Volatility Similarities of Stock Prices within the Same Industries

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Abstract

It is prevalently known in finance, and even economics, that prices are the market players' reflection of its collective reaction to the market. Market players' perceptions on an industry may have direct effects on the volatility levels of its member stocks. Moreover, this theory may have certain effects on the fluctuation levels of stocks within the same industry, thereby; having common intuitions on the industry brings similarities in volatility. Having this ideology, the researchers are fascinated in seeing fluctuation similarities, which may appear contrary to the notion that "there is uniqueness on each stock's fluxes". The study attempts to fill in the gap by studying volatility similarities of stocks with the same industry. Concentrating on volatility, the researchers utilized fractal statistics-- a newly developed science of fractals. The methodology enables users to analyze ruggedness of data in their unsmoothed state and create appropriate analysis. This study is also a test of fractal statistics as a risk measure that does not disregard the inherent ruggedness of the data set. The authors proposes, through fractal statistics, that the area of the data set's ruggedness relates to the stock's risk and compare it with other member stocks of the industry. Consequently, trends of stock's fluctuations levels are compared with other industry-member stocks. It is identified that there are prominent similar trends within each chosen industries. It is found out that industry stocks' fluctuation levels possess trend similarities and even posed same results with stocks in the same sector. Fractal statistics has been confirmed effective in exploring the phenomena on stock price volatility similarities.

Keywords: fractals, fractals in finance, volatility similarities, same industries, stock price volatility

JEL Classification: D4

1.0 Introduction

It is common for finance researchers and financial engineers to put their interest on volatility, especially its measurement, valuation, and mitigation. This is perhaps the reason why volatility is the environment with which most empirical and theoretical finance investigations take place. For the most part, stock price volatility has been of particular interest as this is perceived to be the gateway for volatility mitigation. In finance, volatility implies risk thus; there is a constant clamor to manage volatility. With the thought of avoiding the risk at all reasonable costs, the risk averse investor would endeavor to lessen volatility. On the other hand, the speculative investor and the risk tolerant investor delight in volatility, believing that there can be no reward without any risk. These investors recognize that no one bears the danger without rationally expecting something else in return. No matter the investor attitude, an undeniable interest in risk as measured by volatility coupled with the desire to manage it, is always present. Mainly, the purpose for these efforts is the determination of risk within a stock. On one hand, the researchers find it interesting how an observation of a simple graph of the fluctuation in stock prices yield in a conclusion that no two

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stocks display exactly the same fluctuation trend. The graph of the historical prices of one stock is not even slightly similar to another stock. Bearing this in mind, the researchers believe in the discovery of other indicators of risk, suggesting that a significant likeness in the fluctuation of prices of stocks within the same industry may exist. The researchers further propose the use of fractal statistics, a new science developed by Padua (2013) that analyzes data in its unsmoothed state and further explains the inherent non-normality and ruggedness of a data set. While traditional statistics analyze data in their smoothed state, the researchers recognize that the nature of the data set is far from smooth as evidenced by the erratic dips and peaks of historical prices. The use of fractal statistics gives a more appropriate view into the fluctuations associated with the volatility of stock prices than traditional statistics.

On one end, popular measures in the field of finance have utilized traditional statistical tools. Measuring the standard deviation is one of the most popular ways in risk measurement. Technically, what the standard deviation focuses on is the mean deviation of the data set from the average or expected value. Another widely used risk measure is the correlation of the stock price to microstructural factors such as a market index, or macroeconomic factors such as gross domestic product (Schwert, 1989a, 1989b). An application of this is the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Model (APM), respectively. The CAPM is a model that presents the relationship of risk and return to the notion that an investor takes risks with a premium. Thus, any risk that an investor is willing to take must bring a higher "required rate of return". Basically, the model can be derived by generating the regression function of the market performance, with the market index as the independent variable and an observed stock price as the dependent variable. The latter process generates the Security Market Line (SML), a model developed by the 1990 Nobel Prize winners Markowitz, Millar, and Sharpe. This model projects an ocular examination of the required rate of return relative to market risk. The Arbitrage Pricing Model (APM) is somehow similar to the CAPM regarding the utilization of regression where it defines the analysis of the effects of macroeconomic indicators in relation to stock price (Ross, 1976). The objective of APM is the same with the CAPM but considering macroeconomic factors as the independent variable instead. It is worthy to point out that all tools in determining volatility apply smoothing procedures. Standard deviation gives rise to smoothing data sets where the ruggedness is adulterated. Also, the resulting regression function generated from CAPM and APM results to a smoothed line thus, disregarding pure ruggedness. These volatility measures are until now prominently used by finance professionals, specifically fundamental analysts, in the industry. It is also the purpose of the researchers to discern the benefits of using fractal statistics in analyzing fluctuations.

