TECHNICAL QUALITY ANALYSIS OF GLOBAL STOCK MARKETS

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ABSTRACT

Forecasting is a difficult but necessary area of management. In the present paper we deal with macro-level forecasting. This research focuses on a critical review of forecasting methods for global stock markets analysis with an emphasis on Quality Engineering principles and their financial application. In particular, the authors discuss the Mahalanobis-Taguchi System (MTS), the T-Method and some time series models, which can be used to predict stock market trends. We give an example of forecasting the Standard & Poors (S&P) 100 Index.

The main objective of this research is to propose a conceptual framework for efficient and accurate stock market forecasting.

Keywords: Technical quality analysis, Forecasting stock returns, Quantitative techniques, Market forecasting, Market volatility, Quality Engineering (QE)

1. INTRODUCTION

The ability to accurately predict the future is fundamental to many decision processes in planning, scheduling, purchasing, strategy formulation, policy making, supply chain management and investing. As such, forecasting is an area where much effort has been invested in the past. Change appears to be the only constant, so we expect that accurate forecasts will increase in importance in the future. A survey of research needs for forecasting has been provided by Armstrong (1999).

Forecasting has been dominated by linear methods for many decades. Linear methods are easy to develop and implement and they are also relatively simple to understand and interpret. However, linear models have serious limitation in that they are not able to capture nonlinear relationships in the data. The application of linear models to complicated nonlinear relationships is often unsatisfactory (Makridakis, 1982).

The Financial forecasting or stock market prediction is one of the hottest fields of research lately due to its commercial applications owing to the high stakes and the kinds of attractive benefits that it has to offer. Unfortunately, the stock market is essentially dynamic, nonlinear, complicated, nonparametric, and chaotic in nature. The time series are multi-stationary, noisy, random, and has frequent structural discontinuities. In addition, stock market's movements are affected by many macro-economical factors (Miao et al., 2007) and (Wang, 2003), such as political events, firms' policies, general economic conditions, commodity price change, interest rate, investors' expectations, institutional investors' choices, movements of other stock market and psychology of investors, etc.

In the present paper, after the Introduction, we provide in Section 2 critical discussion of the investigated forecasting methods for stock market analysis with an emphasis on Quality Engineering principles and their financial application to market forecasting. Section 3 proposes integration of the forecasting methods. Finally, in Sections 4 the authors give some concluding remarks.

2. CRITICAL REVIEW OF FORCASTING METHODS FOR STOCK MARKET ANALYSIS

Fundamental Analysis: Fundamental analysis helps investors to buy at low price relative to the intrinsic value of a business. It has its roots in a value investing approach. In his book 'The Intelligent Investor', Benjamin Graham, the father of value investing, refers to fundamental analysis as security analysis (Graham, 1949). He asserts that fundamental analysis deals with the past, the present, and the future of a given security. It identifies a business's attractiveness for purchase by estimating its intrinsic value. The process of fundamental analysis is a useful tool for identifying stocks available at a discount to their intrinsic value. Graham has presented the following expression (1) to estimate the intrinsic value of a company (Graham, 1949).

$$\text{Value} \approx \text{EPS}\,(8{,}5 + 2g) \qquad (1)$$

Where EPS is a trailing twelve-month earnings-per-share (EPS), g is the expected growth in the EPS over the next 7 to 10 years. Since the value computed using Eq. (1) is estimation (a forecast), it cannot be exact. In order to mitigate the effects of inaccurate estimates, Graham advocates the use of Margin-of-Safety (MoS). The MoS is a powerful concept that acts as a risk-inhibitor in the investing process. It provides a price target at which stock may be considered for buying. The goal is to buy a stock at a price sufficiently low compared to its intrinsic value such that errors in the estimation of the intrinsic value can be overcome by a significant upside potential. Value investors believe that the market is irrational when the price is lower than the intrinsic value. Further they believe that the price will eventually rise to its intrinsic value or beyond, ultimately resulting in a profit-making opportunity. If the estimated value is indeed a true value and if the market price approach the stock's true value, then with a 50% MoS, 100% profit can be realized. On the other hand, if the estimated value is not a true value, and if the stock price continues to decline, associated loss will be limited due to low buying price.

