

LAYER HISTOGRAM PATTERNS IN 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 and index data. The phenomena are related to fine structure of non-smoothed frequency distributions drawn from statistically insufficient samples of changes and their patterns in time. 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 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.

Keywords: Histogram, Layer, Pattern, Volatility, Discrete, States

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Introduction and statement of the problem

One of the most important magnitudes in the financial environment that we need to understand is the volatility of price changes. Volatility of price changes is unfortunately not directly observable in the financial markets. Market volatility reflects different events, happening in succession or synchronously. Volatility increases with increasing time scale as information about the future is either inaccurate or unknown. If we can enhance our understanding of volatility, we may be able to accurately forecast price changes and successfully manage financial risk and therefore maximize shareholder wealth. The prediction of price movements is not only important for devising a profitable trading strategy, but also for creating warning mechanisms to protect against or balance abrupt changes that would otherwise lead to losses. To learn about the timing of price changes of any magnitude could aid in managing trading processes aimed at valuing assets more accurately.

Many different models have been developed in recent years in an attempt to understand and model volatility. Fat tails and volatility clustering are two stylised facts that are often encountered in financial time series analyses. Apart from determining or estimating the volatility of a magnitude, an attempt is also made to find patterns in time series that may repeat themselves over the course of time. We often calculate the standard deviation based on historic price changes. However, this figure is certainly only at best a rough estimate of future volatility.

This study focuses on further extending the knowledge of the nature of the mechanisms that drive price changes. Volatility represents a measure of the way financial asset prices change. If financial markets record large declines of asset prices in short periods, one refers to a crash. The international financial system is highly linked, which often results in financial crises spanning more than one economy.

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 describes layer histogram formation based on the work of Shnoll et al., applied to a financial time series. Two layer histogram methods are applied to a South African Rand (ZAR) data set of one minute frequency from 2 months.

The study includes an empirical analysis of a foreign currency exchange rate where the objective is to evaluate aspects of its distributional structure through compiling non-smoothed layer histograms of the currency dataset.

Data used

One minute frequency exchange rate data of the South African Rand (ZAR) against the American Dollar (USD) have been obtained from Reuters for the time period covering 25 August 18:17 until 14:46 on 25

October 2006. The data set size comprises 38 006 values.

Overview of approaches to modelling financial time series

Financial markets are influenced to a large extent by human reactions of players in the marketplace to news that enter the market during trading times. This is especially true of the foreign exchange markets since they are influenced to a large extent by economic activities and trade between countries and generally by economic conditions prevalent in a country.

Many different models have been developed over a number of years in an attempt to encapsulate those variables that drive price changes. 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 financial markets and is usually measured by the standard deviation. However, this is a very simplistic representation in one figure from a complex and dynamic system, where different players interact on different time scales under the influence of information feedback.

A new research field known as econophysics emerged from the vast increase in data availability since the 1990s coupled with the similarities of financial markets to stochastic processes known in the natural sciences. It spans a wide set of approaches to modelling and understanding the dynamics of financial markets, such as statistical analysis of the time evolution of asset prices and microscopic trading models. (Paul and Baschnagel, 1999, 131-132) Roehner also described stock markets from the viewpoint of statistical physics as an "open, out of equilibrium system" (2005, xiii), where different sorts of particles interact and where rules change over time.

Some of the more well known models developed in an attempt to understand financial time series include generalised autoregressive conditional heteroskedasticity ((G)ARCH) models. 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. These are two important characteristics of financial time series. It provides relatively accurate forecasts of variances and covariances of asset returns through its ability to model time-varying conditional variances. GARCH models may be applied to diverse fields such as risk management, portfolio management and asset allocation, option pricing, foreign exchange, and the term structure of interest rates.

