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A HISTORICAL ANALYSIS OF MARKET EFFICIENCY: DO HISTORICAL RETURNS FOLLOW A RANDOM WALK?

Michael J. Seiler* and Walter Rom**

Abstract

This study examines the degree of random walk in daily stock prices for all stocks listed on the NYSE from February 1885 through July 1962. Modern day anomalies are examined in conjunction with historical data in an attempt to explain the return series. While many regularly observed patterns occurred before 1962, they were unable to aid in the prediction of future stock price movements. The results are consistent with the preponderance of modern efficient market studies in that historical stock returns are found to follow a random walk.

INTRODUCTION

Market efficiency is directly or implicitly tested any time a study is performed to identify stock price reactions to certain events such as dividend announcements (Bajaj and Vijh 1995, 1990), earnings announcements (Bamber 1987), stock splits (Copeland 1979), large block transactions (Holthausen, Leftwich, and Mayers 1987; Kraus and Stoll 1972), repurchase tender offers (Lakonishok and Vermaelen 1990), and other public announcements (Kim and Verrecchia 1991a,b).

Traditionally, event study methodology is used to evaluate the reaction of the market to certain corporate events. These studies which are specific in nature are designed to measure market efficiency at certain points in time and only in conjunction with specific events. A more encompassing or macro evaluation of market efficiency can be made by testing whether or not the returns in a market follow a random walk process over a longer period of time.

Financial theory predicts that stock prices should fluctuate randomly in the short run if the stock market is efficient. The semi-strong form of the Efficient Market Hypothesis (EMH) holds that the market instantaneously absorbs all relevant information as it becomes publicly available. Hence, daily returns should fluctuate as random white noise.

This study examines the behavior of daily stock returns over the period from February 1885 through July 1962, the period before the Center for Research in Security Prices (CRSP) tapes were developed, to assess the degree of market efficiency for stocks listed on the New York Stock Exchange (NYSE). Previous studies have examined the market's efficiency since 1962, but periods pre-dating CRSP have not received adequate attention. The results indicate that with the exception of brief periods in the NYSE's history, the market has traditionally been efficient long before the modern era.

The next section provides an abbreviated review of market efficiency studies. Section III discusses the data source and methodology employed. The application of the methodology is described in Section IV. Section V shows the results. The final section concludes with a summary of the study.

LITERATURE REVIEW

The Efficient Market Hypothesis has been tested in hundreds of studies over the past thirty years [Fama and French (1996), McQueen, Pinegar, and Thorley (1996), Malkiel (1995), Brown and Goetzmann (1995), Ikenberry,

*Hawaii Pacific University
**Cleveland State University

Lakonishok, and Vermaelen (1995), Elton, Gruber, Das, and Hlavka (1993), Goetzmann and Ibbotson (1994), Jegadeesh, and Titman (1993), Chopra, Lakonishok, and Ritter (1992), Seppi (1992), Lee, Shleifer, and Thaler (1991), Bernard and Thomas (1990, 1989), Harris (1989), Ippolito (1989), Ball and Kothari (1989), DeBondt and Thaler (1989, 1987, 1985), Henriksson (1984), Foster, Olsen, and Shevlin (1984), Grossman and Stiglitz (1980), Charest (1978), Black and Scholes (1974), Moore (1964), Alexander (1961)][1]. Most studies that appear to uncover inefficiencies in the market are later explained by more comprehensive and rational analyses.

DATA AND METHODOLOGY

Returns are daily for all stocks listed on the NYSE from February 17, 1885 to July 2, 1962. Stocks are not traded on weekends and holidays[2]. At first glance this seems to violate the basic time series requirement that observations be taken at regularly spaced intervals. The requirement, however, is that the time intervals be spaced in terms of the process underlying the series. Here the underlying process is the trading of stock, so prices at the end of each business day are perfectly appropriate[3].

To test historical market efficiency one can examine the pattern of short-term movements in aggregate market returns and attempt to identify the process underlying those returns. If the market is efficient, the model will be unable to identify a pattern, and we will conclude that returns follow a random walk process[4]. If a model is able to establish a pattern, then past market data can be used to predict future market movements, and the market is characterized as inefficient.

There are several forecasting techniques available to identify patterns in time series data. Regression, exponential smoothing, and decomposition approaches, however, assume that the values of the time series being forecasted are statistically independent from one period to the next. As such, they are not appropriate when identifying a pattern in stock series which are inherently autocorrelated[5]. Instead, the Box-Jenkins (ARIMA) methodology, which does consider the statistical dependence of observations from one time period to the next will be used.

