Global Economy and Finance Journal
Vol. 6. No. 2. September 2013. Pp. 54 – 67

Computational Finance: A Very Long Walk Down Wall Street

Tralvex Yeap*

Proponents of the random walk have attempted to show that there seems to be a resemblance between a plot of random price in a time-series and the actual stock market. This paper takes a step further, by simulating such a plot over a period of more than 220,000,000 years and to determine whether among the very long time sequence of values if any sequence resembles that of Dow Jones Industrial Average (DJIA). The experimental simulation presented in this paper is the first to visualize the Random Walk Hypothesis with DJIA actual drift vis-à-vis the DJIA actual outcome. Existing papers on Random Walk Hypothesis attempted to show that a randomly simulated price-time plot seems to resemble the price-time plot of the stock market. In contrast, this paper shows that despite numerous attempts to produce a sequence using randomly generated numbers over more than 220,000,000 of human years, there is no possibility that random walk plots resemble the DJIA.

Field of Research: Computational Finance, Economic Science

JEL Codes: G14, G17 and C23

1. Introduction

An open-ended topic in the field of business finance relates to the Efficient Market Hypothesis, observed by Samuelson (1965). Since then, there has been a series of research publications providing evidence for and against it. Investment practitioners differ in their investment strategies according to whether they believe in the Efficient Market Hypothesis or the Inefficient Market Hypothesis. Practitioners of the former group and scholars from Bachelier (1900) to Mockus and Raudys (2010) consider equity prices in financial markets to be random in nature (the basis of the Random Walk Hypothesis); as the stock price of an individual equity is random, their primary investment strategy lies with index investing. Conversely, in the latter group are practitioners such as Warren Buffet (Ketchen et al. 2008) and George Soros (1994) and scholars such as Graham and Dodd (1934), Chan et al. (2010) and Mockus and Raudys (2007), who consider equity prices in financial markets to be non-random in nature (the basis of the Non-Random Walk Hypothesis); as such, their primary investment strategy lies with the selection of individual stocks available in the capital market.

The objective of this paper is to simulate a DJIA with drift based on random flip-coin outcomes over a period of more than 220,000,000 years to determine whether among the very long time sequence of values to see if any sequence resembles that of Dow

*Dr. Tralvex Yeap, International Graduate School of Business, University of South Australia, Australia.
Email: yeaty001@mymail.unisa.edu.au, rex@yeap.co

Jones Industrial Average (DJIA). The motivation for this paper is to support a subsequent paper that a long and short strategy based for dividend-based equities exhibits significant excess returns with consistency over a period of twenty years. After all, if the random walk hypotheses is truly valid, then any investment strategy to outperform the market would surely be futile.

In the demonstration on whether the markets follow a random walk pattern, the approach taken by existing researchers is based on statistical tests conducted on the indices of actual capital markets (Lo & MacKinlay 2001; Malkiel 2007), showing varying degrees of randomness. For the first time, an extensive empirical tests and simulation are done in a different manner. Starting from an actual DJIA index value, an extensive computational simulation using random number generator for the flip-coin outcome is used. Furthermore, a drift is also considered in this simulation where the drift is taken to be the average index value of DJIA from the first trading day to the last trading day. The primary contribution to finance theory and knowledge is a new proposition that there is no possibility that random walk plots of a financial market resembles a real-world market index, in this case, the DJIA.

A review of past studies will be followed by the methodology used. Thereafter, the findings and results are discussed followed the conclusion.

2. Literature Review

2.1 The Efficient Market Hypothesis

It all began in 1965 with a seminal work by Samuelson (1965, p. 1), who started his paper with an ingenious riddle: 'In competitive markets there is a buyer for every seller. If one could be sure that a price would rise, it would have already risen'. In addition, he asked an important question, 'Is the fact that American stocks have shown an average annual rise of more than 5 per cent over many decades compatible with the alleged "fair game" (or martingale property) of an unbiased random walk?' (Samuelson 1965, p. 1). Through his mathematical theorem, which is also evident in the title of his paper 'Proof That Properly Anticipated Prices Fluctuate Randomly' (Samuelson 1965), the answer to his question is a resounding 'yes'; that is, the price movements of American stocks are random at any point of time.

A few months after the publication of Samuelson's (1965) paper, two seminal papers, titled 'Random Walks in Stock Market Prices' and 'The Behaviour of Stock-Market Prices', were published by Fama (1965a, 1965b). The second paper introduced the term 'Efficient Market Hypothesis', which utilised computer-based simulations to support the observations and explanations of why stock prices fluctuate randomly (Samuelson 1965). Through further empirical studies, Fama (1970) introduced three tests of how security prices adjust to available information:

T1. Weak-form tests take into account only historical prices.

T2. Semi-strong-form tests take into account information that is publicly available (including various corporate announcements of annual earnings, stock splits, etc.).

T3. Strong-form tests take into account private information that is not publicly available.

Fama (1970) concluded that market efficiency is empirically strong in its weak form and, with a few exceptions, is also empirically strong in its semi-strong and strong forms.

Fama (1991) revisited the three tests and replaced them with three more generic tests:

T1': Test for return predictability (replacing the weak-form test), where historical prices, dividend yields, interest rates and a range of dates may also be considered.

T2': Event studies (replacing the semi-strong-form test), where it is only a change in the label towards a more descriptive title.

T3': Test for private information (replacing the strong-form test), where it is also only a change in the label towards a more descriptive title.

The event studies are of particular interest because dividends stocks are related to T2 and T2'. While dividend events are not explicitly disclosed by Fama (1970), they are can still be classified as publicly available information by publicly listed companies that issue dividends as supported in his later paper (Fama 1991).

One major implication of the Efficient Market Hypothesis is that equity prices in the financial markets are always in equilibrium, such that it is not possible for any investor to predict future stock prices. Empirically, this is backed by a number of other publications (Cowles 1960; Kendall 1953; Narayan & Smyth 2007; Osborne 1959; Roberts 1959, 1967; Wang et al. 2010; Working 1960).The Efficient Market Hypothesis remains a contending theory in the explanation of equity price movements in the financial markets (French 1988; LeRoy 1989; Mockus & Raudys 2010; Okpara 2010; Samuelson 1965) because empirically there is still evidence (Bashir, Ilyas & Furrukh2011; Chong, Lam & Yan 2012) to support it.