In general, randomness implies incomplete knowledge of the process on which it is based. One assumes in constructing a financial model of price changes that useful information relevant for the future may be obtained from the patterns and frequencies of

past price changes. Furthermore, one may assume in this context that these frequencies reflect some intimate mechanism of the markets themselves. In such a case one may hope that these frequencies would remain stable over the course of time. (Bouchaud and Potters, 2003, 1-3)

The statistical approach to financial markets is based on the notion that whatever evolution takes place, it will do so sufficiently slowly, so that what happened in the past is relevant for predicting the future. However, this 'weak stability' hypothesis is often quite erroneous and particularly unreliable in times of financial crises. Hence the statistical description of financial fluctuations is imperfect, but nevertheless helpful to describe risks. 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. Forecasting volatility in the financial environment is challenging as volatility cannot be observed directly in the market place (Mantegna and Stanley, 2000, 57, 76). At best, even *a posteriori*, volatility is only approximately available. The volatility process is non-trivial and several stylised facts arise from its behaviour (Zumbach et al., nd, 1). Over the years, various researchers have developed several discrete-time and continuous-time volatility models. In particular, the modelling of volatility is based on the following stylised facts (Fasen et al., 2006, 108):

- time variation,
- randomness,
- heavy tails,
- volatility clustering on high levels (long memory of the volatility).

The different modelling approaches take one or more of these stylised facts into account. Bouchaud and Potters (2003, 122) noted that volatility fluctuations are a multiscale phenomenon. Therefore, 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. Several models have been developed to study one specific aspect of the behaviour of stock price movements, namely the clustering of volatility. Besides volatility clustering, other interesting properties of prices have also been described. These include jumps and downfalls in prices, heavy tails of price distributions, and their long memory. Non-linear models evolved from these findings, as they cannot be understood in the framework of linear models (Schiryayev, 2000, 152). Bouchaud and Potters (2003, 130) described how price-volatility correlations lead to anomalous skewness and volatility correlations induce anomalous kurtosis, i.e. fat tails. The failure of linear models to capture important characteristics of

real time series also led some researchers to consider chaotic modelling for financial markets.

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.

It is often assumed that the evolution of stock prices is driven by a noise sequence. Gaussian white noise is usually used as a first approximation. This distributional assumption is central to many financial applications, such as portfolio risk management and option pricing. Assuming a Gaussian distribution has many important consequences and comforts. Empirical research, however, does not confirm this assumption. The Gaussian distribution does not incorporate important findings such as heavy tails, asymmetry and excess kurtosis. (Stoyanov and Racheva-Jotova, 2004, 299-300)

Stable non-Gaussian distributions have been proposed as an alternative. As the name suggests, they have a desirable stability property as well as domains of attraction. Their use is complicated by their lack of closed-form expressions for probability density functions and cumulative distribution functions as well as their infinite second moment. According to Stoyanov and Racheva-Jotova (2004), the use of an infinite variance model for bounded financial asset returns seems inappropriate. However, since any empirical distribution possesses finite variance, infinite variance distributions may seem inappropriate for any application. Large deviations occurring in stock market price changes suggest that "any statistical theory based on finite-variance distributions is impossible to predict accurately" (Stoyanov and Racheva-Jotova, 2004, 300).

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. Stochastic processes and their properties are also 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. In this context they claimed that a distinction should be made between those types of chaos that differ in their distributions of fluctuations. On the one hand, the probability of fluctuation may fall monotonically with its magnitude, which they agreed is the real (or ideal) chaos. On the other hand they suggested that another chaos may be invented in which the distribution of fluctuations will be non-monotonic, corresponding to the histograms they present. Similarly, Mandelbrot proclaimed the usefulness and even necessity of recognising the existence of several distinct states of randomness and random and non-random variability. He denoted these distinct states of randomness as mild, wild and slow variability. (Mandelbrot, 1999, 2-3)

Layer Histograms according to Shnoll

Shnoll et al. originally applied the method to data from stochastic processes other than financial. 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. It is more likely that patterns may be revealed.