The Box-Jenkins method of forecasting is different from other methods in that it does not assume any particular pattern in the historical data of the series to be forecast. Instead, it uses an iterative approach to identify the underlying pattern. The model is deemed to fit the series well if the residuals between the forecasting model and the historical data points are small, randomly distributed (as white noise), and independent. If the specified model is not satisfactory, the process is repeated by using another model designed to improve upon the original one.

The Box-Jenkins technique is composed of both an autoregressive model and a moving average model. The auto-regressive model takes the form:

Equation 1

$$Y_T = B_1Y_{T-1} + B_2Y_{T-2} + \ldots + B_pY_{T-p} + e_T$$

where:

Y_T = dependent variable,
Y_{T-1},Y_{T-2},Y_{T-p} = lagged variables,
B_1,B_2,B_p = regression coefficients,
e_T = residual term.

The regression coefficients are estimated by using a nonlinear least squares method which employs an iterative solution technique to calculate the parameters. After establishing preliminary starting points, the procedure then systematically improves upon them until an optimal solution is found.

The moving average model takes the form:

Equation 2

$$Y_T = e_T - W_1e_{T-1} - W_2e_{T-2} - \ldots - W_qe_{T-q}$$

where:

Y_T = dependent variable,
W_1, W_2, W_q = weights,
e_T = residual term,
$e_{T-1}, e_{T-2}, e_{T-q}$ = previous values or residuals.

Equation 2 is similar to equation 1 except that the dependent variable Y_T depends on previous values of the residual instead of the variable itself. Moving average models provide forecasts of Y_T based on a linear combination of past errors, whereas autoregressive models express Y_T as a linear combination of some number of actual past values of Y_T.

Combining the two models yields the Box-Jenkins technique. The complete model is shown as:

Equation 3

$$Y_T = B_1 Y_{T-1} + B_2 Y_{T-2} + \ldots + B_p Y_{T-p} + e_T - W_1 e_{T-1} - W_2 e_{T-2} - \ldots - W_q e_{T-q}$$

APPLYING THE METHODOLOGY

There are three separate stages in applying the Box-Jenkins Technique: model identification, model estimation, and testing and construction of confidence intervals around the forecasts. Before identifying the model, the series must be stationary. A stationary time series can be defined as one whose average value and variance do not change over time. Stock prices tend to drift upwards. As such, if they are observed directly, their series is nonstationary. To make the series stationary it is necessary to take the first difference[6]. Once the series is stationary, the model is ready to be identified. This step is accomplished by comparing the autocorrelation and partial-autocorrelation coefficients of the data to the various pre-determined theoretical distributions.

Once a tentative model has been selected, the parameters for that model must be estimated. After several iterative steps the residuals from the final model are analyzed to determine if they are essentially white noise. Sixteen lags are analyzed to test for white noise for both the autocorrelation and partial-autocorrelation coefficients. Box-Ljung statistics are checked at each lag for statistical significance at a level of 5%. The p-value is interpreted as the probability that white noise would have generated autocorrelations as large as or larger than those actually observed. Hence, a p-value of less than .05, implies that there exists an identifiable pattern in the time series being analyzed. Because sixteen lags are typically analyzed, observing one or even two Box-Ljung lags with p-values less than .05 is in line with statistical probabilities. Observing more than two, however, is indicative of a non-random series.

Once an adequate model has been found, forecasts for one period or several periods into the future can be made. Confidence intervals or bands are then constructed around the forecasts. In general, the more predictable the time series, the more narrow will be the confidence intervals[7]. Conversely, a random walk time series is associated with very large confidence bands.

RESULTS

Table 1 shows the mean daily return, standard deviation, number of trading days, and number of Box-Ljung statistics which are significant at a=.05. A separate Box-Jenkins analysis is performed for each of the 77 years under study. When performing a Box-Jenkins analysis it is necessary to choose the length of the time interval to examine. If the interval is too long, it is conceivable that brief market inefficiencies will not be identified because the inefficiency would last only a short period of time relative to the overall interval under study. If the period is too short, not enough observations will be realized to generate a proper model. We study periods of exactly one year to achieve an optimal balance between the two tradeoffs.

Recall that more than two significant Box-Ljung statistics indicates a series that is not a random walk. From Table 1 there are only three years with statistics indicating a time series pattern with less than completely random variation. There also appears to be no reason or economic explanation for the three anomalies. With evidence this weak, at this point there is no reason to refute the semi-strong form of the EMH.

