f_m \times 100 + p^s_r C^s_r \tag{4}$$

$$C^s_r = 10 - \sum_{m} C^f_m \tag{5}$$

$$\sum_{m} C^f_m \leq 10 \tag{6}$$

$$-10C^f_m + C^f_{m+1} \leq 0 \tag{7}$$

where:

CE—Certainty Equivalent (R);
$MAMC_r$—margin above marketing cost in year r (R);
mc^f_{mr}— marketing cost associated with selling signal m in year r (R/ton);
p^f_{mr}—futures price associated with selling signal m in year r (R/ton);
C^f_m—integer indicating the number of futures contracts sold with selling signal m;
p^s_r— end of marketing season spot price in year r (R/ton);

C_r^s—integer indicating the number of contracts sold on the spot market in year r;
r_a—absolute risk aversion coefficient;
R—defines the size of the random sample.

The objective of the optimization model is to maximize the Certainty Equivalent (CE) of risk-averse decision-makers by changing the number of contracts that could be sold consecutively on the futures market for a specific MAC combination. The MAC pricing strategy with the highest CE out of the 435 MAC combinations is identified as the optimal MAC pricing strategy and, combined with the optimal number of contracts sold, defines the optimal MAC marketing strategy.

The distribution of $MAMC_r$ in Equation (4) is calculated as the product of the maize contracts sold on the futures market and the exogenously determined price distribution for the specific MAC combination being optimized, plus the income generated from the spot market sales minus marketing costs. It is important to note that the number of the contracts sold on the futures market is the same, irrespective of the state of nature (marketing year) occurring. Some of the years may have fewer marketing signals than others. In such cases, the number of the contracts not sold on the futures market are sold on the spot market in that specific year. Consequently, the defined MAC marketing strategy for a specific decision-maker could be implemented routinely each year.

Equation (5) restricts the number of the contracts being sold on the spot market to the quantity of maize contracts that were not sold on the futures market, while Equation (6) restricts the total number of contracts sold on the futures market to 10 contracts. Equation (7) ensures that futures marketing at a specific trading signal is allowed, on the condition that some of the contracts were sold at the previous trading signal to enforce consecutive trading.

A $r_a = 0$ indicates risk neutrality and corresponds to the maximization of the average MAMC. The value of r_a for risk-averse decision-makers was chosen to reflect a high level of risk aversion.

The model was implemented in Microsoft® Excel®, and the optimization model was solved using the evolutionary algorithm embedded in Excel®.

2.2.2. SPOT Strategy

The SPOT marketing strategy represents a situation where no active marketing is conducted throughout the production season. By following the SPOT strategy, the assumption is made that the producers will sell their total produce on the last trading day in May at the end of the harvest on the spot market. Furthermore, it was assumed that there are no marketing costs on the spot market, and thus the SPOT strategy quantified a gross production value instead of a MAMC value. The last trading day's closing price for the white maize futures contract in May will be used as the reference price received per ton to calculate the distribution of random gross production values generated with the SPOT strategy.

2.2.3. PLANT Strategy

The PLANT marketing strategy entails selling 10 May futures contracts after planting maize. The planting date used in this study will be the first business day in October. Thus, the reference price for selling the futures contracts at planting will be the futures' price of the white maize May futures contract on the first trading day in October.

2.2.4. PUT Option Marketing Strategy

The options contracts, like the futures contracts, are derivative instruments, with the only difference being that the option contracts derive their value from the underlying futures contract. On the other hand, the futures contracts derive their value from the underlying commodity. An option contract gives the holder the right but not the obligation to buy or sell a futures contract at a predetermined price during a specific period. There are two types of options contracts: calls and puts. A call option allows the option holder to purchase a futures contract at a specified price before or at a particular time. In contrast, a put option allows the holder to sell an asset at a specified price before a particular time. Hedging is seen as taking a position in the futures or options market opposite to the current position in the cash market. According to market terminology, the farmers are said to have a naturally long cash position, since they are in the business of producing the commodity. Thus, the current study will only focus on put options, since the underlying instrument of a long put option is a short futures contract.