2.2 The Inefficient Market Hypothesis

The Inefficient Market Hypothesis (Grossman & Stiglitz 1980) is supported by demonstrating that equity prices in the financial market do not reflect all the available information and can be significantly mispriced on a regular basis (Lee, Lee & Lee 2010). Ray (1992, p. 23) also stated succinctly that the Inefficient Market Hypothesis is to 'provide unexploited pure-profit opportunities from using accounting information'. To be consistent with Fama's (1965a) arguments for the Efficient Market Hypothesis, the 'information' in the Inefficient Market Hypothesis may refer to all available information Fama (1991, p. 1), rather than just accounting information.

In practice, there are three analytical methods that investors tend to use:

- Fundamental analysis,
- Technical analysis,
- A combination of fundamental analysis and technical analysis.

A large part of fundamental analysis (Graham & Dodd 1934; Samaras, Matsatsinis & Zopounidis 2008) is the analysis of a company's financial statements, such as revenue, expenses, assets and liabilities. It involves computing financial variables such as 'book value', 'dividend yield', 'intrinsic value', 'price/earnings ratio', 'price/earnings to growth ratio', 'price/cash ratio' and 'price/sales ratio'. In most cases, portfolio managers who use fundamental analysis in the selection of a portfolio of stocks expect a net positive return over a few years.

The second analytical method is known as technical analysis (Chavarnakul & Enke 2009; Levy 1966), which researches price action in markets through the use of charts and quantitative techniques to predict the market bidding or asking price. In contrast to fundamental analysis, it does not use a company's financial information. Portfolio managers use technical analysis indicators in their selection of a stock portfolio, such as 'Bollinger Bands' (Liu, Huang & Zheng 2006), 'Momentum' (Murphy 1999), 'On Balance Volume' (Yen & Hsu 2010) and 'Relative Strength Index' (Kirkpatrick & Dahlquist 2010). Technical analysis is generally preferred by traders or portfolio managers who expect a short-term outcome from their selection of the stock portfolio (Park & Irwin 2004). Short-term is defined as a few days to a few weeks (Dalton, Dalton & Jones 2007).

The third analytical method is an integration of fundamental analysis and technical analysis (Lam 2004; Samaras, Matsatsinis & Zopounidis 2008).

Other analytical methods include historical stock price optimisers (Katz & McCormick 2000), the seasonality trading method (Gardeazabal & Regulez 2004), the lunar and solar rhythms trading method (Katz & McCormick 2000), the maximum entropy method for the analysis of market cycles (Rompolis 2010), the neural network trading method (Brownstone1996) and the genetic algorithm based trading method (Štěpánek, Šťovíček & Cimler 2012).

2.3 Random Walk Hypothesis

Having reviewed both the Efficient Market Hypothesis and the Inefficient Market Hypothesis, this section reviews two closely related topics, the Random Walk Hypothesis and the Non-Random Walk Hypothesis. This will lead to the novel contribution in which results of a longitudinal simulation of several million years demonstrate that it is not possible for the stock market to be truly random.

Kendall (1953) discovered that stock and commodity prices in the United Kingdom market follow a random walk manner, giving rise to the Random Walk Hypothesis. A random walk entails zero correlation between price change at t and $t+1$ over a period of time. If prices were predictable, competition between investors would eliminate any price advantage where either arbitrage or speculation will force the prices to their efficient values. Prices change on the basis of new information available to all investors; therefore, no investor in the market has an advantage over another. In a widely cited work, Roberts (1959, pp. 4 & 5) found that a time series generated from a sequence of random numbers (see Figure 2.1) was seemingly indistinguishable from a Dow Jones Industrial Index between 6 January 1956 and 28 December 1956 (see Figure 2.2).

Figure 2.1:'Simulated market changes for 52 weeks', reproduced from Roberts (1959, p. 4).

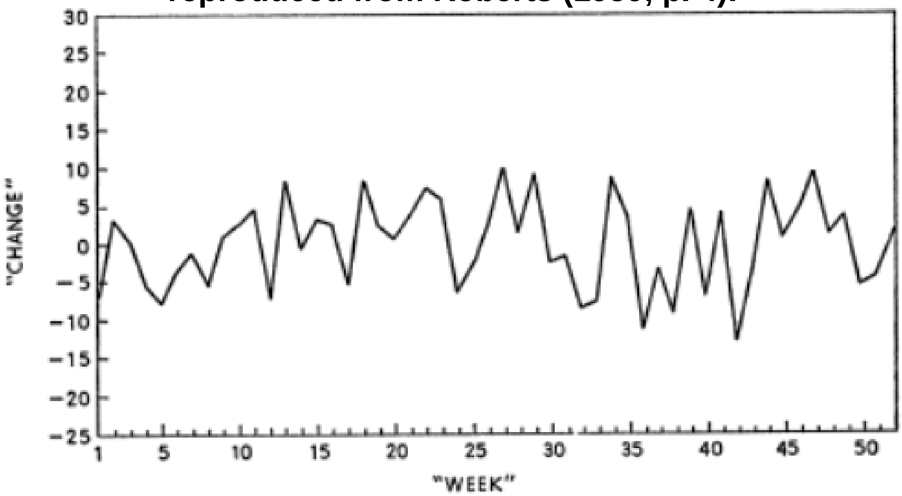
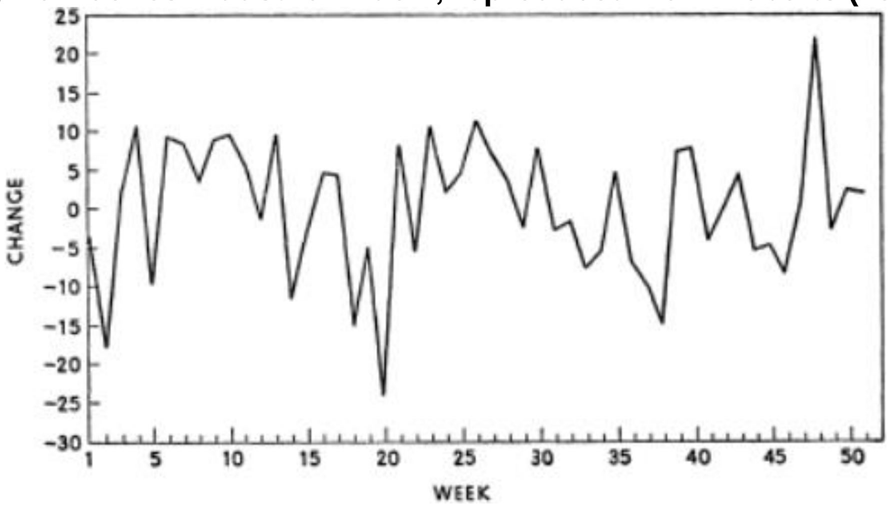


