SEARCHING FOR HISTOGRAM PATTERNS IN USD/ZAR FOREIGN EXCHANGE FINANCIAL TIME SERIES

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Abstract

This study aims to investigate whether the phenomena found by Shnoll et al. when applying histogram pattern analysis techniques to stochastic processes from chemistry and physics are also present in financial time series, particularly exchange rate data. The phenomena are related to fine structure of non-smoothed frequency distributions drawn from tick high frequency currency exchange rates over a period of one week. Shnoll et al. use the notion of macroscopic fluctuations (MF) to explain the behaviour of sequences of histograms. Histogram patterns in time adhere to several laws that could not be detected when using time series analysis methods. In this study, which is a follow up of research by Van Zyl-Bulitta, VH, Otte, R and Van Rooyen, JH, special emphasis is placed on the histogram pattern analysis of high frequency exchange rate data set. Following previous studies of the Shnoll phenomena from other fields, different steps of the histogram sequence analysis are carried out to determine whether the findings of Shnoll et al. could also be applied to financial market data. The findings presented here widen the understanding of time varying volatility and can aid in financial risk measurement and management. Outcomes of the study include an investigation of time series characteristics, more specifically the formation of discrete states and the repetition of histogram patterns.

Keywords: Histogram; Pattern; Volatility; Discrete; Clustering; States

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Introduction and statement of the problem

The prediction of price movements is important to help us devise profitable trading strategies and also to predict changes that will lead to undue financial losses. However, fully understanding what drives price changes in the financial environment can never be complete without an understanding of how humans will behave when receiving new financial information. However, research about this aspect is outside of the scope of this study.

If one can detect recurring patterns in data sets, this could be used to predict coming prices changes especially if we know that we are now at the beginning of a series of successive upwards or downwards changes. Schnoll (et. al., 2000) referred to two aspects concerning the nature of fluctuations in analysing the similarity of histogram shapes, namely the histogram fine structure and the periodic recurrence of histogram shapes over time. He also concluded that traditional time series analyses do not capture the true nature of these fluctuations.

This research extends the research done by Van Zyl-Bulitta, et. al. (2007), by further applying the research done by Shnoll as regards the similarity of histogram shapes and the recurrence thereof, to financial time series.

Objective of the study

The main objective of this study is to apply the method of histogram pattern analysis to financial data, searching for the phenomena found by Shnoll et al. in their investigations of stochastic processes from the natural sciences. This research focuses on the histogram shape and recurrence in financial time series.

The study includes an empirical analysis of foreign currency exchange rate data where the objective is to evaluate aspects of its distributional structure through compiling non-smoothed histograms and comparing their physical shape over time. The study also highlights the weakness of descriptive statistics in capturing the essence of financial time varying volatility over time

Data used

High frequency South African rand (ZAR), US dollar (USD) exchange rate tick data, downloaded from Reuters was used for the research. The data set comprises 88 500 values over the period 11 to 19 November 2008.

Data was analysed by making use of the Matlab (version 7.04) mathematical software package. Although the rand depreciated substantially against other currencies, the volatility over the reseach period was relatively low compared to other times. The data was selected over a week of relative stability so as to improve the probability of recognising patterns in the data.

Scope and limitations of the research

Although reference is made to some of the well known models used for time series analysis, this research deliberately does not attempt to apply these models. The focus is on histogram microstructure alone and looking a patterns purely from a graphical perspective.

The research was limited in terms of the availability of high frequency data. Although tick data for only one week was used, the search for histogram patterns should cover a longer period such as a month. However, this would lead to about 300 000 observations being used for the research.

Schnoll et. al. used specialised software that was developed to compare the histogram shapes which was not available for this research.

Background to approaches to determining exchange rate volatility

In general, randomness implies incomplete knowledge of the process on which it is based. One dangerous assumption that managers often make when building models to forecast future price changes is to base it on what happened in the past. This contradicts the weak form of the efficient market hypothesis (EMH) which states that there is little correlation between past prices. The past can (should) not be used to forecast future price changes. Managers often construct spreadsheet models with different levels of sophistication, with past prices which is used to determine how prices will react in future.

When constructing frequency distributions of price changes or variances, one may be ready to assume that these frequencies reflect some intimate mechanism of the markets themselves. To be of value for management purposes, these frequencies should remain stable over the course of time. The statistical description of financial fluctuations is all but perfect. However it is still helpful to describe (past) risks as it has some value for management purposes - it serves as a starting point. As long as we assume a certain degree of change with a certain probability of occurring, we can take decisions based on this.

While the prediction of future returns on the basis of past returns is much less justified, the amplitude of possible price changes - and not their sign - is to a certain extent predictable. (Bouchaud and Potters, 2003, 1-3) This amplitude reflects the intensity of price changes - in other words their volatility.

In the financial markets, volatility is not the result of a single magnitude that changes but rather represents the outcome of many different events and processes that happen simultaneously. Volatility is an important underlying magnitude that affects pricing of financial instruments. For option pricing, for instance, the historic volatility - calculated from historic prices of the underlying instrument - may be used as one of the inputs to the Black and Scholes model. A second volatility value, also called the implied volatility may be derived from the Black and Scholes model by iteratively finding the volatility for a certain given option market price, strike price, time to maturity and risk-free interest rate. Although this derived or implied volatility can be determined in this way, it gives us no information about the characteristics or processes that make up this value. This is once again a very simplistic representation in one figure of a complex and dynamic system. Different players interact in different places and in different markets to influence these values which is not reflected in these values alone.