Similarities in volatility are studied by only a few number of scholars. One of these studies is the comparison of volatilities of recognized main stock market indexes. Alencar and Safadi (2012) clustered volatilities to identify similarities and differences and compared parameter estimates using an APARCH model to be considered as a baseline level for volatility. They also used the APARCH model to estimate volatilities and use correlation coefficient to cluster the indexes. Stock price volatility has also been examined by Platt, Platt, and Demirkan (2011). The said study concluded that the ratio of terminal value and enterprise value, stock volume, market capitalization, and shareholders' equity all play a role in determining the volatility of stock prices. Gabriel and Ugochukwu (2012) studied the Nigerian stock market in relation to volatility estimation and stock price prediction and came to the conclusion that the risk and return relationship cannot be viewed completely without taking into account volatility.

Kyröläinen (2008) endeavored to inspect the effect of day trading in a stock's volatility. The study ascertained that day-trading by individual investors is positively associated with a stock's volatility. However, only a weak association is observed between volatility and day trading by institutional investors.

It is to be noted that while financial literature is abundant with previously mentioned studies relating to volatility, an examination of this manifestation of risk that utilizes fractal statistics is clearly lacking. In addition, a comparison of the volatility trends of different stocks within the same industry with a view of determining whether they manifest a significant likeness is also absent. This is the gap that this paper aims to address.

This study is about comparing each stock's overall volatility within industries. It is perceived by the researchers that stocks within the same industry will have similar fluctuation levels. The researchers pinpoint factors that build the criteria of the fluctuation similarities. The study employed fractal statistics in determining the price volatility of selected stocks from the US Dow Jones Industrial Average (DJIA). Utilizing the newly developed science of fractals may give benefit to stock analysts because it enables users to analyze data in their unsmoothed state and produce appropriate analysis. The study attempts to fill in the gap by examining a risk measure that does not disregard the inherent ruggedness of the data set and study volatility similarities of stocks with the same industry. The researchers also posit that it is through fractal statistics that the area of the data set's ruggedness is defined to relate to the riskiness of the stock and compare it with other industry stocks.

2.0 Conceptual Framework

It is hypothesized that volatility starts with the perception of the market participants, but it may be inferred that perception comes from the investor's satisfaction of the stock. Thus, it can be said that fluctuation stems from the level of satisfaction. Satisfaction is receiving the maximum benefit through consumption, and consumption is the result when assets are acquired and eventually utilized. On the other hand, owned assets can be exchanged for other assets that are currently needed by an individual. The market, then, is a collection of transactions pertaining to exchanges of assets with the aim of fulfilling an individual's needs and, ultimately, his satisfaction.

An individual's temporal satisfaction is manifested by one's high tendency to accumulate assets for future benefits. The acquisition of a wealth of assets is deemed to bring the owner satisfaction through maximum consumption. The usual behavior displayed by people with regards to wealth accumulation brings the concept of maximum utilization to the forefront, and eventually points out that transactions in the market are influenced and driven by the pressures applied by the market participants. The value for any exchange is affected by the behavior of said market participants in relation to transaction optimization and satisfaction maximization. Demand is the need of acquiring an asset. When one demands an asset, such a person should be willing to give up something for it.

Throughout time, the satisfaction levels that one derives from a certain asset fluctuate. The market creates this collective satisfaction of market participants and reflects it as fluctuations in the value of the asset. The same goes for the stock market arena, with the price reflecting the satisfaction of investors in a stock. This suggests that the perceived satisfaction on the stock's performance affects the volatility. On the other hand, perceptions on other stocks with a business nature close or similar to a particular stock may also be affected, thus, creating similarities of fluctuation levels. The volatilities may possess similarities on prices of stocks within the same industries.

