Trading of White Maize/Witmielies July
Domestic Future Prices Utilizing Entropy Analytics

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Abstract

This paper examines the effectiveness of Entropy Analytics on trading of the South African July domestic futures market for white maize traded on the South African Futures Exchange (SAFEX). This contact has been subjected to numerous market timing trading methods. The contract has not been subjected to an analysis utilizing Entropy. The definition of entropy has been expanded to the measurement of randomness and disorder. This study tested the contract by Sample Entropy.(SaEn) as a trading strategy for the period 2007-2017. The objective behind the study was to facilitate a new market timing technique by introducing a relatively un-tested investment methodology that could be pragmatically utilized in domestic commodity management of South African portfolios. The study found favorable results for such a trading strategy.

1. Introduction

This paper examined the effectiveness of Entropy Analytics on trading of the South African July domestic futures market for white maize traded on South African Futures Exchange (SAFEX). Entropy based investment methods have been developed for market timing and currency prediction models with relatively positive results (Efremidze, Stanley, & Kinsman, 2015; Efremidze, DeLillio, & Stanley, 2014). The entropy statistic is one of the ways that complex systems' statistical properties can be studied. Recent studies found power law properties in financial market behavior, which is a feature of complex systems (Maasoumi & Racine, 2009). Entropy is one of the statistical measurements that characterizes complex systems

White maize is an agricultural commodity of signal importance to the South African economy from the farm producer through the chain to feedstock (albeit limited) through to the consuming public. White maize is a particular important crop since it is a dietary stable. The futures market is an important link for farmers in South Africa who must contend with low profit margins and price volatility. The futures markets enhance the tools available to all major players of white maize.

The futures market for white maize has a large number of contract maturities. It is therefore important that contract dates are of high importance. Previous research (Jordaan and Grove) has identified the July contract of extreme importance in South Africa. They have noted that these contracts have higher price variability from December to early May. The release of new information on local and international growing conditions explains the importance of the July futures. July also follows the conclusion of the South African harvesting season. This makes marketing decisions more important and places pressure on financial decision making to accomplish firm goals. Further adding complexity to such decision making is the presence of domestic arbitrage possibilities as noted by Van der Wath.

This paper focused on only one type of financial contract: the July white maize. This contact, as well as other time dated contracts, has been subjected to numerous market timing trading methods. The contract has not been subjected to an analysis utilizing Entropy. This paper will examine the July White Maize/corn contract utilizing Sample Entropy.(SaEn). Commodity future contracts are by their nature finite in time. For example, the July 2017 contract commenced trading on the SAFEX on January 13, 2016 at 3500 and ended June 30, 2017. The test period will be from the previous year's July contract concluding on the final day of the trading of that contract. The study covered a ten year period (2007-2017). Price data was downloaded from the sagis.org.za website. The objective behind the study is to facilitate a new market timing technique by introducing a relatively un-tested investment methodology that could be pragmatically utilized in domestic commodity management of South African portfolios.

2. WHITE MAIZE/CORN

The importance of white maize/corn has already been noted. This importance has been especially noteworthy due to the recent devastating drought in South Africa. South Africa produces about 12 million tons of maize/corn on average per year. It is normally an exporter of maize/corn but recently became an importer greater than the 1991-1992 deficit of 4 million tons.

White maize/corn is a unique crop for South Africa. White maize/corn in the rest of the world is not extensively cultivated. Indeed, yellow maize/corn is dominant for both human and feedstock consumption. In South Africa, however, over half of the maize/corn production is white. This is due to the South African perception (not alone in the world) that yellow maize/corn is for animal consumption. Thus, white maize/corn has a signal pyscological impact on South Africa.

South Africa is also very dependent on white maize/corn as all important ingredient in its main stable—a starchy, cake-like substance called "pap"

3. WHITE MAIZE/CORN FUTURES

The South African Futures Exchange (SAFEX) is the futures exchange subsidiary of JSE Limited. The JSE is South Africa's largest exchange. The SAFEX consists of two divisions: (1) financial markets division for trading of equity derivatives and (2) an agricultural division (AMD) for trading agricultural derivatives. SAFEX was formed in 1990 to trade financial instruments with the agricultural division added in 1995. White maize/corn was one of the original derivatives introduced. The contact size has changed over time including the recent 2014 change. There are six contact dates with the July contract the most important one due to overall national production needs.

4. ENTROPY AS A MEASURE OF RANDOMNESS AND CAPITAL MARKET THEORY

The Efficient Market Hypothesis is the central tenant of financial economics. In an efficient market, the market price is an unbiased estimate of the true asset value. A deviation between the true asset value and its market price should be temporary and not a systematic relationship. If one finds patterns in financial data then the efficient market hypothesis is challenged. Numerous studies have been conducted in an attempt to find such patterns to challenge the efficient market hypothesis or to exploit the price deviation for economic gain.