From the above it is clear that volatility can not be directly observed in the market place (Mantegna and Stanley, 2000, 57, 76). Forecasting volatility of, for instance, exchange rate fluctuations in the financial environment is difficult. At best, even *a posteriori*, volatility is only approximately available. Van Zyl (et. a.. 2008) refer to several stylised facts (Fasen et al., 2006, 108) that is used to model volatility. These include time variation, randomness, heavy tails and volatility clustering (long memory of the volatility). GARCH modelling builds on advances in the understanding and modelling of volatility in the last decades (Bollerslev 1986, Engle: 1982). It considers excess kurtosis (i.e., fat tail behaviour) and volatility clustering (which is considered in this research). There are two important characteristics of GARCH models. It provides relatively accurate forecasts of variances and covariances of asset returns through its ability to model time-varying conditional variances. GARCH models are also especially suited to forecasting foreign exchange rate volatility. These models do not contradict the EMH since GARCH innovations are serially uncorrelated. Different modelling approaches take one or more of the stylised facts into account. Bouchaud and Potters (2003, 122) noted that volatility fluctuations are a multiscale phenomenon and that the dynamics of volatility cannot be properly characterised on a single time scale. As far as volatility clustering is concerned, Zumbach et al. (nd, 1) pointed out that because of the slow decay of autocorrelations this clustering occurs on all time horizons.

Shnoll referred to two aspects of the nature of fluctuations in analysing the similarity of histogram shapes, namely the histogram fine structure and the periodic recurrence of histogram shapes. Long-term investigations of various time series measurements, led Shnoll (2006) to believe that the laws that may be discovered by examining the fine structure of histograms, are not captured by traditional time series analysis methods. These phenomena have been found in the study of biological, chemical and physical stochastic processes.

This study extends the study of Van Zyl-Bulitta, et. al. (2008), based on the work of Schnoll (2006), in that ZAR/USD histogram shapes are compared to determine to what extent histogram shapes follow each other or recur at some other point in the future. A section of the theoretical discussion from the study by Van Zyl-Bulitta, et. al. (2008) is repeated here before the empirical results are discussed.

Stochastic processes and their properties are at the core of financial modelling today. Shnoll et al. pointed out that accepted statistical methods, based on the central limit theorem, are not suitable for a histogram fine structure analysis. These techniques do not consider the fine structure of distributions, and they are insensitive to the particular shape of histograms. As Shnoll et al. explained, statistical techniques “overlook” (Shnoll et al., 1998, 1034) the fine structure, since they have been developed for different purposes.

Shnoll et al. (2000) formed histograms from an insufficient number of measurements and focused on their fine structure. In contrast to analysing smooth histograms, which Shnoll et al. (1998, 1026, 1033) view as artefacts, their analysis focuses on empirical distributions that have only been smoothed a few times in succession so as to not destroy the extremes present in the distributions. Shnoll posed the question: Given a histogram pair that passed a test of similarity based on a visual comparison, what is their time distance and is there a time period that can be expected to occur more often than expected due to chance? According to this reasoning some predictive power may be gained if a particular histogram were known to reoccur periodically.

Shnoll and Mandelbrot referred to the concept of probability. Shnoll et al. (1998, 1035) state that the concepts of probability and stochasticity by themselves do “not yet predetermine the answer to the question concerning the distribution of fluctuations” (1998, 1035). According to Shnoll et al. these two concepts are closely associated with the concept of chaos.

Forecasting financial time series involves an element of uncertainty. Merely a fraction of the information about future price evolution can be known, based on the stochastic nature of financial systems. A longer prediction time horizon implies more inaccurate results and any prediction thus becomes more difficult due to greater uncertainty.

Recurring histograms patterns

Shnoll et al. originally constructed histograms based on data from stochastic processes in the natural science. The noise sequences that resulted from measurements of the original data resemble white noise. Thus, no structure or repeatable patterns would be expected. Financial data used in this study is inherently different to chemical reactions or radioactive decay. Financial markets, contrary to chemical processes are influenced by humans and their interaction. Although chemical processes may also be influenced by external factors such atmospheric conditions and even human interference, it does not compare well with financial markets where a lot more factors influence the outcome, that is , the price.

In their research Shnoll et. al. (2000, 205) wanted to verify the “fairly high probability of similar fine structure of distributions governing the results of simultaneous measurements of any processes in each time interval”. In their research regarding layer histograms and histogram patterns in time, Shnoll et al. converted pointwise time series to a series of successive histograms where histogram shapes in time were compared. Histograms were compared to other near and far histograms on an individual basis. (Panchelyuga and Shnoll, nd, 1) (Shnoll et al., 1998) (Shnoll et al., 2000, 207).

Distributions with one extreme value can result from smoothing procedures. Shnoll et al. show in their work how after successive smoothing of histograms the distributions become bell-shaped. However, Shnoll et al. (1998, 1026, 1033) state that the smooth distributions may be regarded as artefacts.

Layer histograms represent one of several phenomena found by Shnoll et al. The phenomena that are named under the general term 'macroscopic fluctuations effect' are the near neighbour effect, synchronism, and monthly and annual recurrence of similarly shaped histograms. The research by Van Zyl-Bulitta, et. al. (2008), focused on the layer histograms and their occurrence in a financial time series. This research focuses on similar histogram patterns or shapes in financial time series.

Histogram Construction Details

This section briefly describes the analysis carried out on the exchange rate data to identify the similar histogram shapes. It must be noted that the histograms are compared merely on a simple visual basis. No software is used for this purpose for this research.

Figure 1 below illustrates the daily exchange rates for the tick data in raw format for the period 11 to 19 November 2008. The data was not smoothed or standardised after it was obtained form Reuters.

In order to compile the frequency distributions, the time series is first converted to variances over the period. The daily variances (mainly from 0.005 to -0.005) and the volatility clustering for the period is illustrated in Figure 2 below.