Fluctuation is both uncertain and ubiquitous in the market. Therefore, the market is a gamble because we lose or gain incremental values of assets through uncertainty brought by the fluctuations. Ideally, if only one can get to know the collective reaction of the overall market participants, one can certainly look forward to greater returns. Knowing the collective reaction of the overall market may start with knowing the volatility similarities of stock with the same nature. This also supports the conventional theory that the stock price is the valuation of the stock based on all information available to the market thereby affecting the collective perception of the market players' population.

Stock price volatility is an interesting phenomenon in finance. It is through the volatility of stock prices that we lose and gain. Everybody desires to gain; therefore, everybody is interested in measuring fluctuations through available indicators.

3.0 Methodology

The researchers decided to choose stocks from among the components of the Dow Jones Industrial Average (DJIA). Of the varied industries represented in the DJIA, the researchers focused on those stocks belonging to the Technology and Telecommunications industries. These industries are chosen because the researchers perceive them to be one of the most dynamic and active. The said industries are represented by seven (7) stocks in total, with five (5) coming from the Technology industry and the remaining two (2) from the Telecommunications industry. The timeframe of the stocks analyzed is from January 2008 to December 2012. The researchers pinpointed similarities in fluctuation of each stock relative to their industries.

This study utilized fractal statistics as a measure of risk. The initial procedure in fractal analysis is the determination of the presence of a fractal distribution by using statistical indicators. As such, the researchers generated the histograms of the closing prices of the stocks of the companies to ascertain the absence of a normal distribution. In addition to this ocular inspection of the histograms, the researchers further tested the data set for additional indicators. Using the Kolmogorov-Smirnov Goodness of Fit Test, the researchers performed a normality test on the data sets. The next procedure after establishing the presence of a fractal distribution is the translation of the historical stock prices by means of the fractal statistics formula.

$$\lambda = 1 - \frac{Log\ (1-\alpha)}{Log\ (x)}$$

Where:

$$\alpha = \frac{Rank\ of\ the\ Data}{n}$$

$$Scale = \frac{1}{Log\ (x)}$$

Figure 1 Lambda Formula

The researchers endeavor to find similarities in volatility. This is achieved by having an ocular examination of each stock's historical prices using the fractal spectrum. The researchers identified segment of scales that possess the same volatility levels by fitting a line to a segment. Starting with the point from the lowest scale, the series of points that fall within the fitted line form part of one segment. The points that do not fit with the first fitted line will be the starting point of the next segment. The process is repeated until the last point in the highest scale has been reached, and all segments have been identified. The slope of the line of each of the established segments is then identified by computing the slope of the line.

$$Slope = \frac{d\lambda}{d\,scale} = \frac{\lambda_{n+1} - \lambda_n}{scale_{n+1} - scale_n}$$

Figure 2 Fractal Segment Slope Formula

The slope of the segment implies the fluctuation level. This slope is interpreted to hold an inverse relationship with the volatility of a stock. Consequently, the nearer the slope to zero, the less volatile the segment is. This paper investigates the similarities in volatility of stocks within the same industry and identifies the trend of each segment's fluctuation levels.

4.0 Fractal Model and Analysis of Data

An ocular investigation of the histogram of the historical prices of the stocks enabled the researchers to establish the non-normality of the stock prices observed. The ocular examination banks on the theory that, to qualify as a normal distribution, the data's frequency must form a bell-shaped curve. The histograms are presented in Appendix A.

Based on the figures in Appendix A, it is clear that the stocks do not have a normal distribution. The data set of each stock poses non-normal forms, indicating that it may signify a fractal distribution. Having satisfied this first indicator of a fractal distribution, the researchers proceeded to validate this absence of a normal distribution by performing another statistical procedure – the Kolmogorov-Smirnov Goodness of Fit Test. The normality plots are presented in Appendix B.

The normality plots in Appendix B graphically present to us the data as plotted versus a theoretical normal distribution line (blue line). The Kolmogorov-Smirnov Goodness of Fit Test validates if data is a normal distribution when it fits the theoretical normal distribution line.

Evident in the plots is the outliers from the blue line, which allow the conclusion that, as per the graphical presentation on the normality plots, it is unlikely that the data sets come from a normal distribution. Consistently, the p values of <0.01 also support the non-normality of the data. The P-Value results of the observed stocks (CISCO, IBM, INTC, MSFT, UTC, T, and VZ) are less than 0.01. Shared with the histogram results presented previously, the researchers posit that the data sets do not follow a normal distribution. As such, the researchers proceeded to apply fractal statistics.

