Entropy Risk Factor Model of Exchange Rate Prediction

Darrol J. Stanley[1], Levan Efremidze[1] & Jannie Rossouw[2]

[1] Graziadio School of Business and Management, Pepperdine University, Malibu, USA

[2] School of Economic and Business Sciences, University of Witwatersrand, Johannesburg, South Africa

Correspondence: Levan Efremidze, Department of Finance and Accounting, Graziadio School of Business and Management, Pepperdine University, Malibu, California 90263, USA. Tel: 310-531-3302.

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Abstract

We investigate the predictability of an exchange rate with entropy risk factor model, as there is growing evidence that financial markets behave as complex systems. The model is tested on the data of South African Rand (ZAR) exchange rate for the period of 2004-2015. We calculate sample entropy based on the daily data of the exchange rate and conduct empirical implementation of several market timing rules based on these entropy signals. The dynamic investment portfolio based on entropy signals produces better risk adjusted performance than a buy and hold strategy. The returns are estimated on the portfolio values in U.S. dollars. The results raise the potential attractiveness of complex systems analyses, especially the methods of entropy, for foreign exchange market research and applications.

Keywords: exchange rate, currency trading, market timing, entropy, South African rand, asset pricing, USD/ZAR

JEL Category: 14

1. Introduction

Currency market transactions have grown to more than 5 trillion dollars in average daily volume in 2016 (Bank for International Settlements, 2016). They are the largest segment of global financial markets. Various methods are utilized to predict exchange rates. They range from very simple technical rules to sophisticated fundamental theories. In this paper we explore empirical testing of predicting exchange rate with complex systems indicator called entropy. Studies have shown that financial markets often follow power law distributions, which is a feature of complex systems (Maasoumi & Racine, 2009). Recent financial markets research has focused on applying markers of complex systems to different segments of financial markets. Entropy is a statistical measure of randomness in a complex system and it shows reasonable effectiveness in timing a stock market index (Efremidze, Stanley, & Kinsman, 2015) and style rotation strategies (Efremidze, DeLillio, & Stanley, 2014). Entropy based methods have proven to be a powerful tool in physics, astronomy, biology, and medicine (Pincus, 2008). Entropy conceptually can be thought as another type of variability or risk measure, different from standard deviation, semi-deviation, coefficient of variation, or maximum drawdown. We focus on developing an empirical method using entropy to predict movements in an exchange rate. For this particular paper, as an example for empirical testing, we selected South African Rand (ZAR) data, which is considered to be an emerging markets currency, with substantial fluctuations during the sample period of 2004-2015. The results show substantial predicting power of entropy statistics in the out-of-sample empirical testing.

Currency trading has become a major investment management vehicle globally. Multinational corporations and currency investors are primarily interested in hedging currency risks, but speculative motives are also used in generative active bets on currencies. In addition, Exchange Traded Funds (ETFs) are now available for almost every conceivable investment category. One such category is currency investments. Previously, in general, it was necessary to enter the foreign exchange market in order to make bets on currency movements. This involved a substantial degree of sophistication and resources that often hindered investment professionals, but especially individual investors, to trade such instruments. By contrast, ETF shares that track currencies can be purchased in local currency. Such funds are available for South African Rand as well. (Note 1)

Multitudes of factors influence exchange rate movements: domestics and foreign monetary policies, exchange rate policies, inflation rates, macroeconomic fluctuations domestically and of trading partners, commodity prices, risk appetite in global markets and debt defaults as they are stylized in various models based on interest rate and purchasing power parity theories (De Bruyn, Gupta, & van Eyden, 2015). Mtonga (2011) documents relationship between monetary policy regime and exchange rate dynamics in South Africa. Roodt (2013) notes that as long as the inflation rate of South Africa is higher than the inflation rate of the US the rand will lose value over the long-run to the dollar. In this study, we focus on introducing and testing the entropy methodology to analyze changes in exchange rates, as another type of exchange rate risk measure.

2. Entropy as Measure of Randomness and Capital Market Theory

The concept of entropy was first invented to study features of thermodynamics in the late 1850s, then it was adopted to measure randomness and more recently to the study financial markets (Maasoumi & Racine, 2009; Pincus, 2008; Molgedey & Ebeling, 2000). In the applications of financial time series analysis, a greater entropy level would be associated with less stable securities. Also, it is a non-linear measurement of variability and thus it is distinctly different from standard deviation. There are several statistical algorithms of entropy (B.G. Sharma, Bisen, R. Sharma, & M. Sharma, 2010; Thuraisingham & Gottwal, 2006; Richman & Moorman, 2000), but in this paper we follow the method of sample entropy used in Efremidze et al. (2015), as it was effective in predicting movements in stock market index. Section 3 has more details of sample entropy algorithm implementation.