Once the buyer exercises the put option contract, the buyer assumes the obligation to sell an underlying futures contract at a specific price, referred to as the strike price. The strike price of an option is the price at which a put or call option can be exercised. The strike price of the PUT strategy was assumed to be the white maize May futures contract price on the first trading day in October (at the money). Another aspect of the options trading that needs to be considered is the cost associated with an options contract, which is referred to as an option premium. The Black Scholes Model was used to calculate the option's premium, based on the underlying futures price (at the money) and historical volatilities obtained from SAGIS and the JSE.

2.2.5. THIRDS Strategy

The THIRDS marketing strategy entails selling the expected produce at three different dates in the production season in three equal quantities, using futures contracts. The first segment is sold when the crop is planted, the second segment is sold 115 days after the first segment, and the last segment is sold on the spot market when the crop is harvested.

2.3. Choice amongst Marketing Strategies

Stochastic Efficiency with Respect to a Function (SERF): Hardaker et al. [28] uses CEs to propose a strategy for risk-averse decision-makers by evaluating the CEs of the strategies over a range of risk aversion levels. The SERF strategy provides more discriminating power than stochastic dominance with respect to a function [29], and is considered more transparent and easier to apply because the CEs are measured in the same unit as the outcome variable of the marketing strategy. The negative exponential utility-function provides a reasonable approximation of the risk averse behavior of the decision-makers [28]. The function exhibits a constant absolute risk aversion, which implies that the outcome of the risk will have a relatively small impact on the wealth levels [30]. Consequently, the choices between risky prospects are based on dispersion of the risky prospect without considering the level of wealth [31]. The CE for a discrete distribution of random MAMCs associated with a specific marketing strategy is calculated as follows, for the negative exponential utility function [22]:

$$CE = ln\left\{ \left(\frac{1}{R} \sum_{r}^{R} e^{-r_a MAMC_r} \right)^{\frac{1}{-r_a}} \right\}. \tag{8}$$

where r_a is the level of absolute risk aversion and $MAMC_r$ represents the margin above marketing cost generated with a specific marketing strategy in marketing year r, while R defines the total number of marketing years. Larger r_a values indicate a higher degree of risk aversion compared to the lower values. The relationship between the risk aversion and CE is determined by evaluating Equation (8) over a range of r_a values. Repeating for different risky alternatives yields the relationship for several alternatives, where the preferred alternative at a specific level of risk aversion is the alternative with the larger CE.

Barry et al. [32] derived the value of r_a as a function of Z_α and σ under normality, as follows:

$$r_a = \frac{2Z_\alpha}{\sigma} \tag{9}$$

where Z_α is the percentile of an N(0,1) distribution and σ is the standard deviation of the risk. The upper level of r_a was chosen such that the confidence limit of 89% corresponds to the marketing alternative with the highest risk (σ). The confidence limit corresponds to $Z_\alpha = 1.25$ indicating very high levels of risk aversion [31].

3. Results

3.1. Optimal MAC Marketing Strategy

Table 1 shows the optimal MAC marketing strategies identified for a risk neutral and a risk averse decision-maker. The timing of the sales is determined by the crossover of the 26-day and 6-day moving averages (MAC 26-6) for risk-neutral producers and the 9-day and 1-day moving averages (MAC 9-1) for risk-averse producers. The optimal hedge ratio identified for the MAC 26-6 pricing strategy consisted of selling 100% of the expected produce on the futures market, with 20% sold with the first trading signal and 80% with the second signal. The MAC 9-1 marketing strategy entails selling 90% of the expected produce on the futures market, and the remaining 10% on the spot market at harvest. The 90% share sold on the futures market is divided by selling 10%, 30%, 40% and 10% on the first, second, third and fourth trading signals, respectively.

Table 1. Optimal moving average crossover (MAC) combinations and hedge ratios for risk-neutral and risk-averse producers' marketing strategies.