Figure 2.2:'Changes from Friday to Friday (closing) January 6, 1956—December 28, 1956, Dow Jones Industrial Index', reproduced from Roberts (1959, p. 5).



Roberts' (1959) seminal paper has been cited widely, as many contemporary scholars (Bashir, Ilyas & Furrukh 2011; Okpara 2010) seem to highly regard his results, especially from the randomised returns, as sound. However, a statistically randomly generated numbers and actual stock market prices using the DJIA index demonstrate very different results (see Figure 3.2).

2.4 Non-Random Walk Hypothesis

As a result of mispriced equity, the equity market has been shown to be non-random in nature, which is supported by various empirical studies (Cootner 1964; Lo 1987; Niederhoffer & Osborne 1966; Schwartz & Whitcomb 1977; Steiger 1964). In addition, a recent study by Chan et al. (2010) showed that the stock prices in Australia also exhibit a non-random pattern.

3. The Methodology

The approach taken by existing research is based on statistical tests conducted on the indices of actual capital markets (Lo & MacKinlay 2001; Malkiel 2007), showing varying degrees of randomness, visually from right to left (see Figure 3.1). For the first time, an extensive empirical test and simulation is done from the other spectrum (left to right, see Figure 3.1); that is, from random numbers, attempting to determine if it is possible to generate a sequence of capital market index values that resembles an actual capital market index, such as the DJIA.

Figure 3.1: Spectrum of random walk empirical tests.

A fair coin model (Abhijit 2011) is used in the random walk simulations in this paper. In a fair coin model, there are only two outcomes (0 or 1) with an equal probability of 0.5 each:

$$P(0) = P(1) = \frac{1}{2}$$

For any statement C, the notation [C] is used to denote a fair coin flip outcome, starting with an initial value represented by 'Index'. Whenever the coin flip yields a 0, there is a fixed value, δ decrement to the Index, and whenever the coin flip yields a 1, there is a fixed value, δ increment to the Index:

$$[C] = \begin{cases} Index + \delta & if\ C = 0 \\ Index - \delta & if\ C = 1 \end{cases}$$

For the construction of a DJIA based on the Random Walk Hypothesis, the time period of this random walk simulation is taken to be all trading days between 1 January 1965 to 31 December 2010, which yielded a total of 11,580 trading days in the United States of America. The year 1965 is chosen in honour of Samuelson (1965).

Using the fair coin model, a perfect random walk involving 11,580 trading days involved an alternating sequence of 0 and 1, resulting in 0101010101…01, where there are a total of 11,580 digits. The descriptive statistics for this sequence (random walk sequence) are:

- Mean = 0.500
- Standard Deviation = 0.500
- Variance = 0.250
- Skew = 0.000
- Kurtosis = -2.000

Subsequent tests on coin outcomes during the construction of the random walk generated DJIA sequences will then be validated against the descriptive statistics of the random walk sequence.

Taking into consideration the 11,580 trading outcomes, the initial starting value of the index on the first trading day in 1965 is 869.78, while the average index value change is 0.9248.

Suppose that the random walk follows no drift, then one may argue that a random walk that starts with the initial starting value of DJIA is 869.78 would naturally oscillates around this initial value. Therefore, the random drift for this simulation uses the average index value, which is the value of 0.9428.

Using the fair coin model, 4,313,726 cycles of simulations were conducted in the hope of reproducing the DJIA between 1 January 1965 and 31 December 2010 (51 years). 4,313,726 cycles of simulation yield a simulation of over 220,000,000 human years, which is about how long mammals have been on Earth, as documented by Long (2005).

Table 3.1[1] includes the partial empirical results of the 4,313,726 cycles in the reconstructions of the DJIA.

Table 3.1: Empirical simulation of a random walk generated DJIA.