The modern finance theories (Sharpe, 1964; Lintner, 1965; Merton, 1980; Fama & French, 2004) relate expected risk measured as standard deviation to expected return of efficient portfolios which potentially could include any investable assets such as currencies. Standard deviation may not reflect true underlying risks that investors worry about, nor can we know all of the risks with very high precision. But as markets behave like complex systems, we hypothesize that measures of complexity like entropy could be more effective than standard deviation in reflecting true underlying uncertainties. Thus we test empirically how effective an entropy method is, and in this case in predicting exchange rate movements.

3. Empirical Methods

3.1 The Entropy Metric Employed in This Study

We selected the parameter values for sample entropy (SaEn) series, calculated on each 120 days of ZAR exchange rate. The values of the parameters for sample entropy calculation are presented in Table 1. We followed the same algorithm of SaEn and parameter selection rational as in Efremidze et al. (2015). Sample entropy statistic SaEn (m,r,N) is calculated with equation 1, where N is a length of time series used, m is a length of subseries (with consecutive elements) from N, r is called a tolerance threshold and is a multiple of standard deviation of N time series, D is the number of times any subseries from N with the length m are similar to other subseries with the same length (any two subseries of the length m are considered to be similar if all absolute differences between the corresponding elements of the two subseries are less than or equal to the tolerance threshold r), C is the number of times any subseries with the length $m+1$ are similar to other subseries with the length $m+1$. The self-matches of the subseries are not counted in sample entropy algorithm.

$$\text{SaEn } (m,r,N) = -\,\boldsymbol{ln}\ (C/D) \tag{1}$$

Table 1. Entropy model parameter values

Time Series (N)	Length of Subseries (m)	Tolerance Threashold (r)
Running 120 days of daily series based on a sample from **Jan 1, 2004 to Aug 17, 2015**	2	20% of the standard deviation of the time series (N)

Notes: N, m and r are parameters of Sample Entropy statistic. The values selected for these parameters are based on previous statistical tests of these parameters (see Richman and Moorman, 2000).

3.2 Prediction Methodology

We use daily data of ZAR exchange rate from January 1, 2004 to August 17, 2015. Data is divided into two year periods. The returns are estimated on the portfolio values in U.S. dollars. We use sample entropy as an indicator for selling or buying the Rand. *The theoretical hypothesis is that when uncertainty is high the currency will likely depreciate, and when uncertainty is low the currency will appreciate*. Low sample entropy numbers indicate low uncertainty; high numbers indicate a higher level of uncertainty. *In each two year investment period, the best strategy is based on the previous two year estimation window results.* The estimation period results are calculated for seven (7) different buy or sell signal thresholds of sample entropy. The general model for the buy and sell thresholds are as follows:

Buy signal threshold = mean (30 days of SaEn) - multiple x *standard deviation (30 days of SaEn)* (1)

Sell signal threshold = mean (30 days of SaEn) + multiple x *standard deviation (30 days of SaEn)* (2)

where *multiple* is a variable that takes seven different values: 0.5, 0.75, 1, 1.25, 1.5, 1.75, and 2.

Thus, in our sample we have five (5) estimation periods and five (5) investment periods, each with two years of data (except for the last investment testing period which has about a year and a half of data). In each estimation period, we select the best performing threshold (based on the above mentioned standard deviation *multiple*) with the highest Sharpe ratio. This threshold is then used for the next trading strategy for a two year investment period. Thus we dynamically update the strategy parameters after every two years. We think that allowing the updating of the *multiple* of standard deviation after each estimation period makes model adaptable to more recent information, as the magnitudes of relation could change over time between risk and return. The effectiveness of this methodology is discussed in the next section.

4. Results

Table 2 shows the results for each estimation and investment periods. The best performing trading threshold portfolios in the estimation periods are in bold (columns named *Best Estimate*), while the subsequent investment testing period performance of that strategy is in bold italics (columns are named *Invested*).