	Optimal Marketing Strategy	
	Risk-Neutral	**Risk-Averse**
Strategy	MAC 26-6	MAC 9-1
Moving average crossover combination		
Longer	26	9
Shorter	6	1
Futures market sales (%)		
1st trading signal	20	10
2nd trading signal	80	30
3rd trading signal	-	10
4th trading signal	-	40
Spot market sales (%)	-	10

Since the optimal MAC marketing strategies differ between a risk-neutral and risk-averse producer, the trading frequency and the dates where the trading signals occur will also be different between the two marketing strategies. The number of trading signals produced by the MAC pricing strategy is directly determined by the number of days used to calculate the moving average. In general, the longer moving averages are slower moving, making them less sensitive to short-term price movements than the short-term moving averages. The number of trading signals generated in each marketing year by the optimal MAC pricing strategies is given in Table 2. As expected, the MAC 26-6 strategy generated fewer trading signals over the 11 marketing years than the MAC 9-1 strategy. Therefore, the MAC 9-1 strategy can be considered a higher-frequency trading strategy and will consequently have higher marketing costs than the MAC 26-6 strategy.

The minimum number of trading signals generated with the MAC 9-1 marketing strategy for the risk-averse decision-maker is eight. Ensuring that the MAC marketing strategies could be routinely implemented across the different marketing years requires consecutive sales throughout the marketing year. A risk-averse decision-maker will therefore sell 90% of his produce during the first four selling signals, while ignoring the other signals produced thereafter. The rest of the crop (10%) will be sold at harvest.

Table 2. Trading frequency for optimal moving average crossover (MAC) pricing strategies for risk-averse and risk-neutral decisions makers over the 11 marketing years.

Marketing Year	Number of Trading Signals Generated	
	MAC 26-6	MAC 9-1
2009/2010	4	16
2010/2011	6	12
2011/2012	4	10
2012/2013	4	16
2013/2014	4	15
2014/2015	3	14
2015/2016	2	14
2016/2017	3	11
2017/2018	3	13
2018/2019	4	9
2019/2020	6	8
Minimum	2	8

Figures 3 and 4, respectively, show the timing of the sales for the MAC 26-6 and MAC 9-1 marketing strategy to determine whether an optimal marketing window can be identified for a risk-neutral and risk-averse producer. Figure 3 shows that the MAC 9-1 pricing strategy's marketing window started on the 10th of October and generated most of the trading signals before the 10th of December (the first trading day in a given marketing year is assumed to be the first business day in October, whereas the last trading day is on the sixth last business day in May in the following year). Therefore, the producer would conduct most of his marketing activities early in the production season. Figure 1 shows that the lower octiles started to follow a downward trend after the 10th of December. Consequently, the downside risk increased from this point to the end of the marketing year. A risk-averse producer will attempt to minimize exposure to downside risk, and thus will do better by performing his marketing activities earlier in the marketing season.