We attempt to study incorporation of entropy into asset pricing models and market efficiency tests. The concept of entropy was first discovered to study features of thermodynamics in the late 1850s. Later it was adopted to measure randomness and more recently to the study financial markets. Entropy is a non-linear measurement of variability. After testing several measures in previous papers we chose the sample entropy method as it was most effective.

The modern finance theories utilize expected risk measured as standard deviation to predict expected returns of efficient portfolios. These portfolios could include any investable assets such as currencies. There is a category of hedge fund strategies that focuses primarily on currency investments and speculation. Standard deviation adoption in models is an assumption that it reflects true underlying risks that concern investors. But this may not be correct, if markets behave like complex systems. Thus, we hypothesize that measures of complexity like entropy could be more effective than standard deviation in reflecting true underlying risks.

5. SAMPLE ENTROPY ALGORITHM IN FINANCE

Development of the concept of entropy is traced back to 1850s within the field of thermodynamics as a measure of energy transformation, but since then its modified versions appeared in many other fields. One of its versions is used to characterize level of randomness in a system or in a data series, thus it became applicable to study financial market behavior (Maasoumi & Racine, 2009; Pincus, 2008; Molgedey & Ebeling, 2000). Among many different algorithms of entropy we chose sample entropy, which has been tested in several studies and demonstrated reasonably consistent statistical properties (Richman & Moorman, 2000; B.G. Sharma, Bisen, R. Sharma, & M. Sharma, 2010; Thuraisingham & Gottwal, 2006). This particular method has also been tested in style rotation and stock market index timing studies and attractive results (Efremidze et al., 2015). We discuss the implementation of the sample entropy algorithm in Section 4.

Asset pricing models consider various types of risks to predict equilibrium returns (Sharpe, 1964; Lintner, 1965; Merton, 1980; Fama & French, 2004). Capital Asset Pricing Model assumes standard deviation and market risk as a risk measures of a security, while Arbitrage Pricing Theory generalizes the pricing model and allows many different risks to influence asset returns. One such risk factor we hypothesize to have an influence on asset returns is entropy, as a nonlinear volatility measure. We mentioned earlier in the introduction that there is compelling evidence that asset price movements demonstrate complex systems properties and entropy is one of the ways to characterize randomness in complex systems (Maasoumi & Racine, 2009). Next we elaborate how our empirical method works.

6. EMPIRICAL METHOD AND RESULTS

We initiate the study by first calculating the sample entropy (SaEn) values for the July domestic futures price of White Maize/Corn. Parameter values for sample entropy series in general have been studied by others, and we used their suggested values in this study. SaEn statistics are calculated for each (rolling) 120 day series of the July futures contract. .

It is important to note the daily series used in this study. For example, if the study was to continue past the May 31, 2017, we would continue to use this contract until the last day, June 30th. The daily return for June 30 to July 1 is assumed to be zero. We would then switch to the July 2018 contract. This contract, for example, had a price of 2583 on January 3, 2017. The study would use the prices of the 2018 contract from 120 days prior to July l, 2017. Others have contended that one should use continuous pricing. At this time, we do not believe this is correct. Indeed, there can be signal problems if the size of the contract changes as has been the case for the White Maize/corn contacts.

The active strategy is based on calculated entropy statistic values as follows. If the entropy value is below a predefined long position threshold, that strategy calls for long position in the futures contract, if the entropy value is higher than short position threshold than we take a short position in the futures contract, otherwise portfolio is in cash.

We have tested several different strategies based on the entropy risk factor model for various financial assets. These strategies were based on different values of the thresholds for sample entropy before the rebalancing periods started and on different frequencies of the rebalancing. We have found in these previous papers a somewhat consistent levels to conduct active management.

We utilized in this study preferred strategy metrics to compare the active strategies to the benchmark of buy & hold portfolio of the same futures contracts. Table 2 reports the results for annualized returns, standard deviation, Sharpe ratio (assuming the risk free rate of 2.5%) and maximum drawdown. This is a preliminary version of the paper and Table 2 only reports results for the historically preferred strategy, which is based on 6 rebalancing periods per year (2 months holding for each rebalancing) and on sample entropy long threshold values of 1.1 and short position threshold of 1.5.

As we see in Table 1 active strategy performed substantially better than the benchmark in terms of the annualized returns (12.9% annualized return versus 3.9% for the benchmark). The risk levels are also slightly lower, and overall evaluation is based on the Sharpe Ratio which is drastically higher for the active strategy based on the entropy model than for the benchmark (0.42 vs 0.05). We indent to conduct more extensive analysis in the next iteration of the paper and see if the risk levels could be reduced further.