Table 2. Results of estimation and investment periods

	Value of multiple **in parenthesis**	***1 (0.50)***	***2 (0.75)***	***3 (1.00)***	***4 (1.25)***	***5 (1.50)***	***6 (1.75)***	***7 (2.00)***	***Buy&Hold Strategy***
2004-2005							**Best Estimate**		
Annualized	Return	0.01	0.03	0.05	0.14	0.11	**0.13**	0.06	0.00
Annualized	Standard Deviation	0.15	0.14	0.12	0.11	0.10	**0.08**	0.06	0.15
Annualized	Sharpe Ratio	-0.12	0.01	0.21	0.97	0.86	**1.34**	0.68	-0.17
Maximum	Drawdown	0.16	0.16	0.10	0.07	0.07	**0.03**	0.05	0.19
2006-2007			**Best Estimate**				**Invested**		
Annualized	Return	0.00	**0.01**	-0.02	-0.06	-0.07	***-0.06***	-0.04	-0.04
Annualized	Standard Deviation	0.14	**0.13**	0.12	0.10	0.09	***0.07***	0.06	0.15
Annualized	Sharpe Ratio	-0.15	**-0.09**	-0.41	-0.81	-1.02	***-1.18***	-1.02	-0.39
Maximum	Drawdown	0.26	**0.26**	0.26	0.25	0.21	***0.20***	0.15	0.25
2008-2009		**Best Estimate**	**Invested**						
Annualized	Return	**0.12**	***0.05***	-0.01	0.04	0.00	-0.05	-0.03	-0.04
Annualized	Standard Deviation	**0.26**	***0.23***	0.21	0.19	0.16	0.13	0.11	0.26
Annualized	Sharpe Ratio	**0.34**	***0.12***	-0.18	0.06	-0.17	-0.57	-0.54	-0.24
Maximum	Drawdown	**0.24**	***0.26***	0.25	0.15	0.17	0.15	0.12	0.41
2010-2011		**Invested**				**Best Estimate**			
Annualized	Return	***0.13***	0.15	0.14	0.13	**0.15**	0.10	0.07	-0.05
Annualized	Standard Deviation	***0.15***	0.15	0.14	0.12	**0.10**	0.08	0.06	0.16
Annualized	Sharpe Ratio	***0.69***	0.84	0.80	0.83	**1.26**	0.93	0.75	-0.44

Maximum	Drawdown	***0.12***	0.10	0.11	0.09	**0.05**	0.04	0.06	0.23
2012-2013						**Invested**		**Best Estimate**	
Annualized	Return	0.00	0.02	0.03	0.01	***-0.01***	0.03	**0.05**	-0.11
Annualized	Standard Deviation	0.12	0.11	0.11	0.10	***0.09***	0.07	**0.06**	0.14
Annualized	Sharpe Ratio	-0.22	-0.04	0.03	-0.17	***-0.37***	0.08	**0.33**	-0.98
Maximum	Drawdown	0.17	0.13	0.13	0.12	***0.11***	0.08	**0.05**	0.29
2014-2015								**Invested**	
Annualized	Return	-0.08	-0.06	-0.08	-0.02	-0.04	0.00	***0.00***	-0.12
Annualized	Standard Deviation	0.11	0.11	0.10	0.09	0.07	0.06	***0.05***	0.12
Annualized	Sharpe Ratio	-0.88	-0.74	-1.03	-0.50	-0.88	-0.40	***-0.50***	-1.19
Maximum	Drawdown	0.20	0.18	0.18	0.14	0.15	0.07	***0.04***	0.20

Note: Risk free rate is assumed to be 2.5% in the Sharpe ratio calculation. "Best Estimate" means the strategy with the best performance during estimation period. "Invested" means the results of the strategy that was used during the investment test period. Numbers in parentheses are values used for a *multiple* of standard deviation used in buy and sell signal threshold calculations.

To clarify further, as an example, during the 2004-2005 estimation period the threshold of number 6 strategy (*multiple* of standard deviation here equals 1.75) had a highest Sharpe ratio. Thus in the investment period of 2006-2007 buy and sell signals are based on this value of *multiple.* Similarly, in the estimation period of 2006-2007, best performance comes from strategy 2, thus this strategy threshold is used in subsequent 2008-2009 investment period. This algorithm continues all the way through the other periods too.

The end result is that in different investment periods (5 periods within 2006-2015) we use different strategy thresholds. We calculate the performance of this dynamically rebalanced portfolio (Active) and compare it to buy and hold strategy. Table 3 shows that this active portfolio substantially outperforms buy and hold method on a risk adjusted bases, using levels of Sharpe ratio and also maximum drawdown. Cumulative returns of the active and buy and hold strategies are presented in Figure 1. There is a huge difference between the active and buy & hold strategies by all measures. The cumulative return of the active strategy during the tested period is 70% greater and the downside risk (maximum drawdown) is 50% lower than in the passive buy & hold strategy. It is important to keep in mind that these are out of sample testing results, which make them much more robust and attractive for actual practical implementations in various applications of forecasting, hedging and investing.