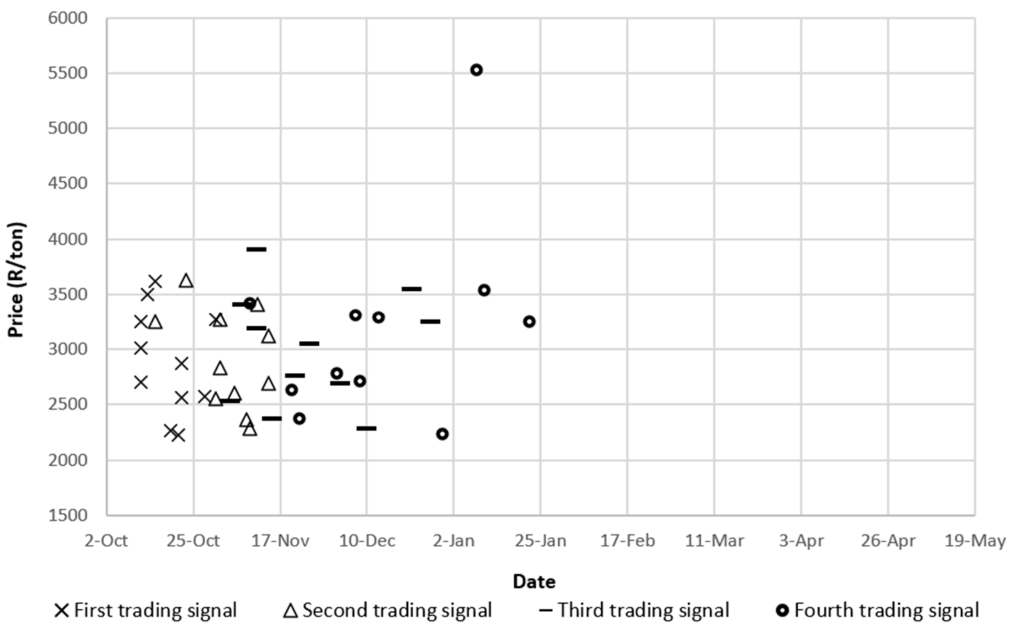

Figure 3. Timing of sales during the 11 marketing years for a risk-averse decision-maker using the MAC 9-1 marketing strategy. Source: Author's compilation.

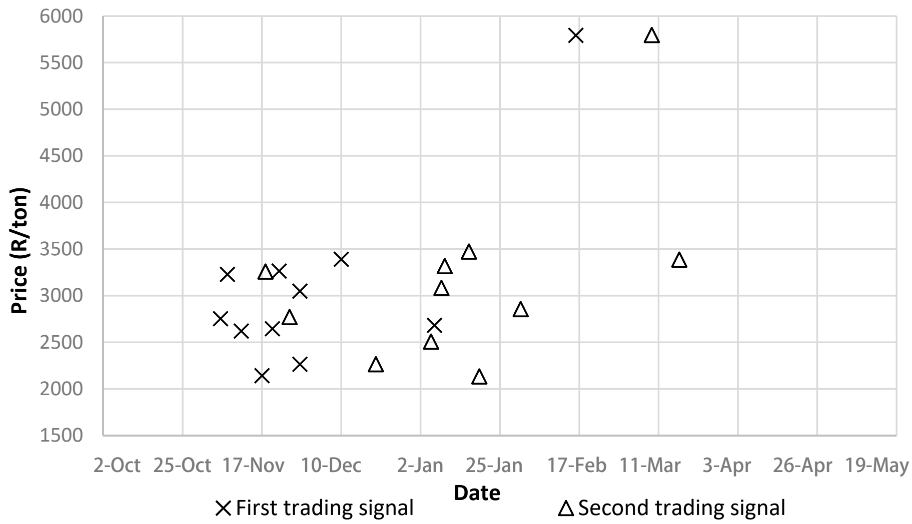

Figure 4. Timing of sales during the 11 marketing years for a risk-neutral decision maker using the MAC 26-6 marketing strategy. Source: Author's compilation.

Figure 4 shows that a risk-neutral decision-maker will begin trading his maize on the 5th of November. The timing of the sales for the MAC 26-6 marketing strategy is more spaced out across the 11 marketing seasons than the MAC 9-1 pricing strategy. Since the timing of the sales of the marketing strategy is more dispersed, a distinct optimal marketing window cannot be identified as with the MAC 9-1 strategy. Such behavior is rational for a risk-neutral decision-maker, who wants to increase the average MAMC.

The historical prices show a significant increase in the maximum prices from the 17th of November. Thus, a risk-neutral decision maker will start selling later to capture the possible price increases, even though the downside risk increases from the 10th of December to the end of the marketing year.

The distributions of MAMC associated with the MAC marketing strategies for a risk-averse and risk-neutral decision-maker are shown in Figure 5. The MAC 9-1 strategy has the highest minimum value, which is expected since a risk-averse producer favors the investments that give a guaranteed minimum return over the possibility of higher-than-average returns.