In their research regarding layer histograms and histogram patterns in time, Shnoll et al. involved as a first step the conversion of the pointwise time series to a series of successive histograms. Shnoll et al. then analysed the properties of histogram shapes in time, where each histogram is compared to each other histogram on an individual basis. (Panchelyuga and Shnoll, nd, 1) (Shnoll et al., 1998) (Shnoll et al., 2000, 207) Their goal was 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" (Shnoll et al., 2000, 205). For the layer histogram, the position in time is not the central focus of attention. The fine structure of the layer histogram provides information

on the shape of the distribution. More likely values would be represented by several pronounced peaks in the distribution, and less likely ones by troughs. Shnoll et al. refer to polyextremity of the distributions exhibiting alternating peaks and troughs, and thus several (poly) extremes.

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. Our focus lies on the discrete states that become apparent in layer histograms. Other phenomena of the MF effect are not dealt with in this study. The focus is on the formation of discrete states in a financial data set by investigating the fine structure of unsmoothed layered histograms.

Discrete States in Unsmoothed Distribution: Peak and Trough Formation in Layer Histograms

Layer Histogram Construction Details

Before the layer histograms are calculated, the time series should be standardised. Figure 1 shows the data in raw format. The outliers are then limited to the specified threshold determined as a multiple of the series standard deviation. The effect of the thresholding may be seen in the higher outermost bins where the outliers are grouped. This ensures that bins represent the same sub-ranges for all layer histograms. Bins represent the frequency of occurrence of particular values within a certain subrange of the minute currency data. After standardisation, the subperiods are formed and layer histograms calculated.

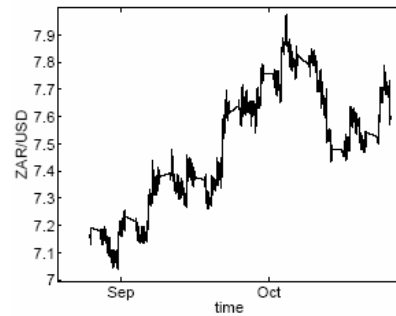


Figure 1. ZAR/USD raw time series points with missing data on weekends

Layer histograms were drawn from ZAR/USD exchange rate data. Table 1 below illustrates that, if the constant increment method is used, each successive histogram is drawn on the total number of data points from the first time series point. Figure 2 illustrates the daily ZAR recordings and from what subsets of the data layer histograms are drawn for each period. Figure 3 illustrates the input data for the layer histogram construction using the increment doubling method.

The fine structure of a data set may be represented by layered histograms. Shnoll found that in the construction of layered histograms, peaks and troughs emerge as more measurements are added. A layer histogram is composed of frequency distributions of a stepwise increasing number of observations. At each step, a fixed number of measurements are added and a histogram of all previous values and the new values is calculated. This step is repeated until the entire data set is exhausted.

Since each new subset contains the previous subset, each bin height of the new histogram will be equal to or larger than the respective bin of the previous histogram, thus giving rise to layers of histograms when all histograms are graphed on the same figure.

The first method, also used by Shnoll, adds a constant number of measurements (constant increment method) to the previous subset of values.

Table 1. Illustration of time series data points used for the constant increment method of layer histogram construction

	time series increments	layer line data	
1	1 - 300	1 - 300	histogram 1
2	301 - 600	1 - 600	histogram 2
3	601 - 900	1 - 900	histogram 3
4	901 - 1 200	1 - 1 200	histogram 4
5	1 201 - 1 500	1 - 1 500	histogram 5