Although fundamental analysis can be used as a good leading indicator of a stock future performance, it has several shortcomings that prohibit its use as a stand-alone-tool. The first shortcoming is the process and logic of valuation. The equation given by Graham is only an approximation to the actual value and hence, it is probabilistic in nature. Further, it relies on the estimates of EPS growth rate over a period of 7 to 10 years. These estimates are subjective and frequently revised by analysts following a particular company. The estimates change frequently for a company or a industry group due to reasons out of investor's control. The second short coming lies in the assumption that the market price will eventually approach intrinsic value. However, there is limited information in the fundamental analysis to predict price action. The second assumption can be valid only if the investor has a reliable forecast of the stock price. Such a forecast would enable investors to time their entry more precisely.

More recently, Phil Town's Rule#1 is similar to Graham's value investing approach (Town, 2007). He integrates meaning, moat, MoS, and management with an easy-to-implement calculation of the intrinsic value of a stock. As a first step, Town advocates the use of a threecircle exercise to identify businesses of interest. The three circles are labeled talent, passion, and money. Once businesses common to these three circles are identified, the next step is to identify and classify economic moat associated with these businesses. The third step focuses on the five fundamental attributes of a business. Town calls them the "big five" numbers: return on invested capital (ROI), equity growth rate, EPS growth rate, free-cash-flow growth rate, and sales growth rate. If these numbers are greater than 10% for the past 10 years, the next step is to consider a business's long-term debt. As a rule, Town suggests that the long-term debt should be payable within the next 3 years using current free cash flow. If a business passes through these initial filters, the fourth step is then to study the profiles of its top executives. Town suggests that investors should purchase shares in a business only if the vision and values of the top management align with their own.

Finally, the intrinsic value of the business is estimated. Town uses the current EPS (trailing twelve month) and compounds it at an estimated EPS growth rate. He then estimates a future price-to-earnings (PE) ratio based on the stock's historical PE ratios and the estimated EPS growth rate. The forecasted stock prices are calculated by multiplying future PE with future EPS. The intrinsic value is the present value of the forecasted stock price discounted using 15% rate of return. The MoS price is 50% of the intrinsic value. Town also uses the term sticker price to refer to intrinsic value. If a stock passes all the filters and is selling at a 50% MoS, technical analysis is then used to identify a buy signal. The following paragraphs introduce technical analysis and describes some important technical indicators.

Technical Analysis and Quality Engineering: Technical analysis is widely used among traders and financial professionals, and is very often used by active day traders, market makers, and pit traders. Brown and Jennings (1989) showed that technical analysis has value in a model in which prices are not fully revealing and traders have rational conjectures about the relation between prices and signals. Technical analysis employs models and trading rules based on price and volume transformations, such as the relative strength index (RSI), moving averages (MA), regressions, inter-market and intra-market price correlations, cycles or, classically, through recognition of chart patterns. However, many technical analysts reach outside pure technical analysis, combining other market forecast methods with their technical analysis. Examining the effectiveness of technical analysis on US stocks, we also advocate for this integrative approach in an attempt to improve portfolio performance.

It is undeniable, however, that the majority of profits come from correctly anticipating and acting upon a trend, and for this reason, almost all technical study is devoted toward early anticipation of a trend. When we set out to create a portfolio, we are usually concentrating on profits. Our underlying objective is to make profits. However, we must be careful not to focus so much on earning profits that we forget about the critical concept of risk. Profitable professionals know the results of investment action from experience and know the risks. Successful professionals always apply some form of risk control, even if it is just a series of mental stop-less levels. Considering risk marks the difference between amateurs and professionals (Kirkpatrick et. al., 2007), so risk must be considered.