Figures 3-1 and 3-2 below illustrate the degree of autocorrelation in the data set at a 95% confidence level. The line indicating the bounds falls on the horizontal axis. Figure 3-1 is drawn from the raw return series and figure 3-2 was drawn from the squared returns. It can clearly be seen that in the case of figure 3-1 that there is virtually no autocorrelation. In figure 3-2 the variance process exhibits some correlation. This clearly illustrates that the data selected displays very little outocorrelation.

Figure 1: USD/ZAR Tick Data Closing Exchnage Rates

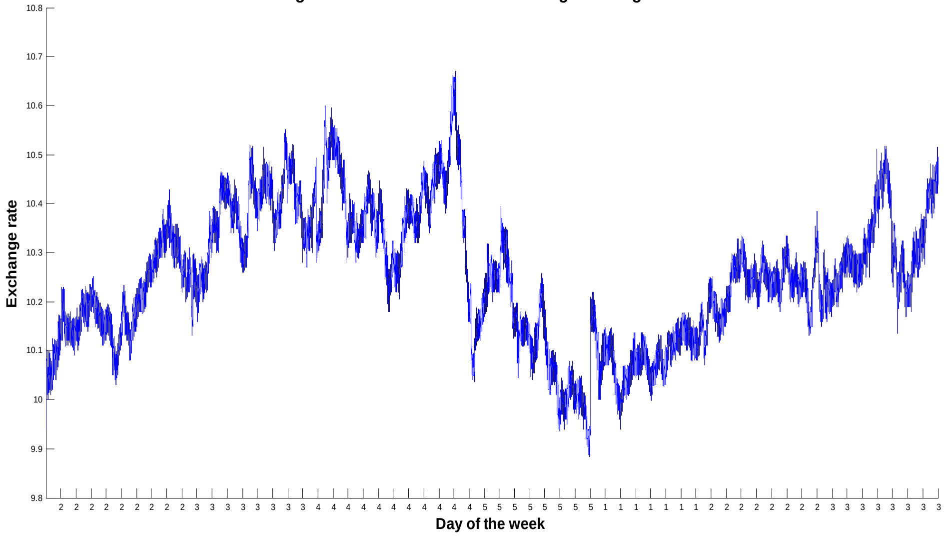


Figure 2: USD/ZAR Tick Data Daily Variances

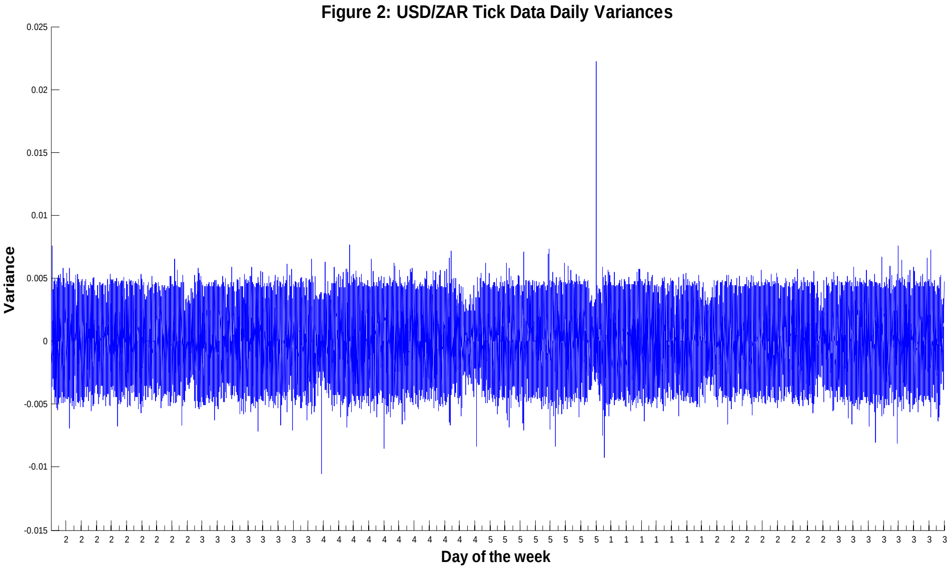


Figure 3-1: Auto Correlation Function with Bounds for Raw Return Series

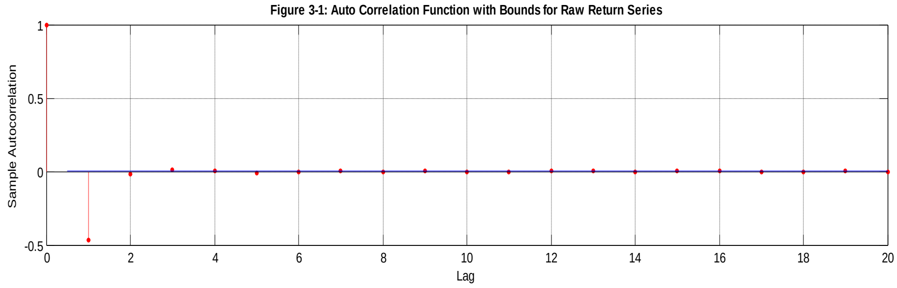
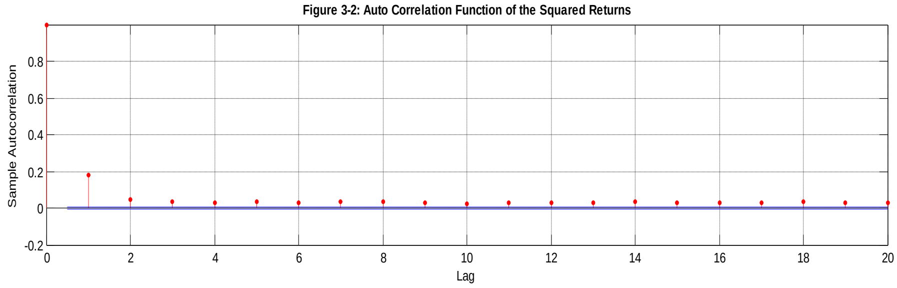
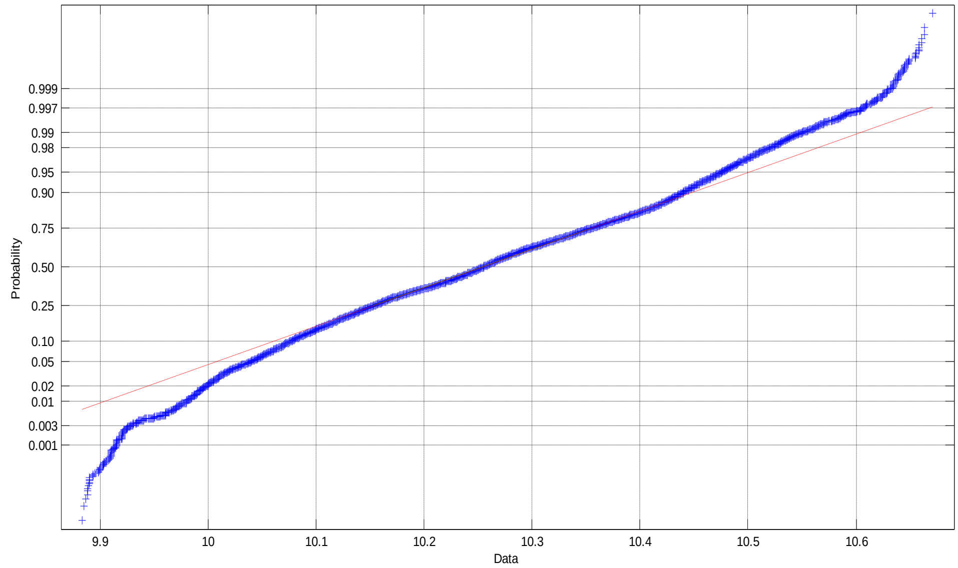


Figure 3-2: Auto Correlation Function of the Squared Returns



The data was also tested for normality. It can be seen in Figure 4 below that the data set is normally distributed. There is a slight deviation from the line indicating the normality of the data set.

Figure 4: Test for Normality



In order to determine whether there are histogram patterns that recur, the data set was reshaped into 59 columns, each with 1 500 observations with the reshape function in Matlab. The histograms were compiled, each having twenty bins. The possible variances of the exchange rates are sorted into twenty bins, with an overall variance ranging between 0.0222 and -0.0105. Matlab uses ten bins by default. However, twenty bins were used for this research as the histogram fine structures become more pronounced with more bins. It is important to understand that the choice of the number of columns and the number of observations for histograms is arbitrary. There is no correct choice of how the data is reshaped or the number of bins used for the histograms.

