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ANALYSIS OF EQUITY RETURNS IN THE JAPANESE FINANCIAL MARKET; TIME SERIES METHODS

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ABSTRACT

The purpose of this study is to examine returns on Japanese equities over nearly a four-decade period and to compare results among the four decade and the entire period of the study. "Long memory" modeling of time series developed to predict slowly moving time series is a method to predict long time components of time series data. Previous, other studies indicated some progress in producing results of predictability by these "long memory" analyses. The authors examined statistically for some of the reasons why long memory forecasting may not be very suitable for predicting equity returns over lengthy periods of time. Data secured from a source that collect information on Japanese equity returns, enabled a study of possible explanations of why lengthy predictions are difficult. The analysis is of an application to financial time series and does not dispute the use of long memory modeling in other applications. The conclusions made are therefore not universal but only to the use in financial engineering and time series analysis. Future work should consider the cost effectiveness of long-memory modeling in other forms of financial time series analysis

Keyword: Long memory modeling, Time series components ,Japanese equity market ,Long-run dependence

INTRODUCTION

One studies Japanese equity markets because of the great growth in its equity markets in the 1980's and subsequent fluctuations in later years and the problem of explaining fluctuations in the predictability of monthly stock prices in Japan. Ziemba and Schwartz(1991) and Ziemba (2012)produced evidence indicating that the dynamics of the Japanese markets had significant effects on the prices of Japanese securities. Many of these include Rothlein and Jarrett(2002);Jarrett and Kyper(2005a, 2005b and 2006);Caporale and Gil-Alana(2002);and Kubata and Takehara(2003).

Studies of changes in the Japanese economy in the 1980' sthrough the1990's and in to the century produce evidence to identify shocks in the Japanese markets leading to changes in the predictability in prices, thus reducing the accuracy of listed Japanese equities .Nagayasu (2000)documented the era when Japan went from great growth in its asset prices to virtual stag nation producing the worst crises in Japan since the out come of World War II.Furthermore,Ray,JarrettandChen(1997)produced evidence of both temporary and permanent components in the time series of as ample of listed Japanese equities. The last study using ARF IMA time series methods identified these component sbut also indicted some of the great difficulties in predicting prices of Japanese securities. They showed that the inclusion of the temporary component in a sample of 15 individual listed Japanese firms. Japanese equities contain 5 to 15%of permanent components and, thus, there may be a small amount of predictability in Japanese equity prices .Nagayasu(2003)using the ARFIMA-FGARCH model studied the efficiency of the Japanese equity market by examining the statistical properties of the return and volatility of the Nikkei 225. He found that there is along range dependence. This differs from the notion of the efficient market hypothesis(EMH)and is valid for the sample periods studied. This suggests that the equity market reform of the early 2000' sdid not produce major efficiency gains.

In addition to the Japanese study noted above others have made similar studies in other equity markets. These studies include Agiakloglou,Newbold, and Wohar, (1992); Baillie, (1996); Baillie,Bollerslev ,and Mikkelsen,(1996); Barkoulas,Baum,andTravlos,(2000); Bollerslev, Tim and Hans Ole Mikkelsen, (1996); Lo, (1991, 1997); Mills, (1993); Sadique, and Silvapulle, (2001); Li, (2015); and Shi and Ho, (2015).In all, these studies conclude that forecasting stock returns is a very difficult and exceptionally rare case when the future is barely predictable over the long term. This is not surprising but is often the case.

The Data Analysis

In this study, we examine the evidence concerning the lack of powerful long memory permanent components in a lengthy period of time series data on returns to the Japanese equity market. As a number previous studies we collected data over four decades from the PACAP databases on Japanese equity markets kept at the University of Rhode Island/CBA [e-mailPACAPD@ETAL.URI.EDU).