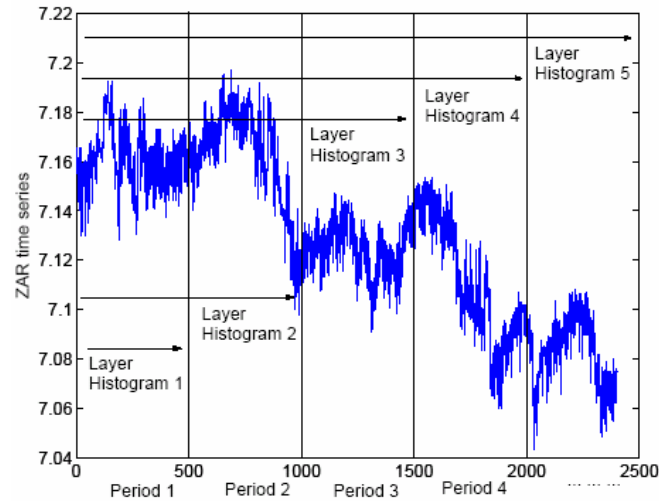


Figure 2. Constant increment method of layer histogram construction

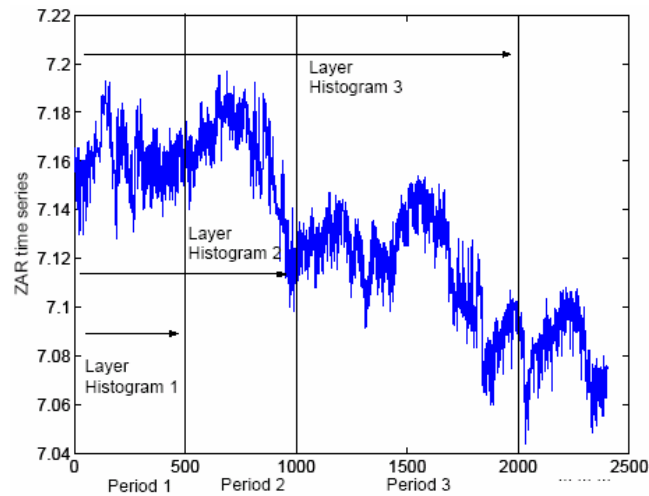


Figure 3. Increment doubling method of layer histogram construction

Figure 2 illustrates how the time series are divided into successively larger subsets using the first 2 400 values of the ZAR time series. The number of values added to each new subperiod is determined by the increment size. Two methods are used for the incrementing.

The second approach (increment doubling method) deviates from the Shnoll layer histogram construction method. Instead of using constant increments at each step, the increment size is doubled. Thus, the doubling of time series subsets at each step of the layer histogram formation leads to a notable decrease in the number of calculated layer histograms as compared to the constant increment method.

Having described the data that enters the histogram calculation and two possible incrementing approaches we now describe the histogram construction parameters given the data. Instead of normalising the entire data set before subsets are formed, an alternative approach to construct layer

histograms would be first to normalise the data at each step before a layer histogram is calculated. However, this would lead to bin ranges to vary as more measurement points are added because the range varies as subsets change.

Especially for the first layer histograms a changing data range changes the bin ranges. Because of the influence of a changing range on the subdivision into bin ranges, the same data point may be counted in different bins for different layer histograms. This approach was not followed, since a consistent bin range subdivision from the first to the last layer histogram was chosen. To illustrate the layered histograms and detect whether discrete states form, it is necessary for the bins to refer to the same interval range at each step.

The convergence of histogram bins to their final assignment makes it necessary to specify bin ranges before any layer histogram could be calculated. Otherwise the bin assignment will only be converging

to the final assignment as determined by the outlier threshold once a section that includes the top and bottom outlier occurs. Thus the programme calculating the layer histograms specifies the bin edges to ensure that bin ranges are fixed from layer histogram one, instead of a gradual convergence of bins to their final values. If an outlier to the top and an outlier to the bottom occurred in the first section from which a layer histogram is calculated, the bins would be fixed at their correct value from the beginning, also without the prior bin assignment.

If this procedure of fixing bin widths from step one is not followed in constructing layer histograms and the outliers do not occur in the first section, bins

will shift around for the first few steps. This shifting continues until outliers are reached for the first time fixing the maximum bin range.