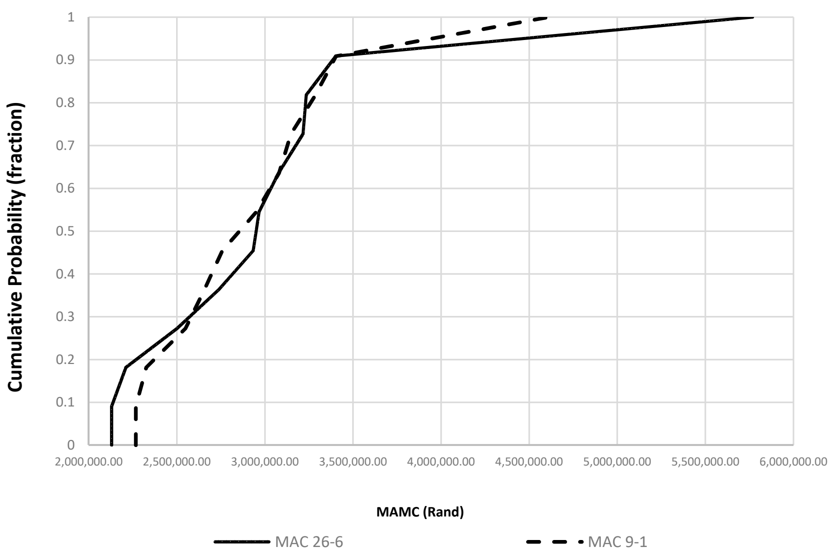

Figure 5. Cumulative probability distribution for optimal moving average crossover (MAC) marketing strategies for risk-averse and risk-neutral decisions makers over the 11 marketing years. Source: Author's compilation.

On the other hand, the MAC 26-6 marketing strategy has the lowest minimum but dominates the MAC 9-1 strategy at higher probabilities. The higher MAMC values obtained by the MAC 26-6 strategy are an indication that a risk-neutral producer is willing to make decisions solely based on maximizing the expected value of his MAMC.

3.2. Optimal MAC Marketing Strategy Performance

The performance of the MAC strategies is evaluated and compared to the previously proposed routine strategy from a risk efficiency point of view by applying the SERF method. Figure 6 summarizes the risk efficiency of the alternative maize marketing strategies for absolute risk aversion levels in the range of risk-neutral (r_a = 0) to risk-averse (r_a = 0.00002333).

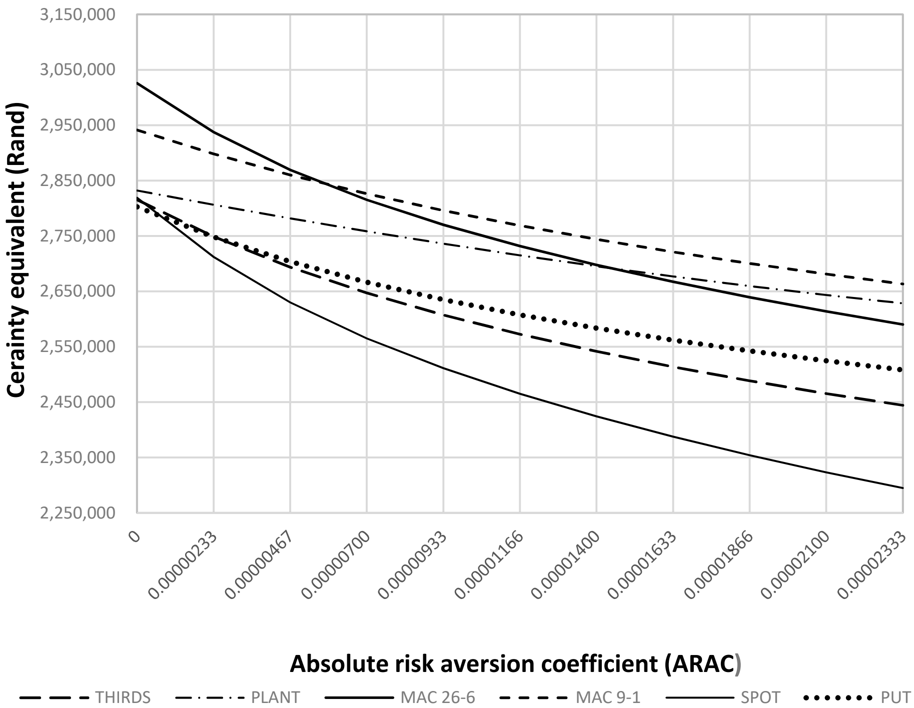

Figure 6. Stochastic efficiency ranking of the alternative marketing strategies. Source: Author's Compilation.