Thepurposeofthisstudyistodeterminewhatfactorsinthetimeseriesof Japaneseequitypricesthatmaycausethisgreatdifficultyinprediction.Weproposetostudythevalueweightedandequalweightedmonthly returnoveralengthyperiodtoexplaintheinabilityofpredictingaccuratelyJapanese equityprices.

In particular, we study the history of equity prices for the Japanese (Tokyo Stock Exchange) over a lengthy period of time what may have caused these prices to have changed during the lengthy period of time.

Stated differently, long run dependence (long run memory) is very important in explaining equity behavior. For example, if long run memory is present such as in predicting the overflow of a river causing floods beyond its banks one may take action by increasing the height of the river banks to prevent the future overflow of the river. This analogy if present in the time series of equity returns may permit one to adjust his/her financial decision make to reduce the disturbing effects of serial long term dependence. Hence, our goal is to examine if serial dependence produced changes that differ in several time periods.

In addition, since we have collected data on Japanese equity over a lengthy period in Japanese currency, we transformed the data in two way. One set of time series over a four decade time horizon applies the principle “value-weighted monthly returns “identified as MVRMWD in the data set of the time series. A second time series is ‘equal-weighted monthly” returns identified by the variably name MERMWD. We distinguish the two data sets since the original data in

Japanese currency is transformed into United States currency and we wish to see if the two methods yields similar results and there is no transformation bias,

Big Data Analytics

First, we analyze and compare the returns for the Japanese stock market by for the entire roughly four-decade sample of value weighted monthly returns denoted on the ensuing tables and figure as variable MVRMWD. The table consists of five panels, Moments, Descriptive Statistics, Statistical Tests for Location, Quantiles and Extreme Observations. In the first panel (Moments), observe that the mean is very small in comparison to the standard deviation. Skewness is slightly negative and kurtosis, that the state or quality of flatness or peakedness of the curve describing a frequency distribution in the region about its mode. In this case a value of 1.353 or so indicates that there are a few extremes in the data than would be seen in a normal curve whose measure would be about 3. The coefficient of variation of 981.354 (the standard deviation divided by the mean) would indicate that the mean would not be a good predictor because the standard deviation is large with respect to the mean.

The second panel contains the descriptive statistics. Note that the mean and median differ by a factor of about 10:1 indicating that the data are highly skewed as noted in the first panel on moments. The standard deviation relative to the mean would also be very large and corroborates the findings of the coefficient of variation noted in the first panel. In addition, the other measures of variation, the variance, range and interquartile range show also that the data is widely dispersed.

The third panel contains the Tests for Location: μ0 =0which were the t-test, M and signed rank. All three test indicated that the null hypothesis should be reject at small p-vales of 0.3030, 0.0147 and 0.0102. Hence, the means were non-zero and positive whether they were tested by parametric or rank statistics. Finally, the last two panels of Table 1 show the wide distribution of the data based on quantiles, quartiles and extreme observations.

For the entire period of the study, the return on Japanese equities tended to be positive but widely distributed and at no time tend to be easily predictable. The question remains how one can observe the wide distribution over a lengthy period of time. Hence, in the next sections, we observe the pattern in the roughly four decade of the study to determine why the permanent component of the time series repeats in each new decade.

Table1 Comparing Japan Stock Market Return by Decade Value Weighted Monthly

Moments (Univariate Procedure)			
N	**455**	**Sum Weights**	**455**
Mean	**0.00525402**	**Sum Observations**	**2.390581**
Std Deviation	**0.05156059**	**Variance**	**0.00265849**
Skewness	**-0.151716**	**Kurtosis**	**1.35303696**

Corrected Sum of Squares	**1.20695631**		
Coefficient of Variation	**981.354192**	**St. Error Of Mean**	**0.0024172**

Descriptive Statistics			
Location		**Variability**	
Mean	**0.005254**	**Std. Deviation**	**0.05156**
Median	**0.0005576**	**Variance**	**0.00266**
Interquartile Range	**0.05635**	**Range**	**0.37645**