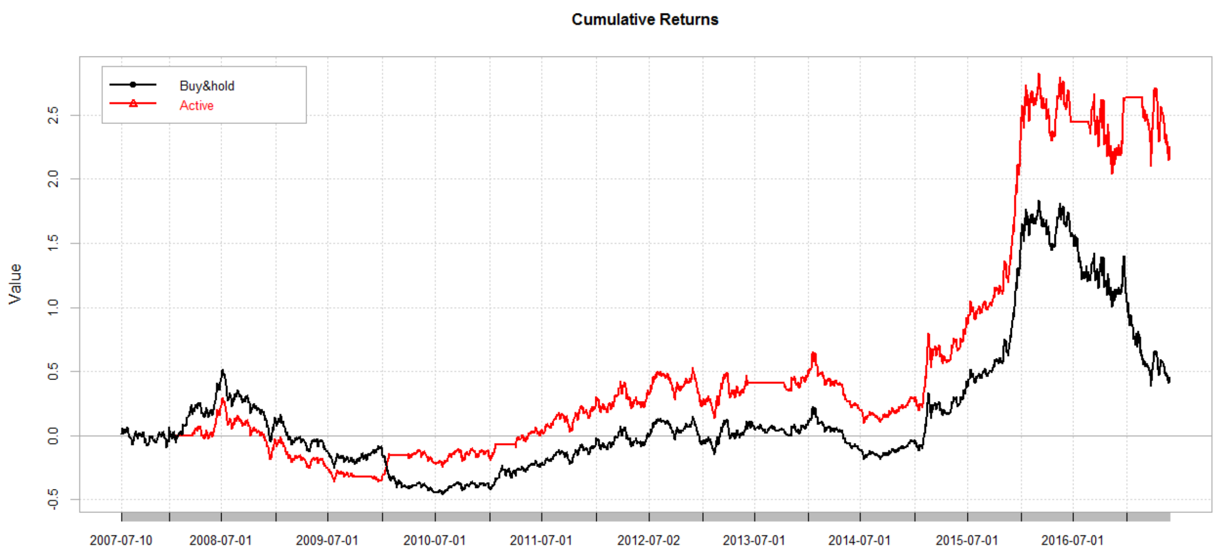
Table 1. Performance Metrics of Active Strategy and Buy & Hold passive benchmark, 2007-2017

		Benchmark	*Active*
Annualized	Return	3.9%	12.9%
Annualized	Standard Deviation	26.5%	24.2%
Maximum	Drawdown	64.6%	50.7%
Annualized	Sharpe Ratio	0.05	0.42

Note: Daily data is from July 1, 2007 to May 31, 2017. In the calculation of the Sharpe Ratio we use risk free rate of 2.5% annualized. The CV of the benchmark is 6.79 as contrasted to the active strategy CV of 1.88. Transaction costs are not calculated in the above results.

In Figure 1 we compare visually the performance of the active and benchmark portfolios. The active strategy produced annualized returns of 12.9% and cumulative performance of 211%. In this preliminary version of the study we have not yet calculated the impact of transactions costs.

Figure 1. Active Portfolio Performance vs Buy & Hold Portfolio, 2007-2017



Note: Active portfolio in this graph is based on the strategy with 2-month rebalancing based on entropy statistics. Daily data is from July 10, 2007 to May 31, 2017.

7. CONCLUSION

In this study we conducted an empirical testing of the investment strategies based on the entropy risk factor model for the white maize futures contract (SAFEX). We found favorable results in this preliminary version. The analysis was based on the daily data of 2007-2017 (10 years of daily data). Previous studies using entropy also found some promising results, but this is the first study that we know that studied the futures markets. It is interesting that futures markets as well as other parts of the financial markets also reveal complex systems behavior, as entropy is tentatively effective in measuring the risk inherent in that market.

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Appendix I

General Entropy Calculation Procedures

1. The entropy calculation begins with 120 observations of daily adjusted closing prices for each instrument.
2. The standard deviation of the 120 days of price change is then calculated. For example, the STD of price changes is 0.0155.
3. The standard deviation number is then multiplied by x0.20. For example, 0.0155 x 0.20 or 0.0031. It is called a “threshold of similarity”.
4. The 120 days of prices are then subdivided into two days subsets (consecutive days). Then, for example, with two subsets [1,2] and [3,4] we calculate the difference between day 1 and 3, and day 2 and 4.
5. If these differences (in absolute terms) are less than the number equal to 0.20 x standard deviation (from item 3) then the two subsets are called “similar subsets”. Let this number of similar sets be denoted with K.
6. Now let us create subsets with a length of 3 days. We do the same type of counting of similar subsets with the length of 3 days. We denote this count with H. We calculate sample entropy (SaEn) with this formula: SaEn = -Ln(H/K). We calculate sample entropy statistic on a daily basis using the past 120 days’ data, and thus we obtain a daily series of sample entropy values.