Presented on Appendix C are the fractal spectra of the observed stocks and identified segment of scales that possess the same volatility levels by fitting a line to a scale segment.

Elbows are identified as the start and the end of a scale segment. On the fractal spectrum, the first segment starts with the point with the lowest scale and the last segment ends with the point with the highest scale. The first elbow is the point with the lowest scale, and the last elbow is the scale with the highest scale. Presented in Appendix D are the coordinates of the elbows identified.

With the information provided by table in Appendix D, we can now compute for the slope of the scale segments. To recall, the slope of the segment implies the fluctuation level. Consequently, the nearer the slope to zero, the less volatile the segment is.

Table 1 Slopes of the Scale Segment

SLOPES							
Stocks	Scale Segment						
	1	2	3	4	5	6	7
Technology							
Cisco	-215	-45.77	-8.40	-2.78			
IBM	-575	-120	-17.46	-3.90	-27.59	-5.94	-1.88
Intel	-500	-150	-43.10	-1.50			
Microsoft	-212.5	-91.67	-30.56	-11.54	-1.54		
United Technology	-457.14	-116.67	-41.38	-3.41	-2.84		
Telecommunications							
AT & T	-184.52	-131.94	-29.22	-9.26	-23.71	-9.35	-3.62
Verizon	-381.58	-158.33	-33.78	-17.16	-42.45	-10.25	-3.81

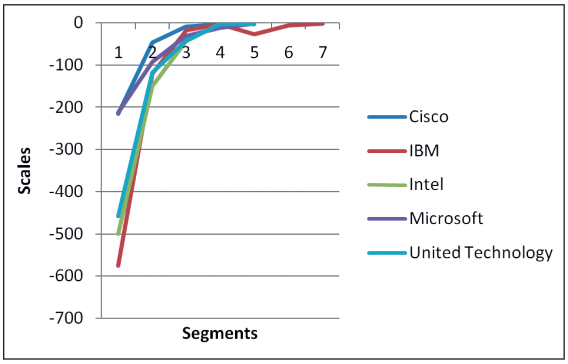


Figure 3 Trends of Fluctuation Levels for the Technology Industry

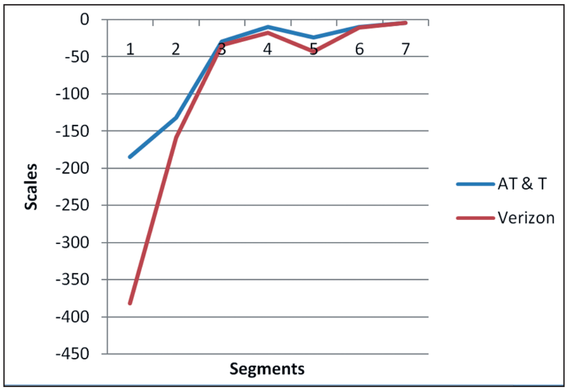


Figure 4 Trends of Fluctuation Levels for the Telecommunications Industry

When observing table 1, similarities in volatility is obscured but graphing the digits on Figure 3 shows these similarities. The graphical image above exposes two distinct stock groups (i.e. sectors) within the same industry. Each of these two sectors exhibits a similar trend in its fluctuations. Cisco and Microsoft can be identified as members of one sector. Common in these two companies is their business model, which is concentrated on the selling of software, services, and networks. On the other hand, the other sector is comprised of IBM, Intel and United Technologies. These companies focus their business model in the sale of computers, electronic modules, and equipment. Viewing the graph in Figure 3, it can be inferred that the fluctuation levels are similar not only within the same industry, but also within the same sector.

For telecommunications stocks, the first segment's volatility levels are diverse from each other where Verizon acquired volatility levels of nearly negative 400 meanwhile AT & T is half as volatile as Verizon. Verizon is 20% more volatile on the second segment while it is 15% more volatile on the third. Still on the fourth until theseventh segment, Verizon is more volatile by 85.31%, 79.04%, 9.63%, and 5.25%, respectively. To sum it all up for the telecommunications industry, Verizon moves variedly as compared with AT & T.

Even Verizon is more fluctuating; Figure 4 clearly shows a similar shape in the fluctuation levels of the two stocks classified under the telecommunications industry. This observation supports the previous conclusion that stocks under the same industry exhibit similar patterns in volatility levels.