Tests for Location: $\mu_0 = 0$			
Test	**Statistic**	**P value**	
t	**2.1736**	**Pr > abs (t)**	**0.0303**
M	**26.5**	**Pr ≥ abs(M)**	**0.0147**
Signed Rank (S)	**7199**	**Pr ≥ abs (S)**	**0.0102**

Quantiles	
Quantile	**Estimate**
Maximum	**0.1791**
99%	**0.1367**
95%	**0.0898**
90%	**0.0638**
75% (Q3)	**0.0342**
50% (Median, Q2)	**0.0056**
25% (Q1)	**-0.0222**
10%	**-0.0585**
5%	**-0.0792**

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Note: Qisforquartile

Extreme Observations			
Lowest	Highest		
Value	Obs	Value	Obs
-0.1973	405	0.1367	228
-0.1963	188	0.1410	290
-0.1571	226	0.1464	193
-0.1388	408	0.1579	134
-0.1266	404	0.1791	189

Analysis by Decade

Presented in Tables 2 - 5 is the same analysis for each decade referred in the table as a group. Group = 1 refers to the first decade of data collected from the source noted before. In turn, Group = 2, 3 and 4 refer to each new decade. The analysis for each decade is the same as in Table 1. Note that the number of observations is smaller than the entire sample studied, hence with less degrees of freedom the significant tests for location may vary. We expect the moments and descriptive statistics to vary as well. By observing the mean rates of return, we observe in Tables 2 - 5 that the mean rate of return was extremely small but with a declining trend with the largest value in Group=2. The coefficients of variation again were very large indication the wide diversity in the mean rates for each firm listed on the exchange. Furthermore, for all the groups, 1, 2, 3, and 4 indicate that the test of hypothesis of mean equals zero could not be rejected. The p-values tended to be very large regardless of whether the test was a t-test or nonparametric analysis was performed.

In addition, the same set of tables indicated the wide diversity in the returns from decade to decade. At no time did we observe a pattern of growth as exhibited in the tables for each decade. The evidence seems to suggest that the Japanese equity market did not appear to have a positive growth during the decadesbut did exhibit wide variation, skewness and kurtosis in the distribution of returns. This may suggest that a permanent component in the time series data was not present. Analysis of data suggests that long memory modeling may not be available as a panacea for predicting future returns in the Japanese equity market.

Table 1Comparing Japan Stock Market Return by Decade Value Weighted Monthly Return(MVRMWD)Group =1

Moments (Univariate Procedure)

N	119	SumWeights	119
Mean	0.0121775	SumObservations	1.449122
StdDeviation	0.03212	Variance	0.00103169
Skewness	0.29980506	Kurtosis	2.02395426
Corrected Sum of Squares	0.12173992		
Coefficientof Variation	263765208	St.Error OfMean	0.00294444

DescriptiveStatistics			
Location		Variability	
Mean	0.012177	Std.Deviation	0.03212
Median	0.009441	Variance	0.00103
		Range	0.22198
		InterquartileRange	0.03269

Tests for Location: µo =O			
Test	Statistic	Pvalue	
t	4.135766	Pr > abs(t)	S.0001
M	18.5	Pr abs(M)	0.0009
SignedRank	1592	Pr abs(SJ	0.0001

Quantiles	
Quantile	Estimate
Maximum	0.1235

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99%	**0.1082**
95%	**0.0662**
90%	**0.0509**
75%(Q3)	**0.0282**
50% (Median,Q2)	**0.0094**
25%(Ql)	**-0.0045**
10%	**-0.0251**
5%	**-0.392**
1%	**-0.0618**
Minimum	**-0.0985**

Note: Q is forquartile

Extreme Observations			
Lowest	**Highest**		
Value	**Obs**	**Value**	**Obs**
-0.0984	**112**	**0.0732**	**115**
-0.0618	**80**	**0.0838**	**9**
-0.0481	**85**	**0.0870**	**1**
-0.0428	**6**	**0.1082**	**23**
-0.0392	**114**	**0.1235**	**110**