A marketing strategy is more risk-efficient than another if the strategy has a higher CE for a decision-maker with a specific risk aversion level. Figure 6 shows that the locus of the CEs that define the SERF efficiency frontier are based on the MAC 26-6 and MAC 9-1 marketing strategies. The MAC 26-6 strategy is considered superior for producers with risk-aversion levels below r_a = 0.000005832, since the MAC 26-6 has higher CEs across the range of risk aversion levels. On the other hand, the MAC 9-1 strategy is the preferred marketing strategy for decision-makers with ARAC levels above r_a = 0.000005832. The SERF results indicated that the THIRDS, PLANT and PUT strategy would not be preferred by risk-averse decision-makers.

The risk premiums were used to assess the decision-makers' confidence in a specific preferred marketing strategy. The risk premiums were calculated as the vertical distance between the strategies defining the SERF efficiency frontier and a specific, less preferred strategy. The risk premiums represent the minimal amount with which a decision-maker would have to be compensated to justify switching from one of the optimal MAC strategies to one of the less preferred routine strategies. Conversely, the risk premiums can also be interpreted as the benefits to the decision-maker if allowed to switch from one of the less preferred routine marketing strategies to one of the optimal MAC strategies. The risk premiums in Figure 7 for the ARAC levels below r_a = 0.000005832 were determined as the vertical distance between the MAC 26-6 strategy and the routine strategies, since the

MAC 26-6 strategy had the greatest CE values below r_a = 0.000005832 in Figure 6. The risk premiums for the ARAC levels above r_a = 0.000005832 were determined as the vertical distance between the MAC 9-1 strategy and the routine strategies in Figure 6.

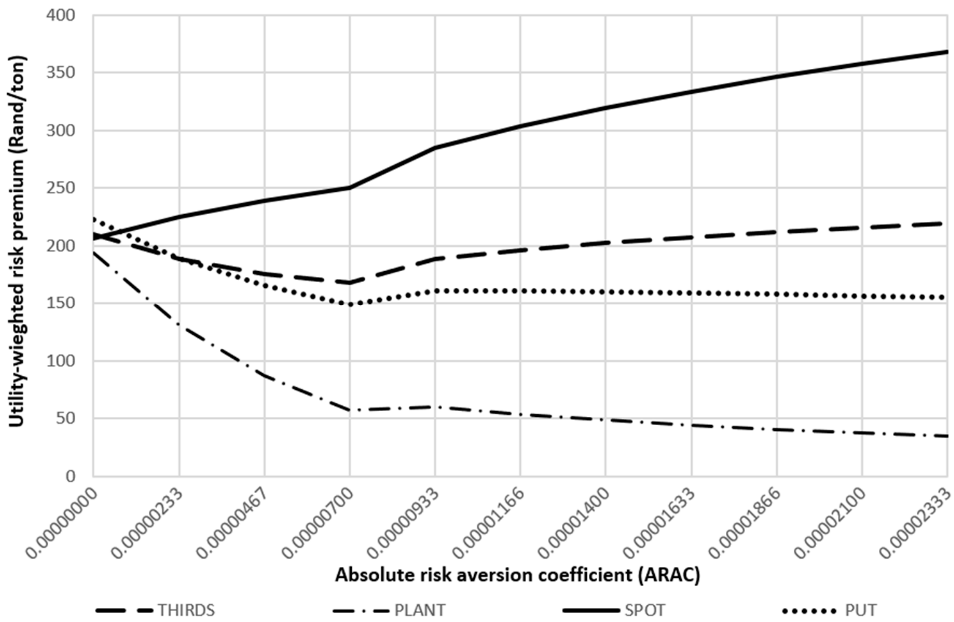

Figure 7. Utility weighted premiums between the efficient frontier moving average crossover (MAC) strategies and less preferred routine hedging strategies. Source: Author's compilation.