As was mentioned before, the data were not smoothed. Shnoll et. al. (2000) pointed out in their research that the histograms become bell shaped after successive smoothing. Figures 5-1 to 5-24 illustrate the first 24 of the 59 histograms and illustrate the striking similarity of some of the histograms. Histograms 3, 4 and 5 are very similar, histograms 10, 11 and 12 are very similar, histograms 15 and 16 very similar and histograms 21 and 22 are very similar.

The graphs underline the clustering of volatility, i.e. the recurrence of these histograms shapes where they are closest to each other which is also called the near neighbour effect. Shnoll found that some of the histograms recurred at later regular intervals i.e. after a month or some other period. However his research was based on chemical processes. Some of the histogram shapes at later points in time do not recur in this research. However, this does not mean that it will not happen. In the financial environment where emotion is often prevalent, it may be highly unlikely due to the many external influences affecting the markets as opposed to the factors that affect chemical processes. In times of extreme stability in the currency markets such a situation might occur. Using time series data extending over longer time periods might also deliver the desired results.

Usually foreign exchange rate data displays significant excess kurtosis which makes GARCH models especially suited to the modelling of foreign currency volatility. However, the kurtosis of the entire data set is 2.4274 which means that there is no excess kurtosis, that the data set is not outlier prone as the value is below 3. A value of more than three means that the data set is outlier prone. However, this research is not about the application of GARCH models as such on the data, but about the comparison of histogram fine structures.