The researchers, after testing and validating all the data, concluded that fluctuation levels of all stocks within the same industries display similar trends.

5.0 Conclusion

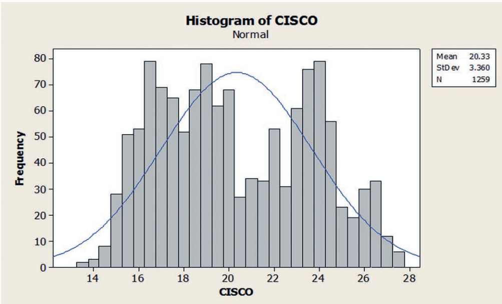
The trend of the fluctuation levels of the stocks is compared with stocks of the same industry thus identifying prominently similar trends with each other. The stocks belonging to the telecommunications industry move in the same manner, thereby allowing the researchers to conclude that they display a similar behavior in terms of volatility levels. On the other hand, the stocks belonging to the technology industry showed two prominent trends. The researchers interpret these two prominent trends as sectors within the said industry. The sectors represent those stocks of companies that deal with software, services, and networks (i.e. Cisco and Microsoft) and those stocks of companies that focus on the sale of computers, electronic modules, and equipment (i.e. IBM, Intel, and United Technologies). It is observed that the stocks that belong to the same sector within the same industry also display a similar shape in their volatility levels. Thus, volatility levels are similar not only for stocks within the same industry, but also for stocks within the same sector.

With the aid of fractal statistics, the researchers then conclude that the fluctuation levels of stocks within the same industry demonstrate the same trend. It has to be noted that these similarities in the fluctuation are dependent on the perception of the market participants within a certain industry. This collective perception, particularly of the investors, towards an industry brings some behavioral responses to the stocks that belong to the said industry. This, in turn, causes similarities of fluctuations.