Table3Comparing Japan Stock Market Return by Decade Value Weighted Monthly Return (MVRMWD) Group =2

Moments(Univariate Procedure)			
N	**120**	**SumWeights**	**120**
Mean	**0.0006542**	**SumObservations**	**0.78504**
StdDeviation	**0.06311431**	**Variance**	**0.00398342**

Skewness	-0.0226193	Kurtosis	0.98950479
Corrected SumofSqua	0.47402645		
Coeff. of Variation	964.755513	St.ErrorMean	0.00576152

DescriptiveStatistics			
Location		Variability	
Mean	0.006542	Std.Deviation	.06311
Median	0.005635	Variance	0.00398
		Range	0.37541
		Interquartile Range	0.07417

Tests for Location: μo= 0			
Test	Statistic	Pvalue	
t	1.135464	Pr > abs(t)	0.2585
M	6	Pr.!:abs(M)	0.37541
SignedRank(S)	456	Pr.!:abs(SJ	0.2339

Quantiles	
Quantile	Estimate
Maximum	0.1791
99%	0.1579
95%	0.1290
90%	0.0763

75%(Q3)	**0.0409**
50%Median,Q2)	**0.0056**
25%(Q1)	**-0.0333**
10%	**-0.0697**
5%	**-0.0976**
1%	**-0.1571**
Minimum	**-0.1963**

Note: Q is forquartile

ExtremeObservations			
Least		**Highest**	
Value	**Obs**	**Value**	**Obs**
-0.196303	**188**	**0.131426**	**211**
-0.157149	**226**	**0.136679**	**228**
-0.124507	**182**	**0.0146419**	**193**
-0.124503	**187**	**0.157948**	**134**
-0.112875	**190**	**0.179105**	**189**

Table4 Comparing Japan Stock Market Return by Decade Value Weighted Monthly Return (MVRMWD)
Group =3

Moments(Univariate Procedure)			
N	**120**	**SUMWeights**	**120**
Mean	**0.0010967**	**SumObservations**	**0.131604**
StdDeviation	**0.05101579**	**Variance**	**0.00260261**

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Skewness	0.19039713	Kurtosis	-0.3175241
Corrected SumofSquares	0.309855		0.30971067
Coefficient of Variation	4651.75421	St.Error OfMean	0.00465708

DescriptiveStatistics			
Location		Variability	
Mean	0.00110	Std.Deviation	0.05102
Median	-0.00309	Variance	0.00260
		Range	0.26458
		InterquartileRange	0.08118

TestsforLocation:μo=O

Test	Statistic	Pvalue	
t	0.235491	Pr > abs(t)	0.8142
M	-3	Pr abs(M)	0.6483
SignedRank (S)	16	Pr abs(S)	0.9668

Quantiles	
Quantile	Estimate
Maximum	0.1410
99%	0.1149
95%	0.0838
90%	0.0628

75%(Q3)	0.0405
50% (Median,2)	-0.0031
25%(Ql)	-0.0407
10%	-0.0643
5%	-0.0776
1%	-0.0856
Minimum	-0.1235

ExtremeObservations			
Lowest		Highest	
Value	Obs	Value	Obs
-0.123537	283	0.102495	286
-0'.085585	306	0.109559	350
-0.084380	318	0.113935	246
-0.084048	329	0.774880	293
-0.079367	241	0.141038	290

Table5 Japan Stock Market Return by DecadeValue Weighted Monthly Return(MVRMWD) Group=4

Moments (Univariate Procedure)			
N	96	Sum Weights	96
Mean	0.000258	Sum Observations	0.02481
Std. Dev.	0.05536	Variance	0.003064
Skewness	-0.57034	Kurtosis	1.13855
Coeff Variation	21415.1414	Corrected SS	0.29111
		St. Error Mean	0.0056497