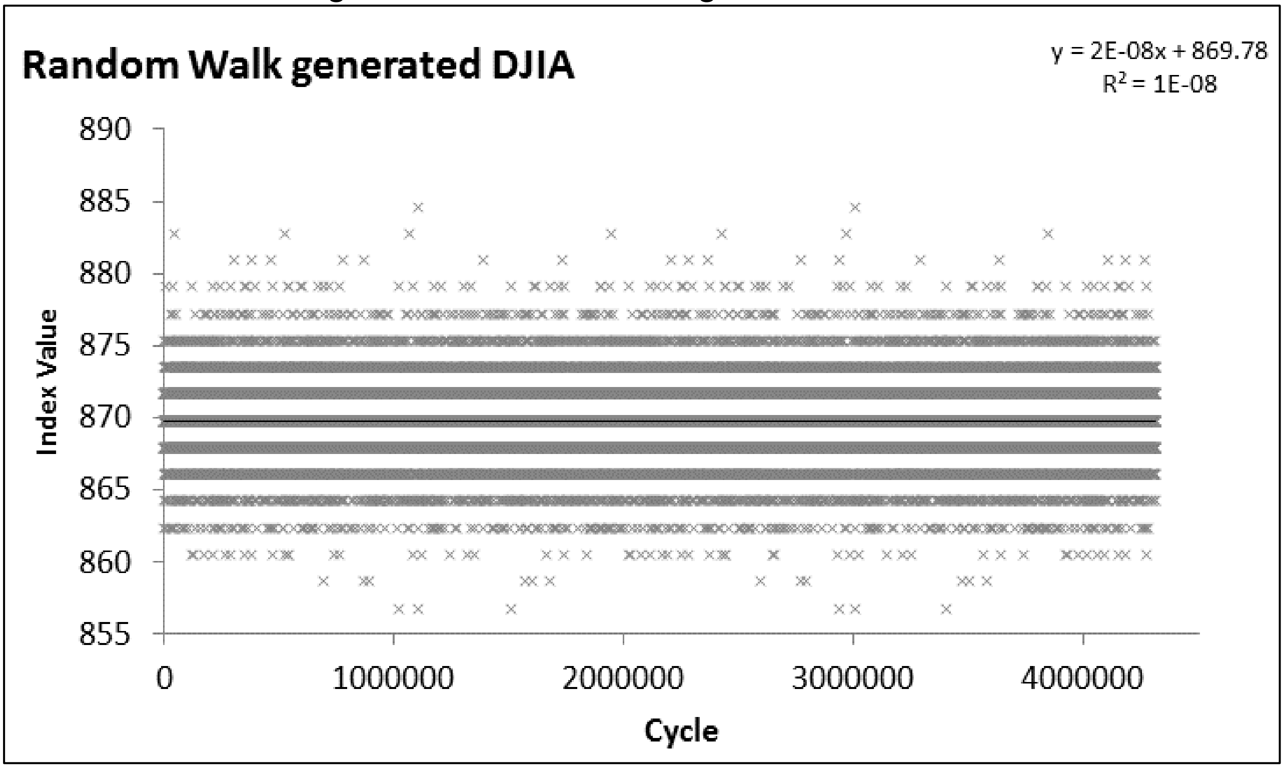
A	B	C	D	E	F	G	H	I	J	K	L
Cycle	**# Trading days**	**Start value**	**End value**	**Min value**	**Mean value**	**Max value**	**Coin: Mean**	**Std Dev**	**Variance**	**Skew**	**Kurtosis**
1	11580	869.78	864.212	861.428	869.71	878.132	0.5	0.5	0.25	0.001	-2
2	11580	869.78	875.348	865.14	875.243	883.7	0.5	0.5	0.25	-0.001	-2
3	11580	869.78	869.78	858.644	869.761	878.132	0.5	0.5	0.25	0	-2
4	11580	869.78	871.636	861.428	869.803	879.988	0.5	0.5	0.25	0	-2
5	11580	869.78	867.924	858.644	867.928	876.276	0.5	0.5	0.25	0	-2
6	11580	869.78	873.492	857.716	869.764	883.7	0.5	0.5	0.25	-0.001	-2
7	11580	869.78	867.924	858.644	866.243	876.276	0.5	0.5	0.25	0	-2
8	11580	869.78	869.78	855.86	867.846	876.276	0.5	0.5	0.25	0	-2
9	11580	869.78	871.636	859.572	867.91	876.276	0.5	0.5	0.25	0	-2
10	11580	869.78	866.068	856.788	865.964	876.276	0.5	0.5	0.25	0.001	-2
4,313,716	11580	869.78	869.78	860.5	869.892	879.988	0.5	0.5	0.25	0	-2
4,313,717	11580	869.78	867.924	860.5	869.816	879.988	0.5	0.5	0.25	0	-2
4,313,718	11580	869.78	873.492	861.428	871.678	883.7	0.5	0.5	0.25	-0.001	-2
4,313,719	11580	869.78	867.924	859.572	867.908	879.06	0.5	0.5	0.25	0	-2
4,313,720	11580	869.78	869.78	857.716	869.805	879.988	0.5	0.5	0.25	0	-2
4,313,721	11580	869.78	871.636	861.428	869.655	879.06	0.5	0.5	0.25	0	-2
4,313,722	11580	869.78	867.924	858.644	867.937	876.276	0.5	0.5	0.25	0	-2
4,313,723	11580	869.78	864.212	860.5	869.519	878.132	0.5	0.5	0.25	0.001	-2
4,313,724	11580	869.78	875.348	865.14	875.109	885.556	0.5	0.5	0.25	-0.001	-2
4,313,725	11580	869.78	871.636	861.428	869.776	878.132	0.5	0.5	0.25	0	-2
4,313,726	11580	869.78	869.78	856.788	867.768	877.204	0.5	0.5	0.25	0	-2
		Average:	869.780	860.205	869.778	879.360	0.500	0.500	0.250	0.000	-2.000

[1] Column A, **Cycle**: Where each cycle involved 51 years or 11,580 trading days of Random Walk based on the results of the fair coin flip.
Column B, # **Trading days**: The number of trading days used in the simulation
Column C, **Start value**: The initial value of the sequence (on the 1st trading day)
Column D, **End value**: The final value of the sequence (on the 11,580th trading day)
Column E, **Min value**: The minimum value within the sequence (from the 1st trading day to the 11,580th trading day)
Column F, **Mean value**: The mean or average value within the sequence (from the 1st trading day to 11,580th trading day)
Column G, **Max value**: The maximum value within the sequence (from the 1st trading day to the 11,580th trading day)
Column H, **Coin:Mean**: The mean or average of all the fair coin flips (0 or 1)
Column I, **Std Dev**: The standard deviation of the all the 11,580 fair coin flips (0 or 1)
Column J, **Variance**: The variance of the all the 11,580 fair coin flips (0 or 1)
Column H, **Skew**: The skewness of all the 11,580 fair coin flips (0 or 1)
Column L, **Kurtosis**: The kurtosis of all the 11,580 fair coin flips (0 or 1)

Prior to analysing the results from the simulation, the first essential step is to verify whether the 11,580 flips (in Table 3.1) using the fair coin for all the 4,313,726 cycles are truly random. The mean, standard deviation, variance, skewness and kurtosis in the simulation for each cycle are computed in Columns H to L, respectively. It is noted that the mean, standard deviation, variance and kurtosis are indeed equal to the expected outcome of a fair coin in a random walk sequence, as established earlier; the skewness value of the simulation ranges between minus 0.002 to plus 0.002, which is insignificant.