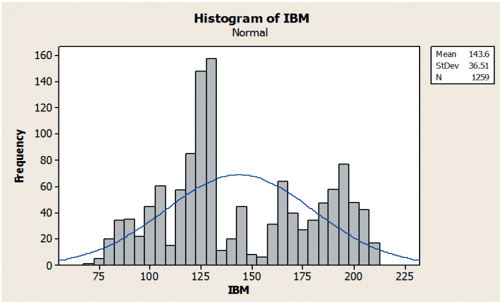
6.0 Appendices

APPENDIX A
Histograms of the Analyzed Stocks

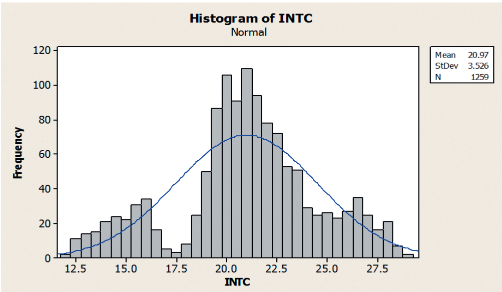
TECHNOLOGY



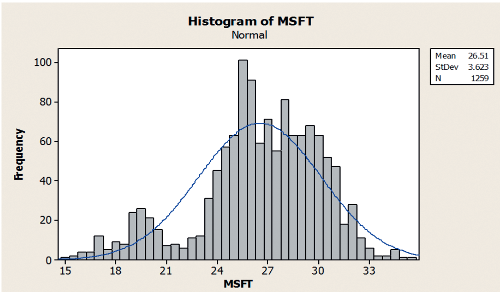
Histogram , CISCO



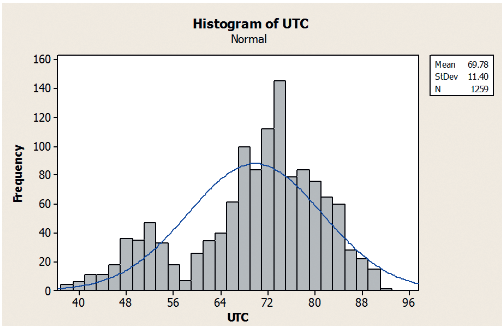
Histogram, IBM



Histogram , Intel Corporation

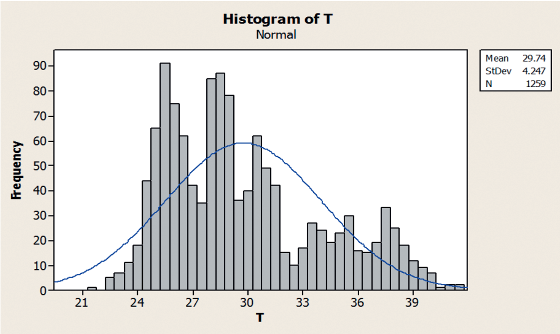


Histogram, Microsoft

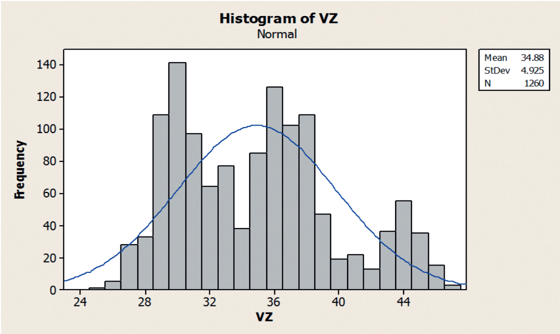


Histogram, United Technologies

TELECOMMUNICATIONS



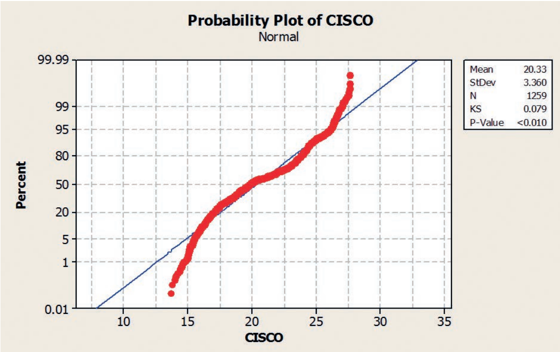
Histogram, AT & T