DescriptiveStatistics

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Location		Variability	
Mean	0.000258	Std.Deviation	0.05536
Median	0.003503	Variance	0.00306
InterquartileRange	0.06946	Range	0.31095

Tests for Location: µo =0			
Test	Statistic	Pvalue	
t	0.045752	Pr > abs(t)	.9636
M	5	Pr abs(M)	.3584
SignedRank	107	Pr abs(SJ	.6979

Quantiles	
Quantile	Estimate
Maximum	0.0036
99%	0.1136
95%	0.0898
90%	0.0720
75%(Q3)	0.0350
50% (Median)	0.0035
25%(Ql)	-0.0344
10%	-0.0629
5%	-0.1027
1%	-0.1973
Minimum	-0.1973

ExtremeObservations	
Lowest	Highest

Value	Obs	Value	Obs
-0.197343	405	0.089771	455
-0.138821	408	0.102213	445
-0.126562	404	0.103183	422
-0.104901	424	0.109199	399
-0.102674	448	0.113605	368

Graphical Analysis

Finally, we observe boxplots of the data on Japanese equity returns by decade in Figure 1. From left to right, the boxplot represents mean (diamond), median (the horizontal line through the box, the limits of the interquartile range (upper and lower limits of the box), and the upper lower range of the data for each decade. Note that for decade 1 the box tends to have less variation than for the remaining three decades. The range is also narrower in decade 1 than for the remaining decades. The mean and median return are very near to each other with decade 2 having a mean and median that are approximate. The boxplot shows that the Japanese equity returns have not shown any growth and are near zero. The boxplot itself shows visually the same conclusion that we observe in the moments, descriptive statistics, hypothesis tests, quantiles and extreme observation noted in Tables 2 - 5. We may conclude that the Japanese equity returns have stagnated over the lengthy study and most important the results appear to verify the conclusions from previous studies of long memory modeling. If we were to buy the entire market, we would observe that wealth creation would be very slow. However, investors do not usually buy an entire equity market but instead purchase and sell individual securities or markets baskets of securities. The like result is that these market baskets would be difficult to predict their returns if the selection process was random. Forecasting such a market basket of securities may be undesirable We must be extremely careful in selecting equities to purchase in this market and this has ramification for mutual funds and ETFs.

[--- Insert Figure 1---]

Data Analysis for Equal Weighted Monthly Returns

The analysis of the equal weighted monthly returns (MERMWD) is performed in the same manner as in the previous sections. First, we examine the data for the entire four decades, in turn, we examine the data decade by decade denoted group 1 through 4 and finally we compare the boxplots of the four decades. We begin with Table 6 where the data for the entire four decade time series sample characteristics appear.

Table 6 Equal Weighted Monthly Return (MERMWD)

Moments (Univariate Procedure)

N	455	Sum Weights	455
Mean	0.00878095	Sum Observations	3.995334
Std Deviation	0.05696745	Variance	0.00324529
Skewness	0.06207574	Kurtosis	1.56248128
Corrected Sum of Squares	1.4733619		
Coefficient of Variation	648.76	St. Error Of Mean	0.00267068

Descriptive Statistics			
Location		Variability	
Mean	0.008781	Std. Deviation	0.05697
Median	0.11278	Variance	0.00325
Interquartile Range	0.06286	Range	0.44543

Tests for Location: $\mu_0 = 0$			
Test	Statistic	P value	p-value
t	3.287915	Pr > abs (t)	0.0011
M	36.5	Pr ≥ abs(M)	0.0007
Signed Rank (S)	10312	Pr ≥ abs (S)	0.0002

Note: Q is for quantile

Quantile	Estimate
Maximum	0.2563
99%	0.1509
95%	0.1011
90%	0.0742
75% (Q3)	0.4138
50% (Median, Q2)	0.0112
25% (Q1)	-0.0215
10%	-0.0583
5%	-0.0855
1%	-0.4167
Minimum	-0.1891