The visualisation of a random walk generated DJIA in Figure 3.2 exhibits both a random walk as well as a mean reversion nature. There is an unexpected support from proponents of the Random Walk Hypothesis (Cunado, Gil-Alana & Gracia 2010; Fama & French 1988; Lu et al. 2010; Poterba & Summers 1988; Serletis & Rosenberg 2009), who claim that the prices from equity markets follow a random walk and is mean reverting. In a random walk generated DJIA, the initial index value is 869.78.

Figure 3.2:A random walk generated DJIA.



From the 4,313,726 cycles of simulation, the terminal value for each cycle is a consistent 869.78 with a varying mean (see Figure 3.3) within each cycle.

Figure 3.3: Mean values of the random walk generated DJIA.

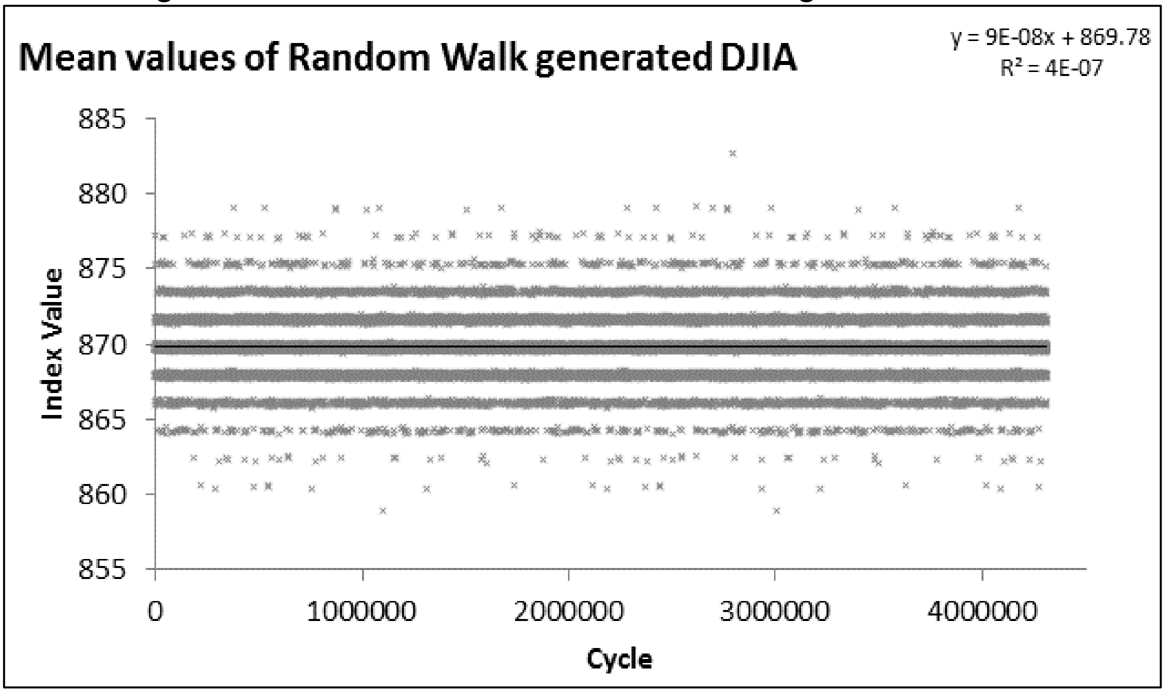
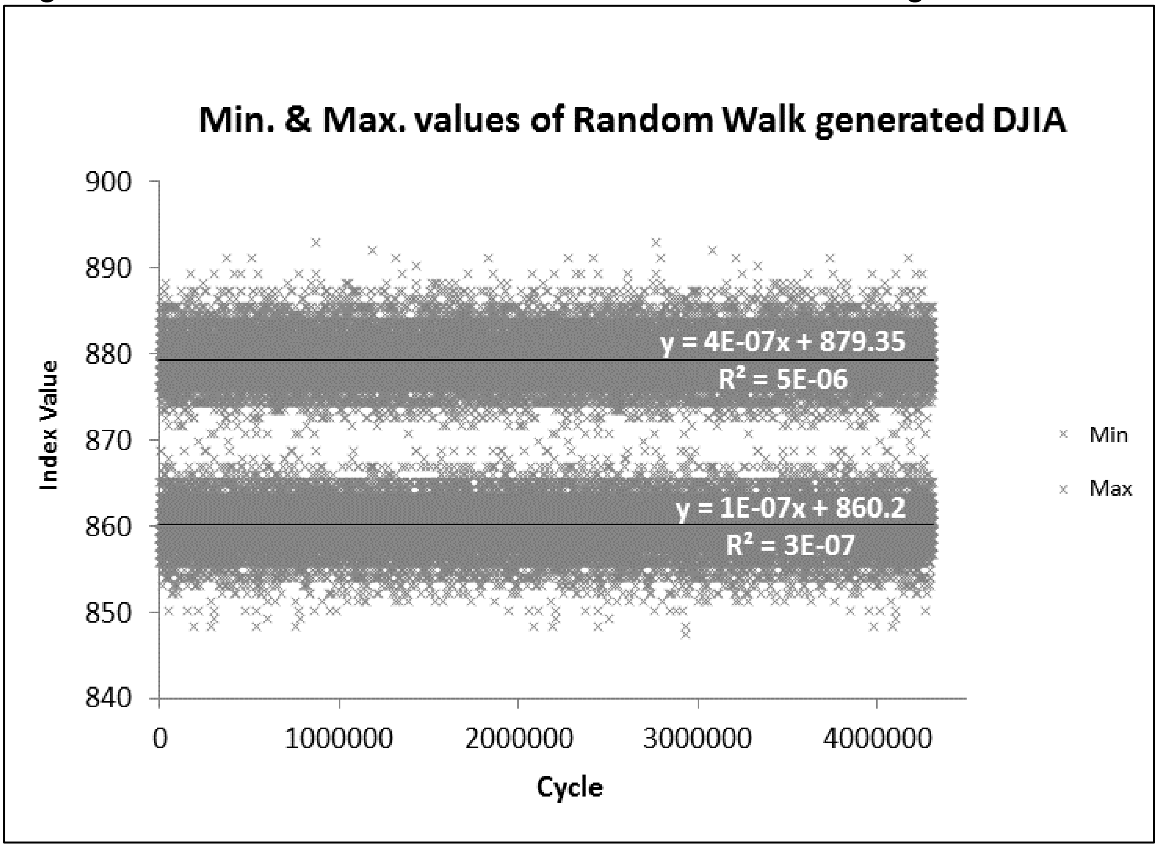