TABLE 1

The Mean Daily Return, Standard Deviation, Number of Trading Days, and Number of Significant Box-Ljung Statistics By Year From the Period 1885 Through 1962 (Total Number of Observations = 22,474)

Year	Standard Deviation	Number of Trading Days	Mean Daily Return	Number of Significant Box-Ljung Statistics
1885	9.44	265	1.143	1
1886	7.35	305	.292	0
1887	7.81	301	-.123	2
1888	6.56	300	.320	0
1889	4.78	301	.349	1
1890	8.64	303	-.340	1
1891	7.29	303	.710	2
1892	6.03	301	-.628**	2
1893	13.43	302	-.692**	0
1894	7.43	304	1.543**	4
1895	9.73	304	2.655**	1
1896	12.40	303	2.040**	2
1897	8.67	302	.825	0
1898	10.42	298	.819	1
1899	9.59	296	.315	2
1900	7.56	300	.697	1
1901	11.29	293	.580	0
1902	6.72	298	2.359**	2
1903	9.11	298	-.507	1
1904	6.47	300	.897	3
1905	7.19	301	.761	1
1906	7.51	304	.079	0
1907	12.58	301	-1.110**	2
1908	8.10	301	1.292*	1
1909	5.83	296	.527	0
1910	7.98	297	-.330	1
1911	5.12	298	.242	2
1912	4.64	301	.252	0
1913	5.98	298	-.181	0
1914	7.78	191	-.429	1
1915	7.89	301	1.399*	0
1916	7.71	301	.126	1
1917	10.92	298	-.537*	1
1918	7.20	297	.552	3
1919	9.16	293	.553	0
1920	10.57	299	-.445	1
1921	8.00	298	.416	1
1922	6.99	300	.800	0
1923	7.24	300	.067	1

TABLE 1 (CONT'D)
The Mean Daily Return, Standard Deviation, Number of Trading Days, and Number of Significant Box-Ljung Statistics By Year From the Period 1885 Through 1962 (Total Number of Observations = 22,474)

Year	Standard Deviation	Number of Trading Days	Mean Daily Return	Number of Significant Box-Ljung Statistics
1924	5.92	302	.930	0
1925	6.68	301	.890	2
1926	7.87	299	.318	1
1927	6.09	301	.880	0
1928	8.57	295	1.258*	0
1929	21.44	291	-.076	0
1930	15.51	298	-.852**	1
1931	22.50	300	-1.680**	1
1932	30.85	302	.152	0
1933	27.62	285	1.870**	2
1934	14.63	301	.040	1
1935	10.65	301	1.349*	0
1936	10.05	301	1.017	1
1937	18.09	299	-1.291**	1
1938	18.96	301	1.017	0
1939	14.59	300	.077	0
1940	12.50	302	-.285	1
1941	8.59	301	.389	2
1942	7.71	301	.648	1
1943	7.32	301	.791	2
1944	5.19	298	.617	0
1945	7.32	286	1.108	1
1946	12.60	281	-.224	1
1947	8.17	283	.230	0
1948	8.69	283	.237	0
1949	6.47	282	.613	0
1950	8.66	281	.993	2
1951	6.40	283	.763	2
1952	4.86	271	.624	1
1953	5.69	251	-.036	1
1954	5.59	252	1.690**	0
1955	9.30	252	1.139	0
1956	7.47	251	.287	2
1957	8.24	252	-.413	1
1958	5.70	252	1.456**	0
1959	5.78	253	.466	0
1960	6.33	252	.040	1
1961	5.02	250	.968	0
1962	12.01	127	-1.756**	1

-- Standard deviations and returns are calculated as 10^{-3}
-- 1885 and 1962 show only partial year observations
* Significant at the 95% level of significance
** Significant at the 99% level of significance

Modern-day research has uncovered several regular patterns in stock price movements that warrant consideration in this analysis. They are non-uniformly distributed returns by month and by day of the week. If returns by month were uniformly distributed, then knowledge that a certain daily return occurred in that month would be irrelevant in helping predict the return. However, if January is historically associated with above average returns, for example, then knowledge that a given daily return occurred in January would aid in the accuracy of our estimate or forecast of that return. That is, all else constant, we would make a prediction that is somewhat higher than we would have made had we not known the actual month during which the daily return occurred. Therefore, if returns are analyzed by month, this added piece of information may enable us to better forecast returns in the stock market. The same analogy applies to returns by day-of-the-week which are also associated with non-uniformly distributed returns. Table 2 displays the analysis of returns by month for the time period 1885 through 1962, the period just prior to modern research analysis.