Polyextremes in a subset of data set

The representation of each time series in sequential layers is now provided. Figure 4 shows the first five layer lines of the ZAR layer histogram using the constant increment method. This illustration shows that the polyextremes already become apparent for a subset of the ZAR data from a few days. Compare the subset layer histogram (Figure 4) to the entire layer histogram figure (Figure 5).

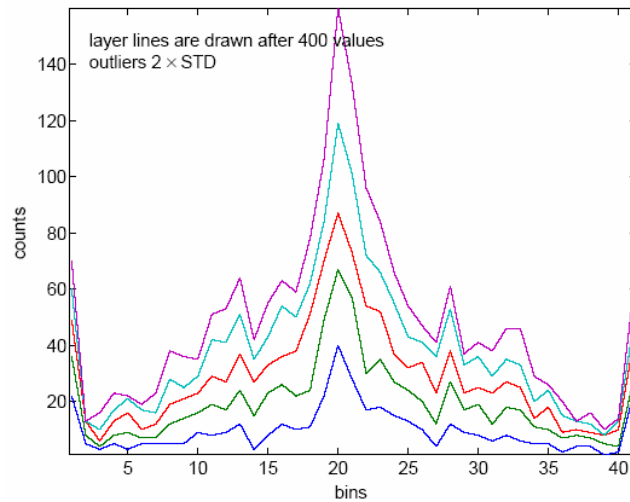


Figure 4. Constant increment method applied to the first 5 layer histograms (layer histogram construction parameters: 400, 40, 2)

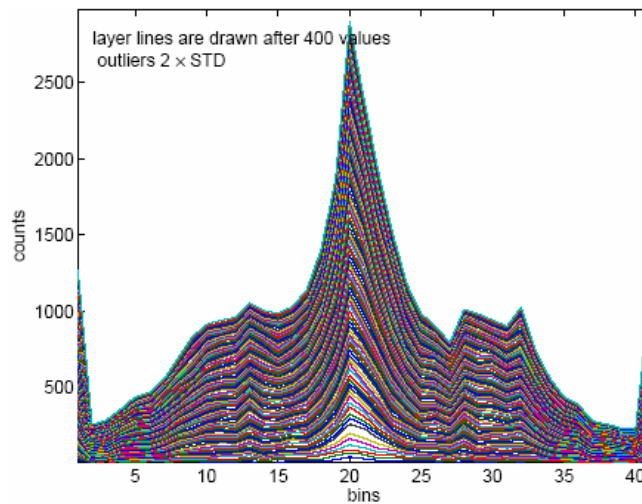


Figure 5. Constant increment method applied to all ZAR data (layer histogram construction parameters: 400, 40, 2)

The sensitivity of the structure of successively drawn layers to parameter settings is illustrated in the next section. These parameters include the number of increments that are added after each layer line, the

number of bins, and the outlier limitation threshold. Figures 5-10 show that the formation of peaks and troughs grows more pronounced as layer lines are added and they show the sensitivity of the fine

structure to changing the number of bins into which measurements are classified. Thus this study shows that the discrete formation effect found by Shnoll for other stochastic processes is also present in financial data sets.

Comparison of Methods

Two methods of layer histogram construction were employed. The original method also used by Shnoll was complemented with another method of incrementing. This serves to test the effect of the incrementing procedure on the final layer histogram shape. Since the addition of a constant number of increments gradually decreases the relative contribution of the latest time series section that is added to the layer histogram shape, the same relative number or measurements has also been used for incrementing in the increment doubling method.

The study expands further on the method employed by Shnoll et al. (1998, 126-1028). It could be expected that the fine structure of layered histograms would grow more pronounced as measurements are increased because of the way Shnoll et al. propose to increment the number of measurements for successive layer histograms. For the method employed by Shnoll et al., the addition of the same constant number of measurements at each step will likely develop the fine structure that is there already.