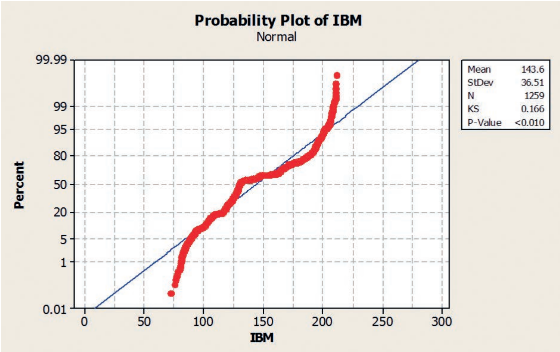
Histogram, Verizon

APPENDIX B
Kolmogorov-Smirnov Goodness of Fit Test Probability Plots

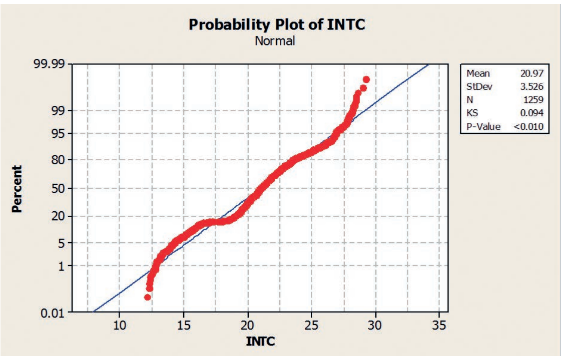
TECHNOLOGY



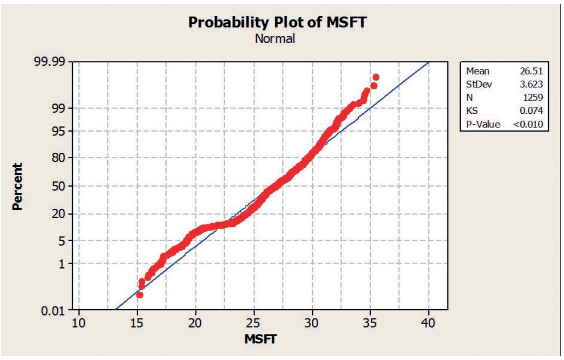
Normality Test, CISCO



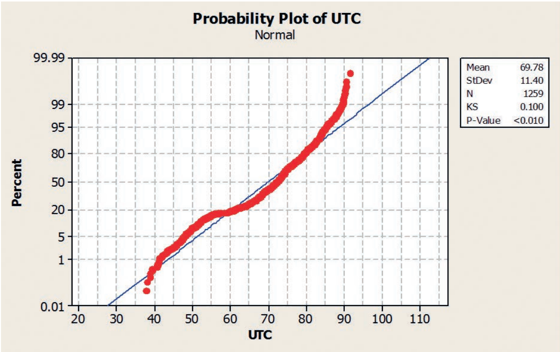
Normality Test , IBM



Normality Test, Intel Corporation



Normality Test , Microsoft



Normality Test, United Technologies

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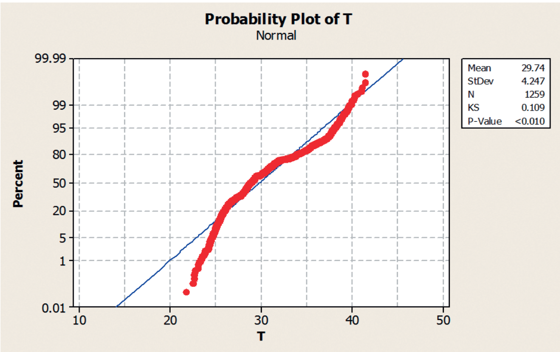
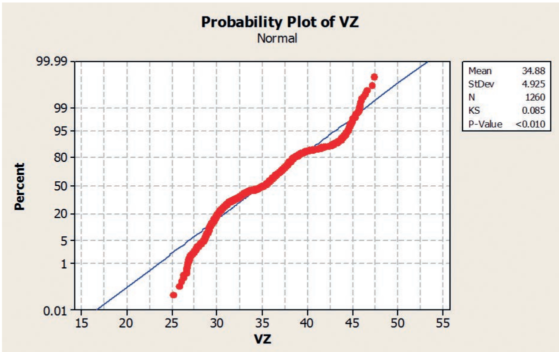