Extreme Observations			
I Lowest		Highest I	
Value	Obs	Value	Obs
-0.1891	188	0.1509	228
-0.1674	405	0.1663	350
-0.1669	226	0.1768	189
-0.1581	187	0.2294	193
-0.1467	190	0.2563	276

Again the number of observations is 455 as in Table 1, but the mean rate of return is 0.0088 (rounded to four decimal places) indicating less than a one percent rate of return compared with0.00525 for the value weighted monthly return in Table 1. The coefficient of variation is again very large (648.76) the skewness coefficient is much smaller for the equal weighted monthly returns (0.0621), but the kurtosis is larger at 1.5625 than for the value weighted monthly returns. Hence, this distribution tends to be less skewed but more, but more flattened. The descriptive statistics indicate that this distribution contains less variation about the mean even though it is still large, but the skewness is no longer negative that is the median is larger than the mean. The tests for location (t-test, M and S) all reject the hypothesis that the mean equals zero at very small levels (0.0011, 0.0007 and 0.0002)

The quantiles and quartiles of the data show large distances between each border of the quantiles and quartiles. Last, the extreme observation at their lowest and highest values are a large number in comparison to the size of the time series data set. Hence the range of the data and interquartile range tend also to be very large indicating wideness in the data set.

Data Analysis by Decade of Equal Weighted Monthly Returns.

Tables 7 - 10 contain the same analysis as appearing in Tables 2 - 5 for the value weighted monthly returns. The sizes of the sample for each decade correspond to the analysis in each decade. Group = 1 and 2, (the first and second decades) possess the largest mean and median rates of return with very large coefficients of variation but not as large for the same statistic in Tables 2 and 3 (the same groups by value weighted data). Skewness and kurtosis statistics ten to indicate similar results in Tables 7 and 8 as they do in Tables 2 and 3. Tables 9 and 10 again show similar results as in Tables 4 and 5. Hence, the method of weighting may show different values for the moments and descriptive statistics, the statistical tests of µ0 =0 do indicate different results. However, the most stunning result refers to the comparison in the results in Tables 7 and 8 with Tables 9 and 10. Again, the results indicate that for decades (groups) 1 and 2, the mean rates are statistically different from zero whereas in decades 3 and 4 this is not statistically evident. This corroborates the results in Table 2 and 3 in comparison to Tables 4 and 5. Hence, the methods of weighting the monthly returns did not affect the interpretation of the results. Japanese equity returns by months deferred as time passed. The result is not an anomaly but indicated that time components did change and returns were probably influenced by changes in the economy of Japan.

Table 7 Comparing Japan Stock Market Return by Decades Group 1

Moments (Univariate Procedure)			
N	119	Sum Weights	119
Mean	0.0152	Sum Observations	1.8102
Std Deviation	0.0299	Variance	0.00089
Skewness	-0.0764	Kurtosis	0.0957
Corrected Sum of Squares	0.1053		0.1053
Coefficient of Variation	196.3424	St. Error Of Mean	0.0027

Descriptive Statistics			
Location		Variability	
Mean	0.0152	Std. Deviation	0.0299

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Median	**0.0299**	**Variance**	**0.0009**
Interquartile Range	**0.0417**	**Range**	**0.1601**

Tests for Location: $\mu_0 = 0$			
Test	**Statistic**	**P value**	**p-value**
t	**5.5560**	**Pr > abs (t)**	**≤.0001**
M	**25.5**	**Pr ≥ abs(M)**	**≤.0001**
Signed Rank (S)	**1923**	**Pr ≥ abs (S)**	**≤.0001**

Quantiles	
Quantile	**Estimate**
Maximum	**0.0964**
99%	**0.0858**
95%	**0.0596**
90%	**0.0535**
75% (Q3)	**0.0351**
50% (Median, Q2)	**0.0172**
25% (Q1)	**-0.0066**
10%	**-0.0228**
5%	**-0.0388**
1%	**-0.0568**
Minimum	**-0.0636**