Academics have long characterized risk as equivalent to volatility. The Capital Asset Pricing Model (CAPM) and options theory consider volatility not only an important variable in markets, but also a measure of risk. These ideas are partially correct, but as anyone who has operated in the markets knows, the real definition of risk is: "How much money am I going to lose?" This is how the technical analyst focuses on risk. Average monthly return and standard deviation of the monthly return are used to estimate the volatility of returns.

The Sharpe ratio: is common measure of the return versus risk of a portfolio or system.

Mathematically,
$$S = \frac{\hat{r}_i - r_f}{\sigma_i} \tag{2}$$

where subscript *i* denotes ith security, $\hat{r}_i$ is the expected return from the ith security, r_f is the return on a benchmark asset, such as the risk free rate of return, and σ_i is the standard deviation of expected return.
However, risk is not just variability, but is also the risk of capital loss. The Sharpe ratio fails to account for skewed deviations of return. An investment that deviates more to the upside, for example, will not be fairly represented by the Sharpe ratio, which assumes a normal distribution. These problems are why portfolio designers shy away from the Sharpe ratio and have designed other ratios of return to risk that are more realistic.

Market Indicators: The time period measured will affect the signal-to-noise (S/N) ratio. S/N ratio is a metric designed to be used to estimate the robustness of a product or process.
From a QE point of view, buy, sell, or hold are the signals that an investor uses to achieve a desired rate of return. Under the ideal conditions, the stability of the stock can be expressed by a positive slope and minimum fluctuation in the stock price.
In QE, slope is denoted with Greek letter β and fluctuations around the slope or volatility is expressed as a standard deviation and denoted by σ. The objective of a screening process is to find stocks with a large β and small volatility. If the buying point *t* equals 0, and the buying price is S_0, then the stock price S_t compounded at rate *r* at any time t can be calculated by Eq. (3).

$$S_t = S_0(1+r)^t \tag{3}$$

We take the log of both sides of Eq. (3):

$$\log S_t = t\log(1+r) + \log S_0 \tag{4}$$

This can be simplified as:

$$\log\left[\frac{S_t}{S_0}\right] = t\log(1+r) \tag{5}$$

Eq. (5) is an equation of a straight line, which can be expressed as:

$$y = \beta M \tag{6}$$

Thus, in Eq. (5) the slope is log (1+r). The objective of screening is to identify stocks that can consistently appreciate at or above a desired rate with minimal fluctuations. Thus $\log(S_t)$ must be a continuously increasing function of t. In other words, increasing values of *t* should produce increasing values of S_t.
S/N ratio has the following properties (Fowlkes and Creveling, 1995):

1. The S/N ratio reflects the variability in the response of a system caused by noise factors. The noise factors are the factors that affect the output performance (the return on invested

capital, for instance) of the financial portfolio but are chosen not to be controlled because it is either difficult or uneconomical to control them.
2. The S/N ratio is independent of the adjustment of the mean. In other words, the metric would be useful for predicting performance even if the target value should change.
3. The S/N ratio measures relative performance, because it is to be used for comparative purposes.
4. The S/N ratio does not include unnecessary complications, such as control factor interactions, when the influences of many factors on product performance are analyzed.

In analyzing short-term market dynamics, such as a recent price change, managers may find it useful to measure market share over a brief period of time. Short-term data, however, generally carry a low S/N ratio. By contrast, data covering a longer time span will be more stable but may obscure important, recent changes in the market. Applied more broadly, this principle also holds in aggregating geographic areas, channel types, or customers. When choosing markets and time periods for analysis, managers must optimize for the type of signal that is most important.

Mahalonobis-Taguchi System (MTS) approach: The MTS is a pattern recognition technology that aids in quantitative decisions by constructing a multivariate measurement scale using a data analytic method. The main objective of MTS is to make accurate predictions in multidimensional systems by constructing a measurement scale (Taguchi et. al, 2002). The patterns of observations in a multidimensional system highly depend on the correlation structure of the variables in the system. Existing research uses the MTS for prediction and diagnosis, which illustrates the methodology's accuracy and effectiveness. However, little is presented to compare the accuracy and effectiveness of the MTS versus other methodologies. The advantage of Mahalanobis Distance is that it takes into consideration the correlations between the variables and this consideration is very important in pattern analysis. So, it is a very good economic approach for multidimensional pattern recognition systems. Mathematically,

$$D_j^2 = \frac{1}{k} Z_{ij}^T A^{-1} Z_{ij} \tag{7}$$

where k is the number of factors, Z is a matrix of standardized values of factors, and A is a correlation matrix for the normal group. Subscript j denotes jth observation.