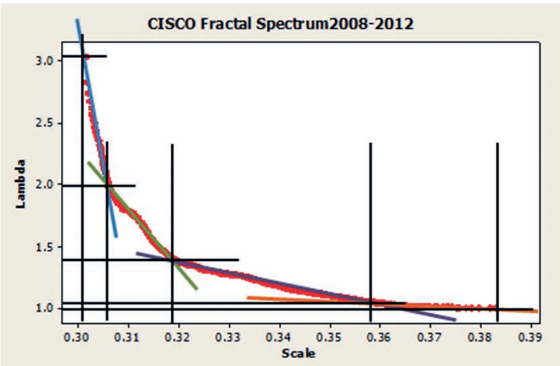
Normality Test, AT & T



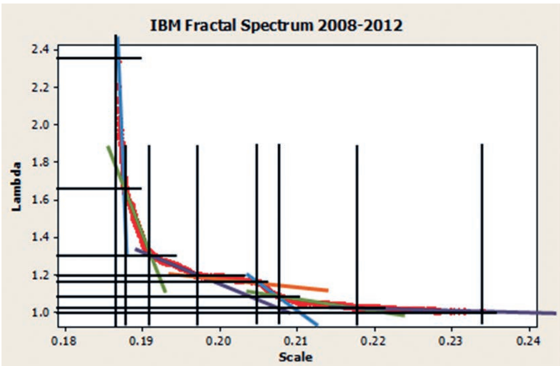
Normality Test, Verizon

APPENDIX C
Fractal Segmentation of the Analyzed Stock Prices

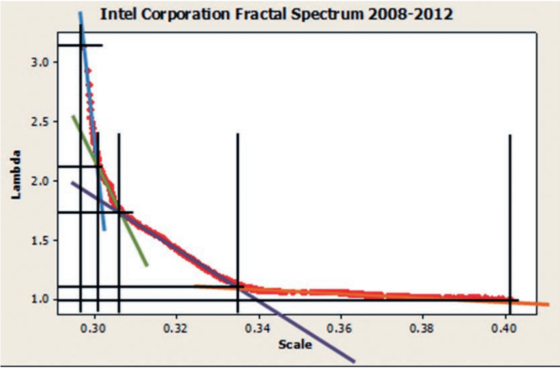
TECHNOLOGY



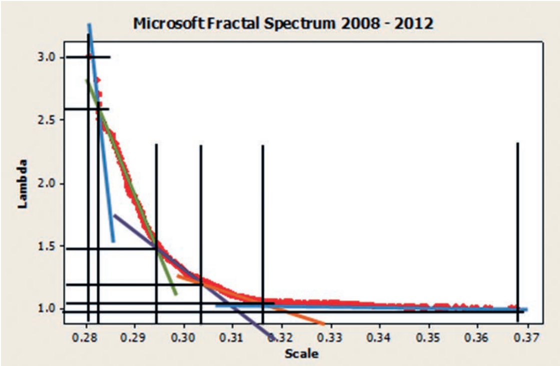
Fractal Spectrum, CISCO



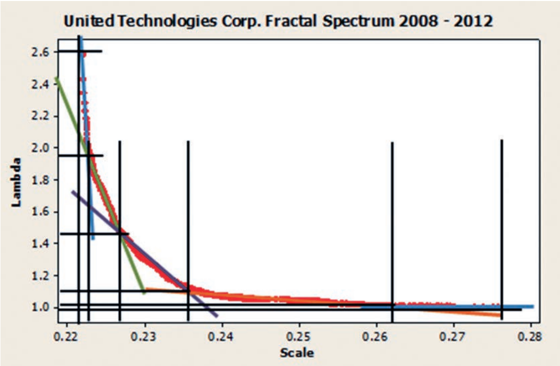
Fractal Spectrum, IBM



Fractal Spectrum, Intel

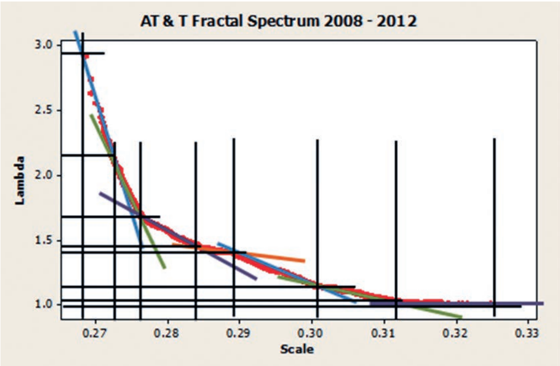


Fractal Spectrum, Microsoft

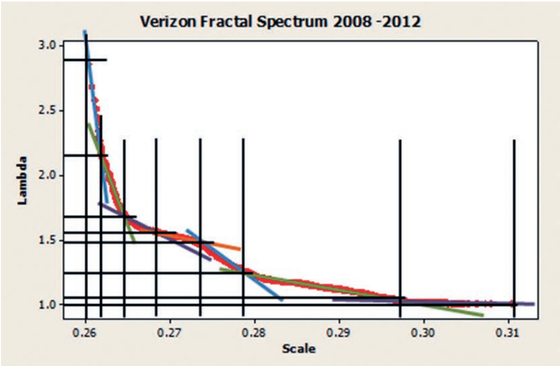


Fractal Spectrum, United Technologies

TELECOMMUNICATIONS



Uractal Spectrum, AT & T



Fractal Spectrum, Verizon

APPENDIX D
Identified Elbows of Stocks

	Elbows							
	1	2	3	4	5	6	7	8
Cisco								
Lambda	3.05	1.975	1.38	1.05	0.98			
Scale	0.301	0.306	0.319	0.3583	0.3835			
IBM								
Lambda	2.35	1.66	1.3	1.19	1.16	1.08	1.02	0.99
Scale	0.1868	0.188	0.191	0.1973	0.205	0.2079	0.218	0.234
Intel								
Lambda	3.1	2.1	1.725	1.1	0.975			
Scale	0.2985	0.3005	0.303	0.3175	0.4008			
Microsoft								
Lambda	3	2.575	1.475	1.2	1.05	0.97		
Scale	0.2805	0.2825	0.2945	0.3035	0.3165	0.3685		
United Technologies								
Lambda	2.59	1.95	1.46	1.1	1.01	0.97		
Scale	0.2214	0.2228	0.227	0.2357	0.2621	0.2762		
AT & T								
Lambda	2.925	2.15	1.675	1.45	1.4	1.125	1.025	0.975
Scale	0.2685	0.2727	0.2763	0.284	0.2894	0.301	0.3117	0.3255
Verizon								
Lambda	2.875	2.15	1.675	1.55	1.4625	1.2375	1.05	0.975
Scale	0.26	0.2619	0.2649	0.2686	0.2737	0.279	0.2973	0.317

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