Figure 3.4 is a plot with a trend line indicating a reversion to the mean value of all the minimum and maximum values, to illustrate their variability within each cycle,

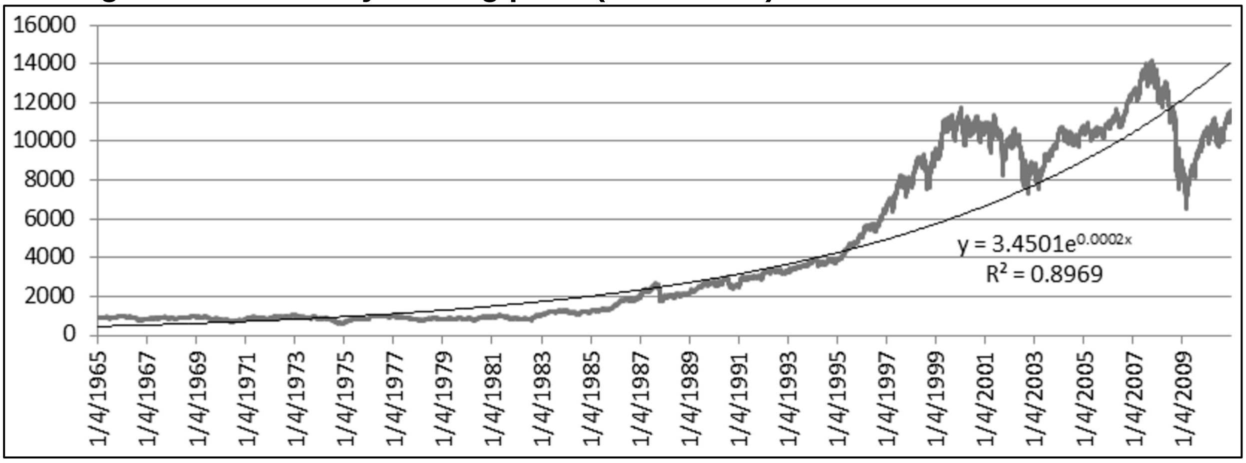
Figure 3.4: Minimum and maximum values of random walk generated DJIA.



4. Findings and Results

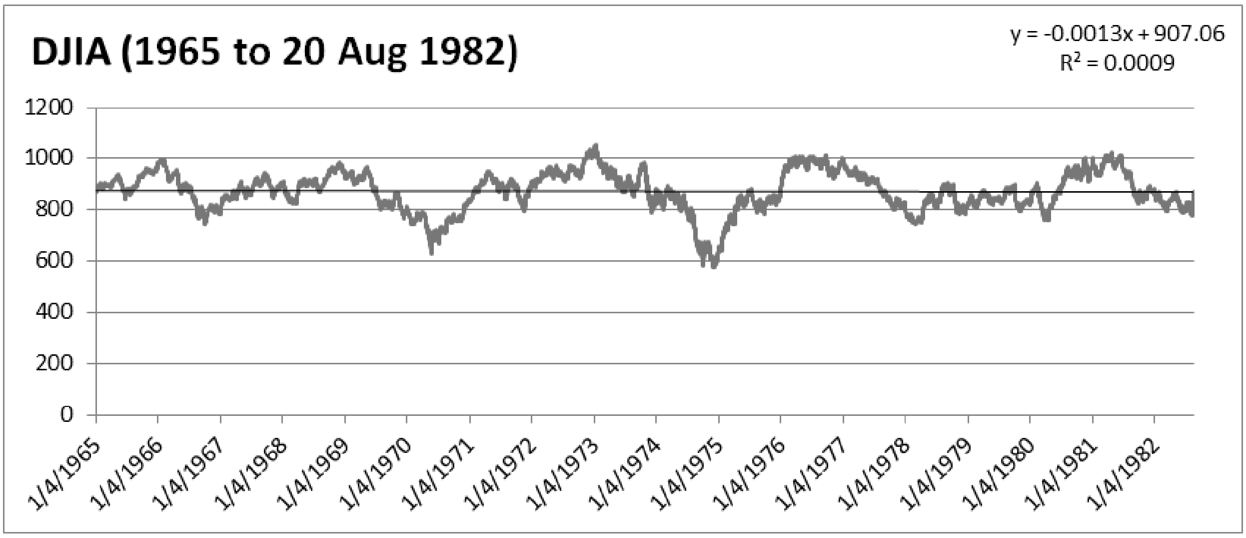
Using data from the CRSP, Figure 4.1 is the visualisation of the DJIA closing value for the 11,580 trading days between 1 January 1965 and 31 December 2010.

Figure 4.1:DJIAdaily closing price (1965–2010). Source: CRSP database.



As a whole, the DJIA values drifted away from the initial value of 869.78 after 1982, hitting a peak of 14,164.53 (9 October 2007) before ending at 11,577.51 (31 December 2010). The contrast between Figures 4.1 and 3.3 is startling. In Figure 3.3 the maximum value based on 4,313,726 cycles of simulation is only 892.98 in the random walk generated DJIA, which is only about 7.7 per cent of the DJIA at the close of the trading day on 31 December 2010. The first few years of the DJIA also appear to exhibit a mean reversion nature. Figure 4.2 is the visualisation of the DJIA between 4 January 1965 and 20 August 1982. In total, there are 35 other instances where the DJIA value crosses its initial value of 869.78 with a mean value of 873.074. This is very close to its initial value, indicating randomness in the sequence (Ryabko & Monarev 2005).