As data are added, each new increment becomes less influential because the number of added values is constant in absolute terms. The distribution then necessarily represents a similar fine structure to the previous histogram. The presence of fine structure will now be tested for using an alternative layer histogram construction method.

Instead of adding the same absolute number of measurements each time, the second method constructs layer histograms by adding the same relative number of measurements at each step. This

means that at each step the number of measurements used is doubled, resulting in an exponential growth of the subset size until the entire data set is included. The original method's subsets grow linearly, and therefore the method is referred to as constant increment method in contrast to the increment doubling method.

The number of increments influences the layer histogram shape less than the number of bins or the outlier limitation, i.e. the outlier limitation and the number of bins determine the layer histogram end result the most. The variations of layer histograms resulting from different parameter choices and different construction methods make it apparent that there is a fine structure in the data. Furthermore, as Shnoll et al. found in their data, peaks and troughs also emerge in financial layer histograms.

It is important to understand that there is no one correct layer histogram. Different shapes and structures may be detected, where the parameter choices play an important role. The first method calculated increments taking much smaller steps, and thus more layer lines were drawn. These represent incrementally less additional information. For the construction method that doubled the increments of previous steps, much less layer lines were necessary.

The sensitivity to parameter settings, as well as the layer histogram construction method, are compared using the ZAR data set. Different settings for the number of bins are illustrated. In doing this, the discrete state structure becomes apparent at different resolutions. The number of increments is kept unaltered among the data sets, namely 400 for ZAR layer histograms. Outlier limitation is kept the same for the ZAR data to focus the illustration on the sensitivity of the final shape to the number of bins used. The effect of a change in the outlier limitation is the reassignment of bin widths and possibly a decrease in the number of empty bins as the total bin range becomes smaller.

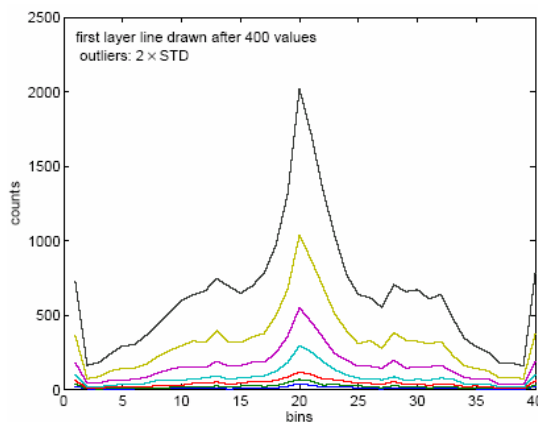


Figure 6. Increment doubling method applied to all ZAR data (layer histogram construction parameters: 400, 40, 2)

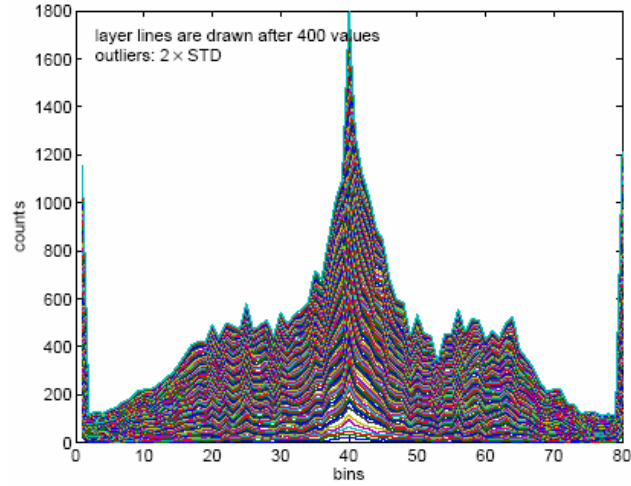


Figure 7. Constant increment method (parameters: 400, 80, 2)