Figure 7 shows that when the risk aversion levels increase, the producers are willing to pay more to avoid selling maize on the spot market at harvest. The producers are willing to pay between R225/ton (r_a = 0.00000000) up to R368/ton (r_a = 0.00002333) to avoid selling on the spot market. The premiums for the PUT and THIRDS strategy did not vary as much as the premiums for the PLANT and SPOT strategy. The PUT strategy's premiums ranged from R148/ton to R223/ton, while the premiums for the THIRDS strategy ranged from R167/ton to R219/ton. It is worth noting that the PLANT strategy had the lowest risk premiums, reaching levels below R50/ton for ARAC levels above r_a = 0.00001400. The lower risk premiums associated with the PLANT strategy further validate our findings in Figure 3, that the risk-averse producers will perform best by performing their marketing activities early in the marketing season.

4. Discussion

The results from our study confirms the results obtained by Venter et al. [10], which show that the PUT strategy outperforms the THIRDS and SPOT strategies, even when our analyses are completed using a different time period to quantify the price risk. Our newly proposed PLANT strategy outperformed the PUT strategy, while the MAC strategies for risk neutral and risk averse decision-makers outperformed all of the marketing strategies.

The optimal MAC combination identified for the risk averse decision-maker uses relatively short moving averages to identify the selling signals, which is in line with the research of Kenyon and Cooper [24] and Querin and Tomek [25]. The relatively short moving average combinations generate many trading signals. Querin and Tomek [25] identified too many trading signals as an undesirable property and evaluated a longer longer-day MAC strategy to reduce the number of trading signals without trying to identify the optimal MAC combination. Our results showed that the shorter MAC combination generates as many as 16 trading signals in a specific year. However, when combined with the optimal number of contracts sold at each trading signal, the total number of trades is reduced to four consecutive sales on the futures market, and one on the spot market at the end of the season.

The research by Cass [7] and Dreyer [20] indicated that the prevailing marketing conditions have a bearing on the best marketing strategy to be followed to manage the price risk. Our MAC marketing strategy was developed so that it will perform better than the other routine marketing strategies, irrespective of the marketing conditions. Consequently, our MAC marketing strategy will be sub-optimal compared to a MAC strategy developed for a decision-maker with a specific risk preference while considering specific marketing conditions. The effectiveness of the MAC marketing strategy could be improved by developing MAC strategies for bullish, bearish and consolidating markets.

5. Conclusions

The main conclusion is that the optimal MAC strategies developed for producers with varying degrees of risk aversion outperforms the routine strategies, because of its ability to adapt to the changing market conditions based on the risk preferences of the decision-makers while still being easy to implement. The results showed that the producers with different risk attitudes should follow different MAC strategies, as is evident from the marketing window identified for risk averse and risk neutral producers. The risk averse producers should market earlier in the production season, while the marketing activities of the risk neutral producers should be spread throughout the season. The conclusion is, therefore, that the producers' risk attitudes should be explicitly considered when developing the marketing strategies, which is in direct contrast to the norm where the marketing strategies are developed and then followed by determining the suitability thereof for risk averse decision-makers.

The current study uses 11 years to quantify the marketing risk on which the MAC strategies were developed. Future research could evaluate the robustness of the MAC strategies under the market conditions that were not considered when the strategies were developed. A limitation of the paper is that historic price data were used to develop the MAC strategies, without the consideration of alternative market conditions. The literature has shown that different marketing strategies should be used to take advantage of different market conditions. The future research could develop an optimal MAC strategy that is not only tailored to risk attitudes, but also for the different market conditions. The paper relied on simple moving averages to develop the optimal MAC strategy. The approach determines the arithmetic mean for a predefined period (previous x number of days). However, more advanced moving averages exist which consider longer periods and place more importance on recent prices. The future research could investigate the use of more advanced moving averages, such as the exponential moving average, smoothed moving average and linear weighted moving average. The paper used South African white maize price data to develop the MAC strategies, however the methods can be used to determine an optimal MAC strategy for any commodity in any country.

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