T-method: In the last decade, the MTS has been used in a variety of applications to solve multivariate diagnosis and forecasting problems. More recently, a new method known as the T-method has shown promise. The T-method, developed by Genichi Taguchi, is founded upon the fundamentals of the Taguchi System of Quality Engineering (TSQE), also known as robust engineering, which is used to calculate an overall prediction based on S/N ratio. Using this method, the required parameters are calculated to obtain an overall estimate of the true value of the output for each signal member.

The T-method, a subset of the TSQE requires the selection of a unit space (or normal space) in which all members of the group must have the same or similar output. In the first step, multivariate data is partitioned into three different classes. The first class is considered as the unit group, and the second class is considered as the signal group. These two groups are used to validate the model. The average output value of the unit group and the average output value of each variable are subtracted from each member of the signal group.

In forecasting using the T-method, the objective is to design a predictive model capable of measuring the actual value of the unknown quantity (y in the future) accurately and consistently in the presence of various noises. The forecasting problem considers explanatory variables which are strongly related to the future value of y. The Taguchi method is of interest since it is one of the few methods that achieve high correlations with relatively little data.

Leading-indicators method: a leading indicator is a measurable economic factor that changes before the economy starts to follow a particular pattern or trend.
Firstly, it is important to identify adequate and more timely index of the leading indicators, as many as possible for more accurate forecasts, and then combining a variety of the factors (checking their relationships in terms of correlation, i.e. collinearity) that can be used to forecast the future financial/economic trends by applying the time series analysis. The principles of the TSQE could be employed and integrated to the time series forecasting technique.
Profitable leading indicators are not trivial algorithms, as they are required to "see" what the market has not yet already seen. Modeling paradigms typically are used to create leading indicators. The very first step toward applying a leading indicator method requires the developer to decide how far into the future the leading indicator is to forecast.

Time-series (TS) models: Although the Random Walk Theory claims that price changes are serially independent, traders and certain academics (Malkeil B., 1996) have observed that the market is not always efficient. The movement of the market may be predictable. Statistical methods are commonly used for time series prediction. Managers' domain knowledge should be incorporated into statistical forecasts. Complex methods have not proven to be more accurate than relatively simple methods. Methods that integrate judgmental and statistical data and procedures (e.g., rule based forecasting) can improve forecast accuracy in many situations.
Market prices are influenced by many factors. Autoregressive Integrated Moving Average (ARIMA) modeling uses differencing and the autocorrelation and partial autocorrelation functions to help identify an acceptable model. The advantage of ARIMA modeling compared to the simple forecasting and smoothing methods is that it is more flexible in fitting the data. However, identifying and fitting a model may be time-consuming.

Moving Averages: The Moving Averages method (MAs) is one of the oldest TS tools used by technical analysts. Daily fluctuations in stock prices, commodity prices, and foreign exchange rates can be large. MAs tone down these fluctuations – deemphasizing, and sometimes distorting, fluctuations. Technical analysts use MAs to smooth data, making it easier to view the true underlying trend.
The principal reason that MAs are used is to smooth out shorter fluctuations and focus on the trend that fits with the investor's time horizon. A MA by its nature is just one number that represents a trend of past numbers. For example, a 20-day MA is one number that represents all the prices for the past 20 days. As such, it filters out each one of the prices during the past 20 days and tells us how the group of 20 days is behaving, rather than its separate parts.
Most MAs of prices are based on closing prices, but they can be calculated on highs, lows, daily means, or any other value as long as the price type is consistent throughout the calculations.
The most commonly used type of MA is the Simple Moving Average (SMA), sometimes referred to as the Arithmetic MA. An SMA is constructed by adding a set of data and then dividing by the number of observations in the period being examined. For example, to calculate the MA for Day 11, we calculate the mean price for Days 2 through 11. In other words, the price