Figure 5-1: Column 1 Histogram

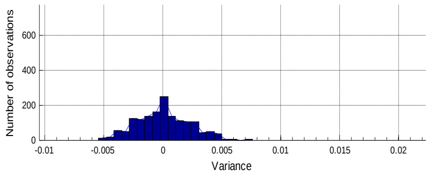


Figure 5-2: Column 2 Histogram

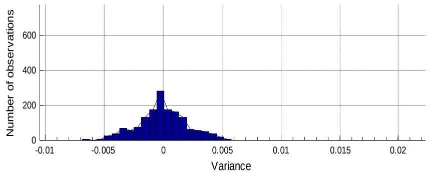


Figure 5-3: Column 3 Histogram

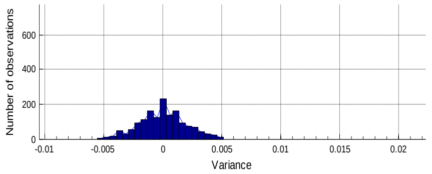


Figure 5-4: Column 4 Histogram

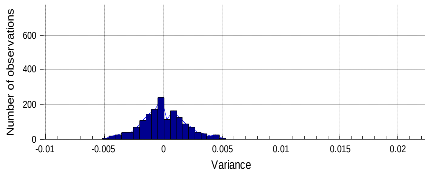


Figure 5-5: Column 5 Histogram

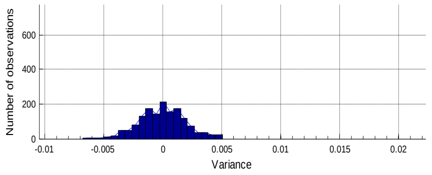


Figure 5-6: Column 6 Histogram

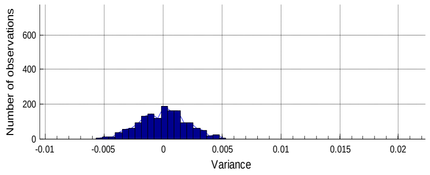


Figure 5-7: Column 7 Histogram

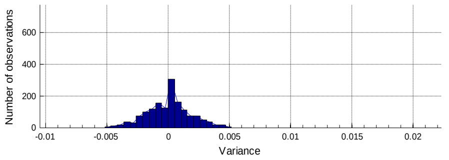


Figure 5-8: Column 8 Histogram

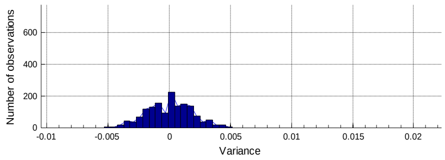


Figure 5-9: Column 9 Histogram

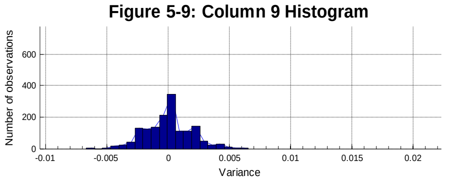


Figure 5-10: Column 10 Histogram

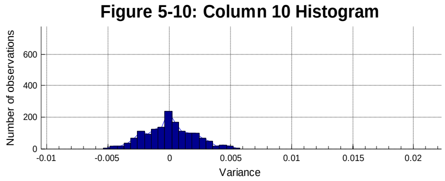


Figure 5-11: Column 11 Histogram

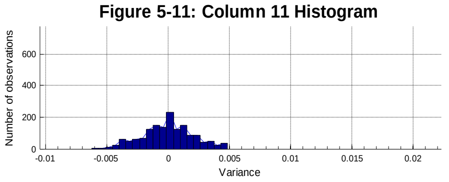


Figure 5-12: Column 12 Histogram

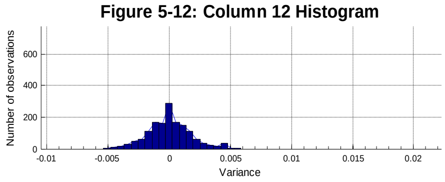


Figure 5-13: Column 13 Histogram

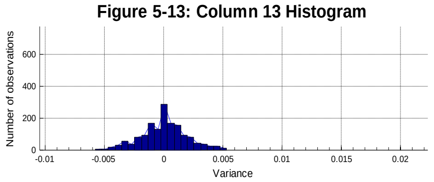


Figure 5-14: Column 14 Histogram

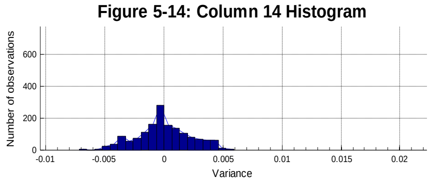


Figure 5-15: Column 15 Histogram

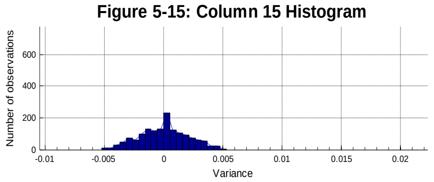


Figure 5-16: Column 16 Histogram

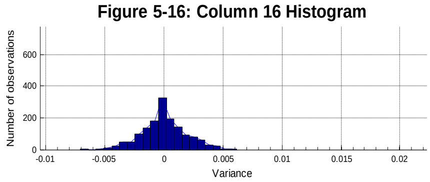


Figure 5-17: Column 17 Histogram

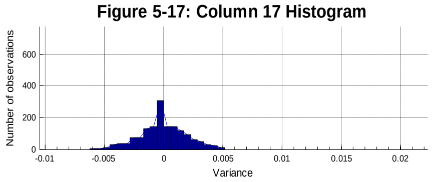


Figure 5-18: Column 18 Histogram

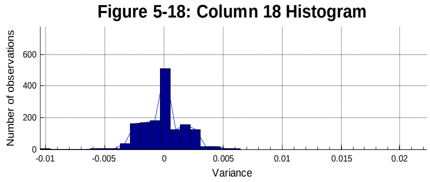


Figure 5-19: Column 19 Histogram

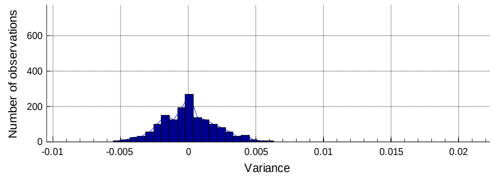


Figure 5-20: Column 20 Histogram

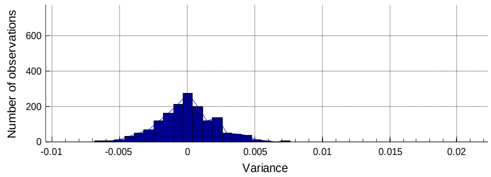


Figure 5-21: Column 21 Histogram

