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Review and New Study of Daily Time Series Data Analysis of Market Prices

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Abstract

The purpose of this paper is to investgate the existence of time series characteristics of daily stock prices of securities marketed on organized exchanges. This study differs from previous studies where the focus was on index numbers of daily stock market prices rather than the actual prices of traded securities. Furthermore, this study is important because of the theory of market efficiency and its application to short term forecasting of closing prices of traded securities.

Key Words

ARIMA; Time Series; Daily Variation; Pandemic: Capital Markets

Capital Markets

Capital market efficiency is an important research topic since Fama (1955, 1970) explained these principles as apart of the efficient market hypothesis. Following Fama's work many studies were devoted to investigating the randomness of stock price movements for the purpose of demonstrating the efficiency of capital markets. In recent years, other studies demonstrated market inefficiencies by identifying systematic and permanent variations in stock returns. Some of these systematic variations, or anomalies as they are referred to are small firm effects, investment recommendations, and extraordinary returns to the time or the calendar effect.

These Calendar or time-series effects do contradict the weak form of the efficient market hypothesis. The weak form refers to the notion that the market is efficient in past price and volume information and we do not predict stock price movements accurately using historical information. If no systematic patterns exist, stock prices are time invariant. On the other hand, if variation in the time series of daily prices of securities markets exist, market inefficiency is present and investors should be able to earn abnormal rates of return not in line with the degree of risk they undertook (Francis 1993). In addition, a large number of studies in the literature on predicting prices of traded securities confirm to some degree that patterns exist in stock market prices. We know that interest rates, dividend yields and a variety of macroeconomic variables exhibit clear business cycle patterns. The emerging literature concerning studies of United States securities include Balvers et al (1990), Breen et al (1990), Campbell (1987), Fama and French (1989) and Pesaran and Timmermann (1994,1995), Granger (1992) provides a up to that time survey of methods and results. Studies in other places (the United Kingdom) include Clare et al (1994) Clare at al (1995), Black and Fraser (1995) and Pesaran and Timmermann (2000). Furthermore, Caporale and Gil-Alana (2002) pointed out that for US stock returns their degree of predictability depends on the process followed by the error term.

The expansion of time series analysis as a discipline permits one to analyze stock market prices in ways not heretofore explored. What is the predictability of the error term and is there predictability in daily stock market returns? Peculiar problems arise when daily patterns are present in stock price data. We know that stock prices possess patterns known as daily effects. For example, Kato (1990a) results suggested that were our patterns in stock returns in Japanese securities. He observed low Tuesday and high Wednesday returns within weekly prices. If a week did not have trading on a Friday, he would observe effects related to the Monday of the following week. The following Monday would have low returns indicating that transference of the pattern that would occur on the Friday if trading had occurred which it did not. A second study by Kato (1990b) found considerable anomalies on the Tokyo Stock Exchange (TSE), which is an organized exchange similar to the ones in North America.

Only a few studies focused on the investigation of time series components of equity prices and the predictability of these prices. Ray, Chen and Jarrett (1997) investigated a sample of 15 firms and found both permanent and temporary systematic components in individual time series of stock market prices of firms over a lengthy period of time. Moorkejee and Yu (1999) investigated the seasonality in stock returns on the Shanghai and Shenzen stock markets. They documented the seasonal patterns existing on these exchanges and the effects these factors have on risk in investing in securities listed on these exchanges. Thus, they showed that risk in investing is related to the predictability of security prices. Rothlein and Jarrett (2002), investigated the existence of seasonality present in Japanese stock prices, which affect the prices of these securities. They documented the evidence of seasonality in the prices of 55 randomly selected Tokyo Stock Exchange firms over a lengthy period of 18 years (1975 through 1992). In addition, they indicated the accuracy of forecasts or predictions of these firms' prices are seriously decreased if one does not recognize the patterns in the time series. Jarrett and Schilling (2008) studied time series characteristics of the Frankfort stock market, one of the largest markets in the European Union. Pan and Jarrett (2014) other properties of time series of corporate earnings. Finally, Jarrett and Pan (2020) used another method of multivariate exponential weighted average method to analyze time series method to predict data for similar data in another application involving time series.

Last, Jarrett and Kyper (2005) indicated how patterns in monthly stock prices have predictable patterns. This study differs in that we examine the predictable patterns in the closing daily prices of stock prices. In goes further than the study of Caporale and Gil-Alana (2002) noted before because it attempts to determine the patterns in daily prices of listed securities.