Table 3. Results of dynamic investment portfolio (active) strategy, 2006-2015

		Active	***Buy&Hold***
2006-2015			
Annualized	Return	0.02	-0.07
Annualized	Standard Deviation	0.14	0.17
Annualized	Sharpe Ratio	-0.02	-0.53
Maximum	Drawdown	0.26	0.54

Note: Risk free rate is assumed to be 2.5% in the Sharpe ratio calculation.

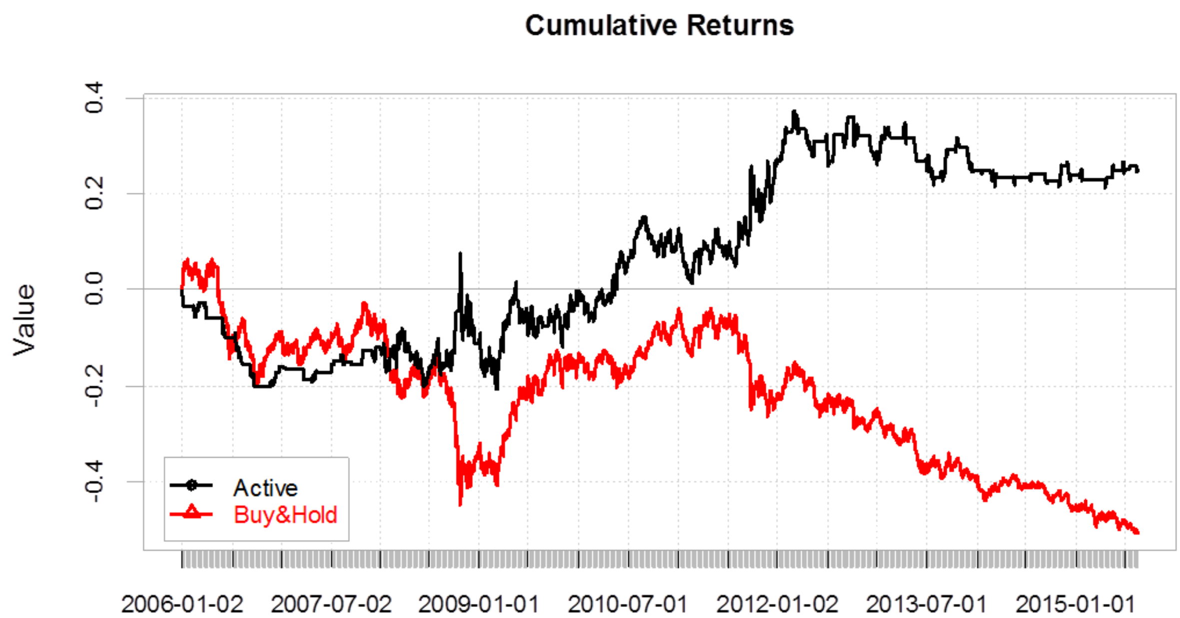

Figure 1. Cumulative Returns of Active and Buy & Hold Strategies, 2006-2015

Note: Values are cumulative returns in decimals.

These results are preliminary and need to account for reasonable transactions costs, which are very small in liquid currency markets. There were approximately 100 round trip transactions in the active strategy in Table 3, thus cumulative transactions costs will have negligible impact on the results. We will explore this question in future research more systematically.

5. Conclusion

We investigated the predictability of the South African Rand exchange rate with sample entropy analytics for the period of 2004-2015. Sample entropy was calculated on the daily data of the exchange rate and then used in prediction algorithm of the exchange rate change. The dynamic investment portfolio based on entropy signals produces better risk adjusted performance than buy and hold strategy and thus it shows that entropy can help predict exchange rate moves. The returns are calculated on the portfolio values in terms of U.S. dollars. These results point toward currency market inefficiencies in the South African Rand market, which can be exploited using entropy based algorithm developed in this paper. Overall, the evidence suggets that complex system characteristics like entropy could be incorporated in financial and exchange rate applications for forecasting and investment management.

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Note

Note 1. ABSA Currency ETNs: while there ultimately be numerous currency ETNs in South Africa, we principally want to note the existence of three currency ETNs offered by the South African institution ABSA, a member of the Barclays Group. These three are (1) NewWave USD Currency Dollar ETN; (2) NewWave GBP Currency ETN; and (3) NewWave EUR Currency ETN (see ABSA, 2016). These funds will, of course, behave differently from each other due to the currency relationship of each noted currency and the Rand.