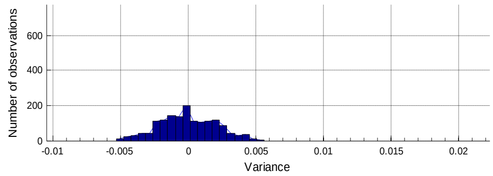


Figure 5-22: Column 22 Histogram

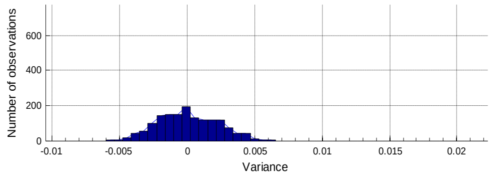


Figure 5-23: Column 23 Histogram

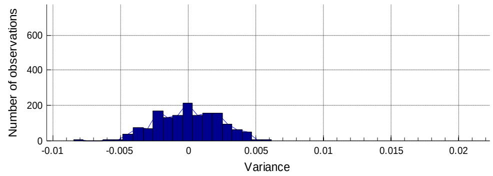


Figure 5-24: Column 24 Histogram

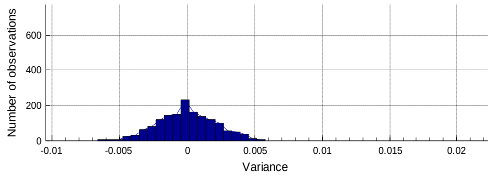


Figure 6-1 below illustrates a three dimensional view of the 59 histograms drawn on the same axis next to each other. The histograms illustrate distributions of variances over a very narrow range. It clearly illustrates the near neighbour effect or memory effect as the circles indicate on the graph. The circles are draws at the positions where there is a slow change in the highest frequency, either gradually up or gradually down. This indicates volatility increases or decreases. Figure 6-2 is a sideways view of Figure 6-1.

Figure 6- 1: USD/ZAR Tick Data Variances Surface Plot

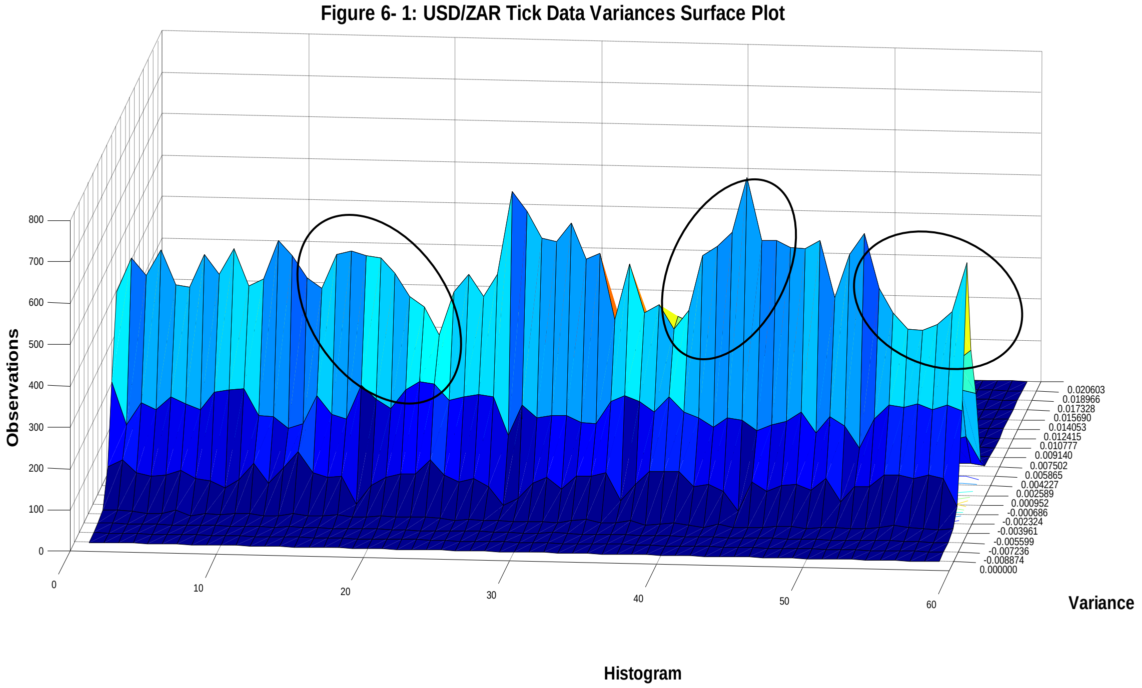
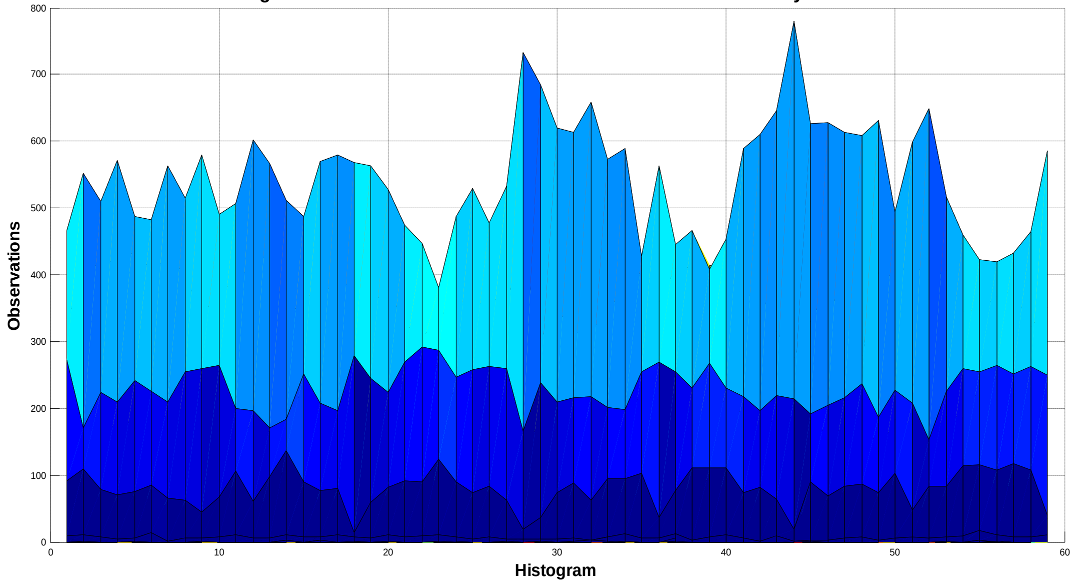


Figure 6-2: USD/ZAR Tick Data Variances Surface Plot Sideways View



To test for similarity of the histogram shapes the average frequency count of all the histograms were calculated. Descriptive statistics were also calculated. The average frequency count of each of the individual histograms were calculated and compared to the mode and the median (See Table 1 below). In case of the average frequency count and median there are very little differences. The mode indicates that a change of 0.0001 is the most recurring (468 times) value which is relatively close to the other two values.