Methodology and Results

The ARIMA (p,d,q) model is a linear combination of two linear models and thus is itself still linear. Autoregressive Moving Average Model of order p, q is a time series model

A time series model, is an autoregressive moving average model of order d, ARIMA (p,d,q,) where d is order of differencing. The difference is done to reduce the white noise measured by the variance of the error term. One of the key features of the ARIMA model is that it is parsimonious and redundant in its parameters. Stated differently, an ARIMA model will often require fewer parameters than an AR (p) or MA (q) model alone.

To determine if a daily pattern can be modeled for a sampled time series, we employ the

Dickey-Fuller (1979) tests which we now illustrate. First an autoregressive process, AR (1), $YT = \mu + \rho y_{t-1} + \epsilon_t$, where μ and ρ are parameters and ϵ_t is white noise. Y is a stationary time series if $-1 < \rho < 1$. If $\rho=1$, y is a nonstationary series (a random walk with a drift), if the process is started at some point, the variance of y increases steadily with time and goes to infinity. If absolute ρ is greater than unity (1), the series is explosive. Thus, the hypothesis of a stationary series can be evaluated by testing whether the absolute value of ρ is strictly less than unity. The Dickey-Fuller (1979) test takes the unit root as the null hypothesis, that is, H_o: $\rho = 1$. Since explosive series do not make much sense in economic terms, the alternative hypothesis is stated in terms of H_a: $\rho<1$. The test is usually carried out by estimating an equation with y_{t-1} subtracted from both sides of the equation:

$\Delta y_t = \mu + \gamma y_{t-1} + \epsilon_t$ where $\gamma = \rho-1$

and the null and alternative hypotheses are

H_o: $\gamma = 0$ and H_a: $\gamma < 0$.

[a single-sided test]. Although this appears as a conventional t-test on the estimated γ, the t-statistic under the null hypothesis of a unit root does not have the conventional t-distribution. Dickey and Fuller (1979) showed that the distribution under the null hypothesis is not standard, and simulated the critical values for selected sample sizes. MacKinnon (1991) implemented a larger set of simulations than those tabulated by Dickey and Fuller. . He estimates the response surface using the simulation results, permitting the calculation of Dickey-Fuller (1979) critical values for any sample size and for any number of variables on the right-hand side of the equation. We report our results based on these MacKinnon critical values for the unit root test.

We must also recognize that the simple unit root test noted before is valid only for a series, which is AR (1) {first degree auto-regressive}. If the series is autocorrelated at higher order lags, we violate the assumption of white noise disturbances. The augmented Dickey-Fuller approach controls for higher order autocorrelation by adding lagged difference terms of the response variable y to the right-hand side of the regression model:

$\Delta y_t = \mu + \gamma y_{t-1} + \tau_1 \Delta y_{t-1} + \tau_2 \Delta y_{t-2} + \ldots + \tau_{p-1} \Delta y_{t-p+1} + \epsilon_t$
This augmented specification is in turn used to test:
$H_o: \gamma = 0$ and $H_a: \gamma < 0$.

In the time-series regression model. An additional important result obtained by Fuller is that the asymptotic distribution of the *t*-statistic on γ is independent of the number of lagged first differences included in the augmented DF regression. Further, the parametric assumption that *y* follows an AR process restricts the use of the DF test, Said and Dickey (1984) demonstrate that the augmented DF test remains valid even when the time series is moving-average (MA), provided that enough lagged difference terms are augmented to the regression.

Additionally, one may choose a model with or without a constant term, and with or without a linear trend. The purpose of this analysis , however, is not to determine the precise model that best generates the time series of daily observation, but to consider whether a model could be built or not. If we find that the model has a unit root which can be expressed by an AR, MA or mixed ARMA process, we have shown that there is pattern in the daily observations and the notion that daily observation are completely random is nullified.

The Investigation

The analysis includes monthly closing stock prices for 49 randomly selected firms listed on organized exchanges in the United States (NYSE and NASDAQ). The original sample was larger but due to problems with acquiring objective data for the sample period several firms from the original sample were not included in the final study. Therefore, we used only firms having the complete sets of time series data that covered the study period (April 1992 to September, 2002). The study period was lengthy enough to minimize any effects of short-term economic fluctuations. In particular, 300 observations on daily closing prices is included in each data set and this number far exceeds the necessary sample size for successful application of Time Series Analysis by *ARIMA* methods (autoregressive integrated moving average methods).Table 1 contains a list of those firms included in the sample. Note that the firms are also well known enough to eliminate any problems with start-up firms and problems associated with mergers and acquisitions. All data account for stock splits, stock dividends, which may dilute the usefulness of unadjusted information.