Figure 4.2:DJIA daily closing price (4 January 1965 to 20 August 1982). Source: CRSP database.



The random walk generated DJIA has clearly failed to produce a sequence similar to the DJIA (1965–2010).

Therefore, the result of this research give rise to a new proposition that there is no possibility that random walk plots of a financial market resembles a real-world market index (DJIA).

5. Summary and Conclusions

Despite simulating a random walk generated DJIA over 4,313,726 cycles, this simulation has not produced any sequence that is similar to the DJIA (1965–2010). As the maximum deviation of a random walk generated DJIA is only 23.2, it is impossible for a random walk generated DJIA to cross even 1,000, let alone reach 11,577.51, the closing value of the DJIA as of 31 December 2010.

There are a few limitations to this study. Firstly, the simulation is done over 220,000,000 human years instead of an even longer period of time such as 13.8 billion years which is the estimated age of this universe (Bromm 2009). Secondly, this simulation is done for Dow Jones Industrial Average only; similar simulations could be extended to the other indices such as the Standard & Poor's 500, FTSE 100 Index, All Ordinaries, Straits Times Index and the rest. The third limitation is the use of the average daily increment of the DJIA as the drift, where there might be other better values that can be used for this drift value.

In this paper, the random walk generated DJIA contributes to the finance theory by showing that it is improbable for a random walk model of the financial market to resemble that of the real-world market index.

Acknowledgement

The author would like to express his appreciation to the anonymous reviewer(s) of this paper who suggested that the drift in the random walk simulation should be more evident as well as some editorial improvements.

References

Abhijit, D 2011, ‘Mathematical foundations of randomness’, in Prasanta Bandyopadhyay and Malcolm Forster (eds.), *Philosophy of statistics*, Amsterdam: Elsevier, pp. 641–710.

Bachelier, L 1900, ‘Theorie de la speculation’, *Annales Scientifiques de L’Ecole Normale Superieure*, vol. 3, no.17, pp. 21–86.

Bashir, T, Ilyas, M & Furrukh, A 2011, ‘Testing the weak-form efficiency of Pakistani stock’, *European Journal of Economics, Finance and Administrative Sciences*, no. 31, pp. 160–175.

Bromm, V., Yoshida, N., Hernquist, L., McKee, C.F., 2009. The formation of the first stars and galaxies. *Nature* 459, 49–54.

Chan, HWH, Chang, X, Faff, R & Wong, G 2010, ‘Financial constraints and stock returns: evidence from Australia’, *Pacific-Basin Finance Journal*, vol. 18, Issue 3, pp. 306-318.

Chavarnakul, T & Enke, D 2009, 'A hybrid stock trading system for intelligent technical analysis-based equivolume charting', *Neurocomputing,*vol. 72, nos. 16–18, pp. 3517–3528.
Chong, TTL, Lam, TH & Yan, IKM 2012, 'Is the Chinese stock market really inefficient?', *China Economic Review*, vol. 23, no. 1, pp.122–137.
Cootner, P 1964, *The random character of stock market prices*, MIT Press, Cambridge.
Cowles, A 1960, 'A revision of previous conclusions regarding stock price behavior', *Econometrica*, vol. 28, no. 4, pp. 909–915.
Cross, J 2010, 'System and method for selecting securities for investment', *United States Patent and Trademark Office*, United States patent no. 7739179.
Cunado, J, Gil-Alana, LA & Gracia, FP de 2010, 'Mean reversion in stock market prices: New evidence based on bull and bear markets'. *Research in International Business and Finance*, 24(2), pp.113-122.
Dalton, JF, Dalton, RB, Jones, ET, 2007, '*Markets in Profile: Profiting from the Auction Process*', 1st ed. Wiley, Hoboken, New Jersey.
Domian, DL, Louton, DA & Mossman, CE 1998, 'The rise and fall of the Dogs of the Dow', *Financial Services Review*, 7(3), pp. 145-159.
Fama, EF 1965a, 'Random walks in stock market prices', *Financial Analysts Journal,* vol. 21, no. 5, pp. 55–59.
Fama, EF 1965b, 'The behaviour of stock-market prices', *Journal of Business*, vol. 38, no. 1, pp. 34–105.
Fama, EF 1970, 'Efficient Capital Markets: A Review of Theory and Empirical Work', *Journal of Finance*, pp. 383-417.
Fama, EF 1991, 'Efficient Capital Markets: II', *Journal of Finance*, 46(5), pp. 1575–1617.
French, KR 1988, 'Crash-Testing the Efficient Market Hypothesis', *NBER Macroeconomics Annual*, 3, pp. 277–285.
Gardeazabal, J & Regulez, M 2004, 'A factor model of seasonality in stock returns', *The Quarterly Review of Economics and Finance,* vol. 44, no. 2, pp.224–236.
Gonzalez, L, Powell, J, Shi, J, Wilson, A 2005, 'Two centuries of bull and bear market cycles', *International Review of Economics & Finance*, 14(4), pp. 469-486.
Graham, B & Dodd, D 1934, *Security analysis*, Harper, New York.
Grossman, S & Stiglitz J 1980, 'On the impossibility of informationally efficient markets', *American Economic Review*, vol. 70, no. 3, pp. 393–407.
Karpoff, JM & Walkling, RA 1990, 'Dividend capture in NASDAQ stocks', *Journal of Financial Economics,* vol. 28, nos. 1–2, pp. 39–65.
Katz, J & McCormick, D 2000. *The Encyclopedia of Trading Strategies*, 1st ed., McGraw-Hill.
Kendall, MG 1953, 'The analysis of economic time-series—part I: prices', *Journal of the Royal Statistical Society*, Series A (General), vol. 116, no. 1, pp. 11–34.
Ketchen Jr, DJ, Adams, GL & Shook, CL 2008, 'Understanding and managing CEO celebrity'. *Business Horizons*, vol. 51, no. 6, pp. 529–534.
Kirkpatrick, CD & Dahlquist, JR 2010, *Technical analysis: the complete resource for financial market technicians*, 2nd ed., FT Press, Upper Saddle River, New Jersey.
Lam, M 2004, 'Neural network techniques for financial performance prediction: integrating fundamental and technical analysis', *Decision Support Systems*, vol. 37, no. 4, pp.567–581.