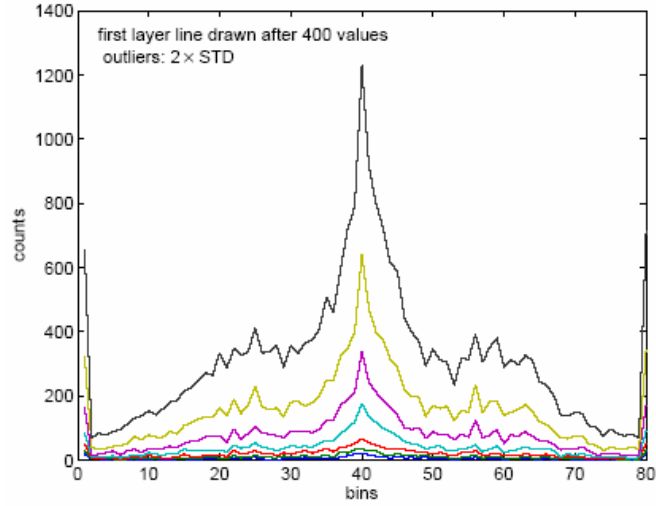


Figure 8. Increment doubling method (parameters: 400, 80, 2)

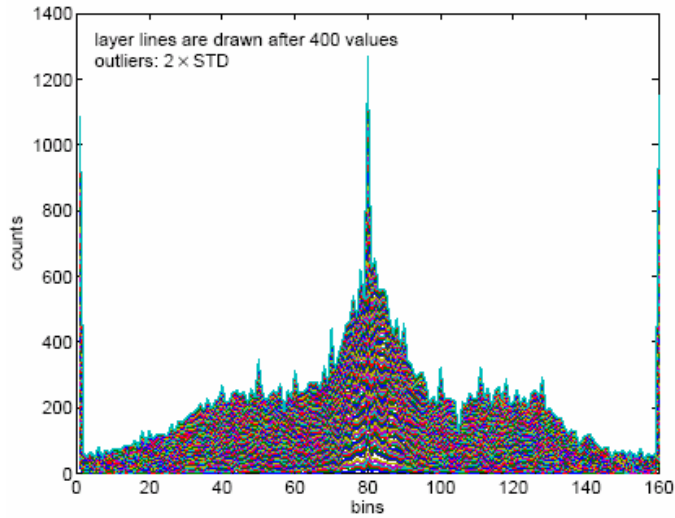


Figure 9. Constant increment method (parameters: 400, 160, 2)

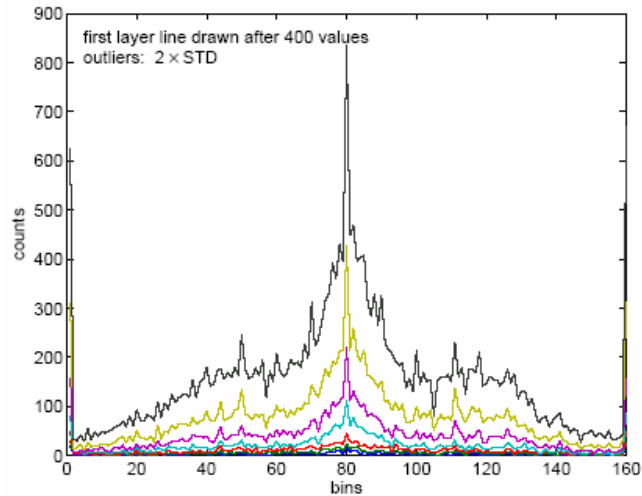


Figure 10. Increment doubling method (parameters: 400, 160, 2)

Figure 6 shows the same parameter settings as Figure 5 using the increment doubling method. Figures 7 to 8 show a finer resolution (80 bins) and Figures 9 to 10 show layer histograms using 160 bins. It can be detected that more peaks and troughs emerge as the number of bins is increased. The three major polyextremes at about 13, 21 and 30 is apparent in all illustrations. Thus, besides the most likely value (centre extreme), in a time series of 2 months we found two more likely states that the process occupies. When looking back again at Figure 2, the three polyextremes already become apparent after applying this method to only 2 days data. Layer histograms consider time information (date and time) of time series values deterministically in presenting the distributional structure of the data. The subsets of each layer histogram are increased by counting the subsequent number of values to be added, which disregard their position in time. A particular layer histogram counts the frequency distribution of values in respective bins and ignores the sequential information as any histogram does. It may be expected by construction that the information that is added to sequential layer lines represents new information occurring later in time.