for Day 1 is dropped from the data set, while the price for Day 11 is added. The Eq. (8) for calculating a ten-day SMA is as follows:

$$SMA_{10} = \sum_{i=1}^{10} data_i \,/10 \tag{8}$$

Of course, MAs of different lengths can be constructed. Although a MA can smooth prices over any desired period, some of the more popular daily MAs are for the periods 200, 60, 30, 20, and 10 days. Once calculated, MAs are plotted on a price chart. A rising MA indicates an upward trend, while a falling MA indicates a downward trend. Although the MA helps us discern a trend, it does so after the trend has begun. Thus, the MA is a lagging indicator. By definition, the MA is an indicator that is based on past prices. According to technical analysis principles, we want to be trading with the trend. Using a MA will always give us some delay in signaling a change in trend. The most common usage is comparing the current price to the MA that represents the investor's time horizon.

Volatility Index Approach: The CBOE VIX index has been developed by the Chicago Board Options Exchange in 1993, the CBOE Volatility Index (Chicago Options: VIX) is one of the Street's most widely accepted methods to gauge stock market volatility. Like conventional indexes, VIX employs rules for selecting component options and is a measure of implied volatility in the S&P 100 options. Traders and investors become anxious when the market declines and become complacent when the market advances. Thus, VIX becomes a sentiment indicator. Generally, when the market is bottoming, VIX is high, because of the investor anxiousness. When the market is topping, VIX is generally low, indicating the complacency among investors.

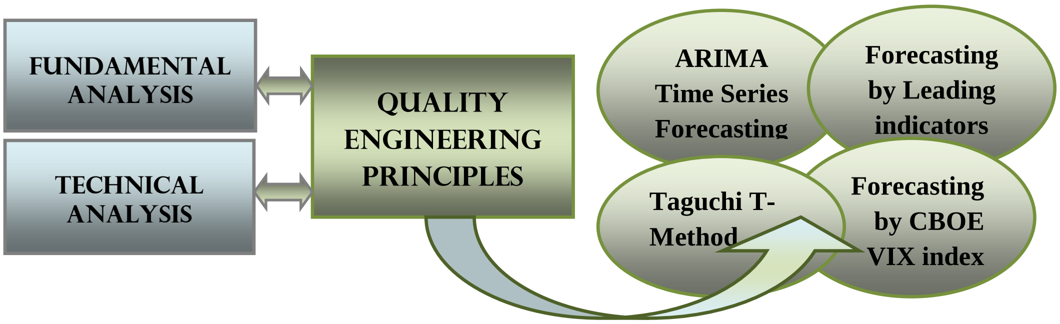
Larry Connors (1998) introduced a number of short-term price patterns that were based on the behavior of the VIX. The principle behind these patterns is to watch for changes in VIX, as a measure of sentiment, at extremes. A more general strategy for the VIX is to look at the deviation from a MA (Connors, 2004). If the VIX is below the SMA by 5% and the market is above its 200-day MA, the odds favor a continuing upward trend but not necessarily a good time to buy. When the ratio is above 5%, and even more, of the SMA, the time is usually excellent to buy. Thus, the VIX in this instance gives general zones of when action in certain directions can be contemplated. The opposite relationship is valid when the market is below its 200-day MA. Generally, bottoms are more reliably signaled by the VIX than tops (Connors, 2004).

3. THEORETICAL CONCEPTUAL INTEGRATIVE FRAMEWORK

Macroeconomic variables play a key role in asset pricing theories. For this reason, many authors have empirically studied the link between macroeconomic variables and stock market volatility. Investors raise the question whether macroeconomic variables that capture business cycle fluctuations help to forecast stock market volatility.