Table 1. Descriptive statistics of histograms

Bin number	Bin centre value	Average frequency count	Median	Mode
1	-0.0097	0.03	0.00	0.00
2	-0.0081	0.10	0.00	0.00
3	-0.0064	1.10	1.00	0.00
4	-0.0048	29.76	28.00	28.00
5	-0.0031	150.47	148.00	148.00
6	-0.0015	317.27	317.00	317.00
7	0.0001	559.05	553.00	468.00
8	0.0018	306.17	302.00	300.00
9	0.0034	102.90	102.00	98.00
10	0.0050	32.58	29.00	28.00
11	0.0067	0.47	0.00	0.00
12	0.0083	0.07	0.00	0.00
13	0.0100	0.00	0.00	0.00
14	0.0116	0.00	0.00	0.00
15	0.0132	0.00	0.00	0.00
16	0.0149	0.00	0.00	0.00
17	0.0165	0.00	0.00	0.00
18	0.0181	0.00	0.00	0.00
19	0.0198	0.00	0.00	0.00
20	0.0214	0.02	0.00	0.00

Graph 7 below illustrates a surface plot of the variances of the 59 individual time series each with 1 500 observations used to compile the histograms. The variance is mostly between 0.005 and -0.005. Figure 8 below is similar to figure 7 except that the graph was drawn from a 5 minute Reuters ZAR/USD exchange rates data set that was gathered from during a week characterised by a lot more volatility in October 2008. Even though the magnitude of changes (see the graph) are substantially lower than 0.005 and -0.005 as in the case of the data set used for figure 7, the are a lot more extreme movements visible. This just underlines how the a data set based on the same financial magnitude, can change over time – the so called time varying volatility or heteroskedasticity.

Figure 7: USD/ZAR Tick Data Variances Surface Plot

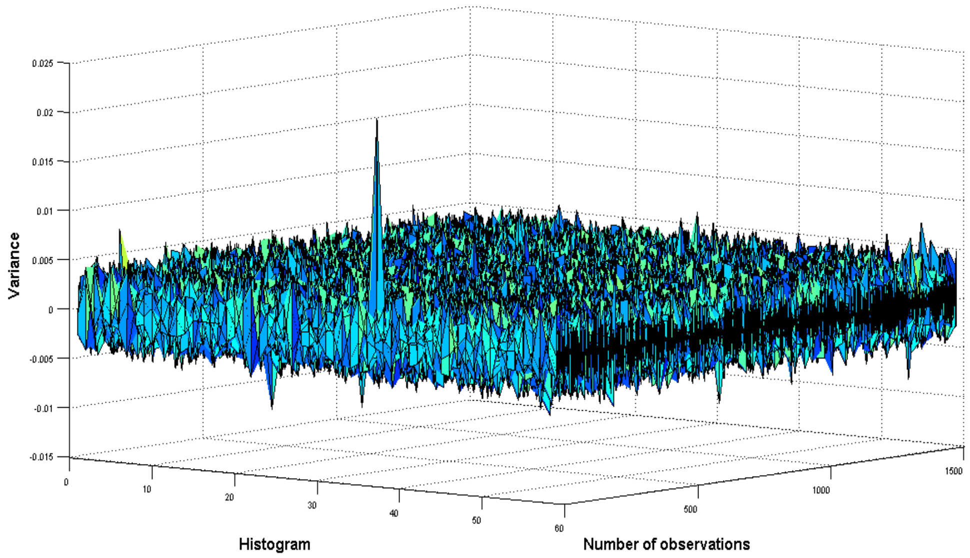
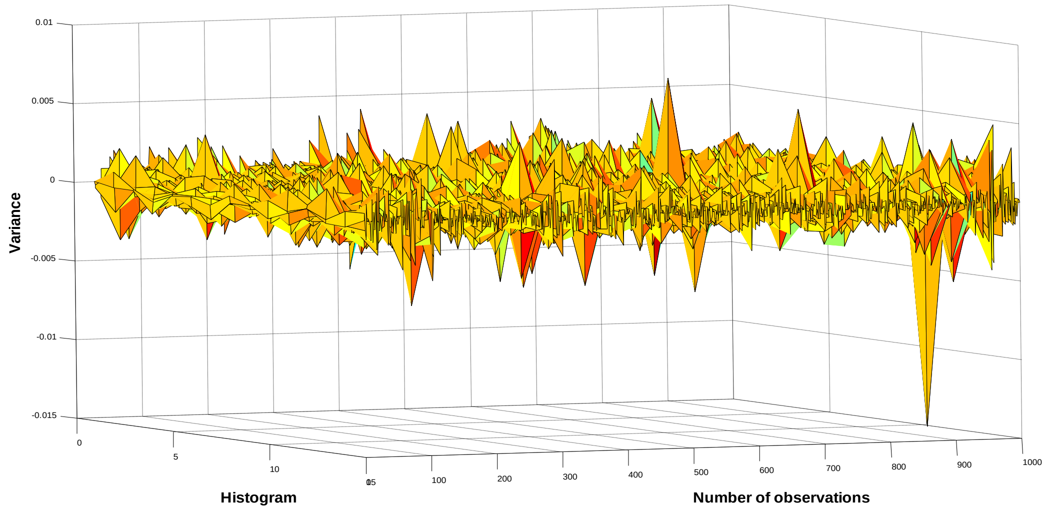