Lee, C, Lee, J & Lee, C 2010, ‘Stock prices and the efficient market hypothesis: evidence from a panel stationary test with structural breaks’, *Japan and the World Economy*, vol. 22, no. 1, pp. 49–58.

LeRoy, S 1989, ‘Efficient Capital Markets and Martingales’, *Journal of Economic Literature*, 27(4), pp. 1583–1621.

Levy, A 1966, ‘Conceptual foundations of technical analysis’, *Financial Analysts Journal,* vol. 22, no. 4, pp. 83-89.

Liu, W, Huang, X & Zheng, W 2006, ‘Black–Scholes’ model and Bollinger bands’, *Physica A: Statistical Mechanics and its Applications*, vol. 371, no. 2, pp.565–571.

Lo, AW & MacKinlay, AC 2001, *A non-random walk down Wall Street*, Princeton University Press, Princeton, New Jersey.

Long, J 2005, *The big picture book*, Allen & Unwin, Australia.

Lu, YC., Chang, T, Hung, K, Liu, WC, 2010,‘Mean reversion in G-7 stock prices: further evidence from a panel stationary test with multiple structural breaks’, *Mathematics and Computers in Simulation,* vol. 80, no. 10, pp.2019–2025.

Malkiel, BG 2007, *A random walk down Wall Street: the time-tested strategy for successful investing*, W. W. Norton & Company, New York.

Mockus, J & Raudys, A 2010, ‘On the efficient-market hypothesis and stock exchange game model’, *Expert System with Applications,* vol. 37, no. 8, pp. 5673–5681.

Murphy, JJ 1999, *Technical analysis of the financial markets: a comprehensive guide to trading methods and applications,* New York Institute of Finance., Paramus, New Jersey.

Narayan, PK and Smyth, R 2007, ‘Mean reversion versus random walk in G7 stock prices evidence from multiple trend break unit root tests’, *Journal of International Financial Markets*, Institutions and Money, 17(2), 152-166.

Niederhoffer, V & Osborne, M 1966, ‘Market making and reversal on the stock exchange’, *Journal of the American Statistical Association*, vol. 61, pp. 897–916.

O'Higgins, M 1991. *Beating the Dow*, Harper Collins, New York.

Okpara, GC 2010, ‘Stock market prices and the random walk hypothesis: further evidence from Nigeria’, *Journal of Economics and International Finance,* vol. 2, no. 3, pp. 49–57.

Osborne, M 1959, ‘Brownian Motion in the Stock Market’, *Operations Research*, vol. 7, pp. 145-173.

Park, CH & Irwin, SH 2004, ‘The profitability of technical analysis: a review’, *AgMAS Project Research Report 2004-04*, University of Illinois at Urbana-Champaign Urbana.

Perry, B 2007, *The 25% cash machine: double digit income investing,* Wiley, Hoboken, New Jersey.

Poterba, JM & Summers, LH 1988, ‘Mean reversion in stock prices: evidence and implications’, *Journal of Financial Economics*, vol. 22, pp. 27–59.

Ray, BJ 1992, ‘The earnings-price anomaly’, *Journal of Accounting and Economics*, vol. 15, nos. 2–3, pp. 319–345.

Roberts, H 1959, ‘Stock-market patterns and financial analysis: methodological suggestions’, *Journal of Finance*, vol. 14, pp. 1–10.

Roberts, H 1967, ‘Statistical versus clinical prediction of the stock market’, *unpublished manuscript*, Center for Research in Security Prices, University of Chicago, May.

Rompolis, LS 2010, ‘Retrieving risk neutral densities from European option prices based on the principle of maximum entropy’, *Journal of Empirical Finance,* vol. 17, no. 5, pp.918–937.

Ryabko, BY & Monarev VA 2005, ‘Using information theory approach to randomness testing’, *Journal of Statistical Planning and Inference*, vol. 133, no. 1, pp.95–110.

Samaras, GD, Matsatsinis, NF & Zopounidis, C 2008, ‘A multicriteria DSS for stock evaluation using fundamental analysis’, *European Journal of Operational Research*, 187(3), pp. pp. 1380-1401.

Samuelson, P 1965, ‘Proof that properly anticipated prices fluctuate randomly’, *Industrial Management Review*, vol. 6, pp. 41–49.

Schwartz, R & Whitcomb, D 1977, ‘The time-variance relationship: evidence on autocorrelation in common stock returns’, *Journal of Finance*, vol. 32, pp. 41–55.

Serletis, A & Rosenberg, AA 2009, ‘Mean reversion in the US stock market’, *Chaos, Solitons & Fractals*, 40(4), pp.2007-2015.

Soros, G 1994, *The alchemy of finance: reading the mind of the market,* 2nd ed., Wiley, New York.

Steiger, W 1964, ‘A test of nonrandomness in stock price changes’, in P Cootner (ed.) *The random character of stock market paces*, MIT Press, Cambridge, Massachusetts, pp. 303-312.

Štěpánek, J, Šťovíček, J & Cimler, R 2012, ‘Application of genetic algorithms in stock market simulation’, *Procedia: Social and Behavioral Sciences*, vol. 47, pp.93–97.

Tigue, J 2006. *The Standard & Poors Guide to Building Wealth with Dividend Stocks*, 1st ed., McGraw-Hill.

Wang, J, Wang, Q & Shao, J 2010, ‘Fluctuations of stock price model by statistical physics systems’, *Mathematical and Computer Modelling*, vol. 51, nos. 5–6, pp. 431–440.

Weiss, G & Lowe, J 1990, *Dividends Don’t Lie: Finding Value in Blue-Chip Stocks*, Longman Financial Service.

Working, H., 1960, ‘Note on the Correlation of First Differences of Averages in a Random Chain’, *Econometrica*, 28, 916-918.

Yen, SMF & Hsu, YL 2010, ‘Profitability of technical analysis in financial and commodity futures markets—a reality check’, *Decision Support Systems,* vol. 50, no. 1, pp.128–139.