Summary

We find that discrete states form in the financial data, similar to that found by Shnoll et al. in the data that were used by them. Both methods for constructing layer histograms discussed above show similar structures forming in the data. These structures are represented by polyextremes growing more pronounced.

The unsmoothed distributional character of the entire data set was illustrated via layer histograms. The fine structure of the entire distribution and the effect of polyextremity became apparent. The shape of a layer histogram differs according to the parameter

choice used to calculate it. The construction parameter choices are the number of increments chosen to calculate each successive layer histogram line, the number of bins into which these measurements are classified, and the outlier limitation threshold.

The method Shnoll et al. applied to construct layer histograms was implemented and extended. Both methods showed that the polyextremes present in the histogram of the entire data set appear already in small subsets, i.e. after a few layer histogram lines were drawn. The polyextremes shown by both layer histogram construction methods coincide approximately. Previously it was shown (van Zyl, 2007) that the increment size has a mild effect on the final layer histogram shape, while the choice of the outlier limitation threshold and the number of bins substantially affect the layer histogram shape. The outlier limitation directly influences the bin assignment.

Too many polyextremes - especially when they appear jagged - and empty bins may be an indication that too many bins have been chosen. To calculate a meaningful layer histogram that provides insight into the statistical properties of the process, the relation of the number of bins to the increment size needs to be well chosen. The bin width could be controlled by the outlier limitation threshold.

If polyextremes are present in the layer histogram of the entire data set, as well as in the first layer lines, this means that information from a smaller subset of the data could provide information relevant for a longer time scale.

Several (poly-) extremes of a layer histogram provide more detailed information about the expected value of the process. In the ZAR example, there are 3 more likely states for the entire 2 months, which are already apparent after the data of a few days has been represented by a layer histogram. These states are the polyextremes, namely bins 13, 20, and 30. This

information could be made useful for the purpose of prediction.

Layer histograms focused on distributional characteristics of price changes without taking their time explicitly into consideration. Discrete state formation was detected, as predicted by Shnoll. Shnoll's method of constructing layer histograms was applied first, and a new method was proposed to investigate the fine structure of these distributions. It was shown that discrete states also form and fine structure also emerges from the use of this alternative method.

It must be remembered that the choice of parameters may substantially influence the final shape of histograms. These parameters include outlier limitation, the selection of the number of bins from which histograms are constructed, not so much the number of measurements.

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 patterns that emerge from the layer histograms analysis reflect the cumulative actions of dealers. 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.

Suggestions for further research

This research draws attention to the variation inherent in financial data sets as well as preferred states of a financial process. Traditional statistical techniques describe different aspects of the variation in price changes. For this reason visual comparison of histogram shapes was attempted by Shnoll et al. to show a different aspect of time series variation in an attempt to bypass some of the inherent weaknesses of traditional statistical analysis techniques.

Further research may include developing intelligent computer systems that will search for such patterns in data sets and present the results in such a way that management may be able to use it for risk management and profit maximisation purposes. Artificial intelligence systems may be helpful in this respect.

The other phenomena found by Shnoll et al. can also be built upon, namely the synchronous variation

of price changes, the near neighbour effect and the recurrence of similar histogram shapes after one week, one month, or one year. The findings of Shnoll show two specific year periods where histogram shape recurrence probability peaks. The methods used to detect the phenomena could be automated and comparison methods could use a variety of appropriate distance measures.

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