Finding an answer to this question may help investors to refine theories of derivative pricing, to compute more exact solutions to problems of optimal portfolio selection, and to efficiently monitor and manage financial risks. It may also be useful for macroeconomists, politicians and central bankers to develop a better understanding of potential macroeconomic determinants of systematic financial-sector risk. For an investor who seeks to forecast stock market volatility based on macroeconomic variables, a key question is whether it is important to account for the fact that macroeconomic data are subject to substantial historical revisions. Forecasting volatility is important to financial market participants and other agents who need to hedge risk. So, for more reliable global stock market forecasting we recommended an integrative approach, as shown in Figure 1.

Figure 1: Integrative Framework for Global Stock Market Forecasting



Stock indexes, such as the S&P 100, can be calculated using the prices of their component stocks. Each index employs rules that govern the selection of component securities and a formula to calculate index values.

Example - Forecasting the Standard and Poors (S&P) 100 Index:
Using short-term near-the-money call and put options, the CBOE VIX index measures the implied volatility of S&P 100 options index over the next 30 day period. The index is maintained by the Standard and Poor's economists and index analysts. According to the Standard and Poor's white paper on the index mathematics methodology, the VIX S&P 100 is calculated using Eq. (9).

$$\text{S\&P } 100 = \frac{\sum_i P_i Q_i}{Divisor} \tag{9}$$

The numerator is a multiplication of the price of each stock and the number of shares included to calculate the index value. The multiplication is summed across all the stocks in the index. The divisor is the total capitalization of all the stocks included in the index. Table 1 shows the two noise states for two corresponding time periods. During N_1, the S&P 100 gained 8.22%, and during N_2 it lost 39.53%.

Table 1. Noise States [Source: Ragsdell and Jikar, 2010]

N_1: Up-market	Oct 20, 2006 to Nov 30, 2007	Return from S&P 100 : 8.22%
N_2: Down-market	Dec 1, 2007 to Jan 9, 2009	Return from S&P 100: -39.53%

During 2008 and 2009, major indices of the US stock market saw historic movements. Certainly, this was one of the most volatile markets of our times. A ripple effect was soon felt the world over. This market upheaval had many implications for individual and institutional investors. Traditional ways of selecting securities and forecasting market movement were also challenged during these turbulent times. In the quest to identify stable investments that consistently yield a desired rate of return Ragsdell and Jikar (2010) proposed a screening metric for selecting stocks based on a S/N ratio. Further, they investigated an optimal screening and portfolio management strategy based on the principles of the TSQE. Their major results show that the portfolio management methodology developed by combining the principles of QE, value investing and the discussed here forecasting methods was able to beat the average market return with a huge margin. The portfolio management methodology allowed long and short positions on stocks and options. The portfolio management process developed by them made the portfolio focused and as a result the expenses associated with the transaction costs were lower.

4. CONCLUDING REMARKS

In contemporary market conditions, three questions are crucial: What to buy or sell? How much to buy and sell? When to buy or sell? Measures of the correlation between a stock's performance and the market can help in assessing expected rise or fall in a stock's price given a reliable prediction of market movement (Bodie et. al., 2005). Indirectly, to forecast the performance of a stock portfolio, the performance of the market must be known in direction and magnitude. The fundamentals of the TSQE have been used extensively to rapidly design and manufacture high quality, low cost products and services. The product parameter design phase of TSQE provides an integrative model for prediction of quality characteristics even before the product is produced. A model of volatility should incorporate characteristics of volatility such as mean reversion, pronounced persistence and allow for the possibility of exogenous variables that affect its behavior. The ability of volatility models to forecast future fluctuations of different asset classes is of interest to financial market participants. These arguments motivate our empirical future examination of the forecast quality of the S&P 100 implied volatility.

We believe that the proposed integrated modeling conceptual approach and framework, making a practical use of the ARIMA time series forecasting in consideration with changes in the leading indicators and CBOE VIX index, may outperform other approaches especially when the market is volatile and provide a well-defined technique of forecasting. Real case analysis and the forecasting results will reveal the limitations and the advantages of the proposed theoretical integrative-framework.

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