Descriptive Statistics			
Location		**Variability**	
Mean	**0.0152**	**Std. Deviation**	**0.0299**
Median	**0.0299**	**Variance**	**0.0009**
Interquartile Range	**0.0417**	**Range**	**0.1601**

Table 8 Comparing Japan Stock Market Return by Decades

Group 2

Moments (Univariate Procedure)			
N	**120**	**SUM Weights**	**120**
Mean	**0.0118**	**SUM Observations**	**1.4180**
Std Deviation	**0.0671**	**Variance**	**0.0045**
Skewness	**-0.1101**	**Kurtosis**	**1.3312**

Corrected Sum of Squares	**0.5357**		
Coefficient of Variation	**567.7790**	**St. Error Of Mean**	**0.0061**

Descriptive Statistics			
Location		**Variability**	
Mean	**0.0118**	**Std. Deviation**	**120**
Median	**0.147**	**Variance**	**0.0045**
Interquartile Range	**0.0620**	**Range**	**0.4186**

Tests for Location: $\mu_0 = 0$			
Test	**Statistic**	**P value**	**p-value**
t	**3.287915**	**Pr > abs (t)**	**0.0011**
M	**36.5**	**Pr ≥ abs(M)**	**0.0007**
Signed Rank (S)	**10312**	**Pr ≥ abs (S)**	**0.0002**

Quantiles	
Quantile	**Estimate**
Maximum	**0.2295**
99%	**0.1768**
95%	**0.1302**
90%	**0.0841**
75% (Q3)	**0.0443**
50% (Median, Q2)	**0.0147**
25% (Q1)	**-0.0175**
10%	**-0.0713**
5%	**-0.1013**
1%	**-0.1669**
Minimum	**-0.1891**

Note: Q is for quantile

Extreme Observations			
Lowest		**Highest**	
Value	**Obs**	**Value**	**Obs**
-0.1891	**188**	**0.1351**	**184**
-0.1669	**226**	**0.1410**	**219**

-0.1581	**187**	**0.1509**	**228**
-0.1467	**190**	**0.1768**	**189**
-0.1039	**199**	**0.2295**	**193**

Boxplot Analysis of Equal Weighted Monthly Returns

By observing the boxplot by decade in Figure 2, we note its similarity to Figure 1 indicating that the method of weighting had little effect on the sample statistics developed to analytically observe the patterns in the data over the four decade intervals. However, some results should be noted. The limits of the first decade's central box are the narrowest in decade 1 in Figure 1 and same is true for Figure 2. The middle 50 percent boxes in decades 2 - 4 are larger than in decade 1 in both figures. The relation of the mean and median are also the same. Hence, it is likely that both methods of weighting did not change the results and conclusions that one can draw.

[---Insert Figure 2---]

Although the two figures were drawn using different time series, one observes the great similarity in the boxplots of monthly returns. Visual representation appears to indicate that the result are similar, not the same, and conclusions drawn from this visual information should be very similar.

Conclusions

The purpose of this study was to study if long memory modeling could possibly improve prediction of returns in at least one significant nationwide equity market. Previous studies indicated some predictability in producing results that would aid financial analysts and economists in forecasting returns to equity markets. This study does not dispute earlier result but clarifies some of the results of previous studies employing long memory modeling. We conclude that earlier studies may have opened the enthusiasm of utilizing these modern and well respected time series methods. However, for the purpose of forecasting returns to equities, long memory modeling may simply not be enough to be useful. Although producing long memory modeling of equity returns may be economically cost-effective in managing one's portfolio decisions, alternative may be more accurate and useful. This analysis does not conclude that there are great many uses of long memory modeling, but predicting future returns over a lengthy period may not be one of them.

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