Figure 8: USD/ZAR Tick Data Variances Surface Plot



Summary

The fine structure of the entire distribution of the histograms show significant similarity. However, this fact does not mean much yet from a risk management and currency management point of view. The data shows little autocorrelation. However, this may be more significant over a longer time period. We know that there is long memory in exchange rates mean reversion. Although the exchange rate jumps to various levels, it will tend to revert back to an average level over time (Hull, 2000 : 374). The research shows that even during a week of low volatility, it is difficult to find patterns in the data that are usable. It must be pointed out, however, that this research could have included tick currency exchange rate data over a much longer time period.

Conclusion

The research underlines the fact that, according to the histogram analysis, the currency values as contained in the financial time series, are the result of non-random events/actions of participants in the market place. The analysis as is carried out in this research attempts to find patterns that may be used to better manage exposure to market changes to maximise profit and eventually shareholder's wealth. The research further illustrates that the findings of Shnoll et al. (applied in the natural sciences field) can also be applied to financial market data.

Although this research shows that there are patterns that are very similar, this information does not on its own add much to our ability to forecast exchange rate volatility other that what is usually used in the financial environment. Finding these histogram patterns is somewhat different to chemical processes in the natural sciences. Apart from economic and country influences, the patterns that emerge are in the financial environment subject to the cumulative effect of human behaviour which is difficult to quantify at this stage. In this regard, herding, overconfidence, and fear, for instance, affect markets. Statistical and other financial models do not cater for this element of volatility. The question that remains is, to what extent is the market affected by some of these behavioural issues and how may it be incorporated into financial forecasting models?

Suggestions for further research

This research draws attention to the variation inherent in financial data sets as well as preferred states of a financial trading process. Traditional statistical techniques describe different aspects of the variation in price changes which often is not sufficiently accurate to be used in turbulent times such as has been experienced in recent times due to the sub-prime problem.

Further research may include developing intelligent computer systems or artificial intelligence systems incorporating aspects of human behaviour that may be used to search for such patterns within certain specified parameters.

A further factor that may be considered is determining the Maximum Likelihood by determining the variance (v) of (m) frequency distributions from the average and determining the most likely variance (v) per bin per histogram. A process may be initiated in which these values are constantly updated and used for management purposes.

The research should focus on finding ways to better quantify and manage the exchange rate volatility. Although we use ways to transfer risk (such as with derivatives) to other parties willing to take on that risk, we still need to find some useable value for volatility before we will be able to better price derivatives and consequently manage risk more effectively and efficiently.

References

1. Bouchaud, J.-P., Potters,M., and Meyer,M. (2003). Apparent multifractality in financial time series. *arXiv:cond-mat/9906347 v1 23 Jun 1999*.
2. Bouchaud, J.-P. and Potters, M. (2003). *Theory of financial risk and derivative pricing - from statistical physics to risk management*. Cambridge : Cambridge, United Kingdom, 2nd edition.
3. Fasen, V., Klüppelberg, C., and Lindner, A. (2006). Extremal behavior of stochastic volatility models. In Shiryaev, A. N., Grossinho, M. R., Oliveira, P. E., and Esquivel, M. L., editors, *Stochastic Finance*, pages 107–155, Bellingham, Washington. Springer.
4. Hull J.C. (2000). Options, Futures and Other Derivatives. Prentice-Hall : New Jersey. 4th edition.
5. Mandelbrot, B. B. (1999). N1. In *Multifractals and 1/f noise - Wild self-affinity in Physics*, Selecta Volume N, pages 1–35. Springer, New York.
6. Mantegna, R. N. and Stanley, H. E. (2000). *An Introduction to Econophysics -correlations and Complexity in Finance*. Cambridge University Press, Cambridge, United Kingdom.
7. Panchelyuga, V. and Shnoll, S. (n.d.). Experimental investigation of spinning massive body influence on fine structure of distribution functions of alpha-decay rate fluctuations. Retrieved on 26.09.2006 from: http://arxiv.org/ftp/physics/papers/0606/0606173.pdf.
8. Shnoll, S. E., Kolombet, V. A., Pozharskii, E. V., Zenchenko, T. A., Zvereva, I. M., and Konradov, A. A. (1998). Realization of discrete states during fluctuations in macroscopic processes. *Physics Uspekhi*, 10(41):1025–1035. Uspekhi Fizicheskikh Nauk.
9. Shnoll, S. E., Kolombet, V. A., Pozharskii, E. V., Zenchenko, T. A., Zenchenko, K. I., and Konradov, A. A. (2000). Regular variation of the fine structure of statistical distributions as a consequence of cosmophysical agents. Physics Uspekhi, 43(2):205–209. Uspekhi Fizicheskikh Nauk.
10. Van Zyl, V. H. (2007). Searching for histogram patterns due to macroscopic fluctuations in financial time series, Masters thesis, University of Stellenbosch
11. Van Zyl-Bullita V., Otte R. and Van Rooyen J.H. (2007). Corporate Ownership and Control. 6(3), Spring.
12. Zumbach, G., Pictet, O. V., and Masutti, O. (n.d.). Genetic programming with syntactic
13. restrictions applied to financial volatility forecasting. Retrieved on 26.09.2006 from:
14. http://www.olsen.ch/research/working papers.html.