The mean daily return during the month of January is one of the highest months, along with July and August. Hence, although the historical January effect is much weaker than its modern day counterpart, there does seem to be weak evidence of non-uniform return distribution as early as 1885. The Box-Jenkins methodology is again employed for each of the twelve periods to test the return generating process of the overall stock market. The suspicion of random walk clearly holds again as there are no months with more than two significant Box-Ljung statistics.

TABLE 2

The Mean Daily Return, Standard Deviation, Number of Trading Days, and Number of Significant Box-Ljung Statistics By Month From the Period 1885 Through 1962 (Total Number of Observations = 22,474)

Month	Mean Daily Return	Standard Deviation	Number of Trading Days	Number of Significant Box-Ljung Statistics
January	.505	8.66	1921	1
February	-.041	9.41	1689	0
March	.204	10.32	1990	2
April	.428	9.86	1891	0
May	.039	10.53	1925	1
June	.420	10.80	1932	0
July	.786	10.37	1873	1
August	.878*	9.93	1922	2
September	-.196	11.95	1788	0
October	.103	12.94	1924	1
November	.328	11.87	1727	0
December	.553	10.34	1892	1

-- Standard deviations and returns are calculated as 10^{-3}
* Significant at the 95% level of significance

French (1980) was the first to use the phrase the day-of-the-week effect. This refers to the regular observation of significantly negative returns on Mondays and significantly positive returns on Wednesdays and Fridays. Although French found this to be free from random walk violations, it is possible that if the trend also occurred prior to 1962, the regular pattern could be used to predict or forecast stock returns in the short run.

Table 3 shows the mean daily return, standard deviation, number of observations, test-statistic and number of significant Box-Ljung statistics for each day of the week from 1885 through 1962. Note that Mondays are associated with significantly negative returns while Wednesday, Friday and Saturday have higher than expected returns. Applying the Box-Jenkins methodology, however, yields only slight evidence of a lesser degree of random walk. Hence, While historical returns do appear to exhibit the same day-of-the-week pattern as do post 1962 returns, they are not enough to enable models to successfully forecast future returns.

TABLE 3
The Mean Return, Standard Deviation, Number of Observations, Test Statistic, and Number of Significant Box-Ljung Statistics By Day of the Week From the Period February 1885 Through July 1962 (Total Number of Observations = 22,474)

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Mean Return(%)	-1.32	.474	.730	.426	.932	.840
Standard Deviation	11.43	10.69	11.49	10.46	10.75	8.09
Observations	3781	3862	3936	3866	3857	3172
test-statistic	-8.32**	0.79	1.96*	0.46	3.12**	3.07**
Box-Ljung	2	1	1	0	1	2

-- Standard deviations and returns are calculated as 10^{-3}
* Significant at the 95% level of significance
** Significant at the 99% level of significance

The conclusion of random walk stems from the failure of any model's ability to identify a discernable pattern in the series of stock price returns. As such, it is not possible to conclude with 100% certainty that there is no pattern, just that the pattern, if any, is so advanced and complex that techniques are not available to identify the pattern.

CONCLUSIONS

Historical stock returns are analyzed to test the efficiency of the NYSE from 1885 through 1962, the period before the CRSP tapes were available. The Box-Jenkins methodology was employed in an attempt to identify patterns which could be used to predict stock returns.

The confidence intervals associated with each of the three tables are consistently and significantly widened with each successive forecasting period indicating that changes in historical stock prices are completely random. Although monthly and weekly return patterns were found to be significant, they were still unsuccessful in predicting future stock price movements. Since changes in stock prices are random, we can do no better than to predict that the next period's price will be somewhere around where it was the last time we knew it. This conclusion is not surprising, and moreover, is consistent with modern efficient market studies.

ENDNOTES

1. See Fama (1991, 1970) for a review of theory and empirical work surrounding market efficiency.
2. Historically, however, stocks did regularly trade on Saturdays.
3. See French (1980).
4. Actually, the conclusion of random walk implies that either the returns truly follow a random walk process or that the model attempting to identify the pattern is unable to determine the true underlying return generating process.
5. These procedures have been employed in earlier attempts, but were completely inadequate because of the violation of the serially independent assumption.
6. It may be necessary to difference a series more than once to make it stationary, but rarely if ever is it necessary to do so more than twice.
7. Also, the further into the future the forecast is, the larger the confidence interval will be.

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