The Analytics

ARIMA methods permitted us to model the underlying mathematical process which gives rise to the time series. Table 2 is the results of modeling the 300 observation time series data sets for the forty-nine firms under study. Observe, all of the forty-eight of the 49 firms required one degree of differencing to result in series suitable for modeling. This is consistent with earlier studies of time series data of closing prices, which contain nonstationary properties in the mean. This is usually an existing trend in the data requiring a filter to generate a stationary series. Usually, one degree of differencing is sufficient to find suitable data for modeling. Only Hillenbrand Industries (hb) did not require a degree of differencing. The autoregressive (AR) terms and the moving average (MA) terms in the time series model are in turn indicated in Table 2 for each of the forty-nine-time series. A term of 1 indicates that the model contains a *first-order* AR or MA term. The value 2 indicates the existence of a *second-order* AR or MA term. Last, the value 5 indicates a ***fifth-order*** AR or MA term. Since the number of trading days in a week is five, it is conceivable that daily data may contain a *fifth-order* term. Most models do not contain a *constant* term in the final model equation. This is consistent with the notion that first-differenced series usually do not contain constant in the underlying theoretical model.
Next, the investigation of all modeled time series and producing both plots of the correlograms of the autocorrelations of the residual series. All series that violated the notion that autocorrelations up to 36 lags be within approximate *two-sigma* limits of zero were eliminated and series was modeled again. Two-sigma limits are applied to indicate significance levels of 5%, which is standard for time series modeling of this type.
In addition, we calculated the Portmonteau *Q-statistics* for each order of the series for all residual data sets up to 36 lags. In Table 2, we report the *Q-statistic* for order 5 only. The null hypothesis for each test (if not rejected) indicates that no additional time series modeling is necessary. The probability if large leads one not to reject the null hypothesis. With two exceptions, not all the hypotheses are rejected as indicated by the large p-values or probabilities for the Q-statistics. Only the series for Caterpillar (cat) and Hillenbrand Industries (hb) could not be modeled properly. Stated differently, these two series contained too much noise to indicate that predictability was

possible. Thus, the daily closing properties could be model by time series methods and thus pattern exist in these forty-seven series.

Last, Table 2 indicates the existence of inverted roots in the sampled time series. In turn, the augmented Dickey-Fuller (1979) test discussed before was completed for the forty-nine-time series of 300 observations. The test statistics and p-values for the null

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\.Summary Documented in this study is the conclusion is that daily closing prices for a sample of firms contain properties and with enough time, patience and understanding of the mathematics of the underlying processes that give rise to a time series can properly model that time series. The result would permit one to note that time series of closing prices are not random and have daily affects. Therefore, the data indicates the existence of time series components in closing prices of a randomly selected set of firms traded on organized market exchanges in the United States. The results corroborate results of previous studies of international markets and previous studies of markets in the United States where time series daily and monthly components are present in closing prices and indexes of prices of securities. When these properties in closing prices exist, it is possible to forecast the patterns, and thus investors can benefit from this information. Furthermore, the results indicate that the weak form of the efficient markets hypothesis is in question when one must make decisions concerning investing in stock market securities. Daily variation is neither random nor stochastic and it is possible to predict daily patterns with some degree of accuracy. We suggest, for purposes of prediction that forecasters predict systematic time series components of closing prices. In addition, one cannot understate the importance of stock returns and portfolio risk. These factors coupled with recognition of systematic time series components in stock prices can make one a better forecaster for prices of individual securities. This study was given for a time period that

Table 2
The Dollar Value of IPR
Changes in Interest Rates and the Cost of Debt

E(X)	S(X)	Debt cost	*Z Score*	Normal probability	$IPR
2,100	600	500	2.66667	0.996170	2,091.96
2,100	600	1,200	1.50000	0.933193	1,959.70
2,100	600	1,400	1.16667	0.878327	1,844.49
2,100	600	1,600	0.83333	0.797672	1,675.11
2,100	600	1,800	0.50000	0.691462	1,452.07
2,100	600	2,000	0.16667	0.566184	1,188.99

One last example, Table 3: we alter the example by comparing the monetary value of IPR when the cost of debt and debt: equity ratio in columns 1 and 2 of Table 3. In turn, both columns 3 and 4 (cost of debt and net cash, respectively) change from row to row. The *Z*-statistics and normal probabilities change, and the monetary value of IPR changes from row to row with the highest in row 1 and descending thereafter.

Table 3
Comparison of the Debt-to-Equity Ratio)
(Equity = $200,000)

Debt	D:E ratio	Debt cost	Cash inflow	S(X)	*Z Score*	Normal prob.	$IPR
50,000	0.25	2,000	2,300	230	1.304	0.903942	180,788
60,000	0.30	2,400	1,900	190	–2.632	0.004249	850
70,000	0.35	2,800	1,500	150	–8.667	0.000000	0
80,000	0.40	3,200	1,100	110	–19.091	0.000000	0
90,000	0.45	3,600	700	70	–41.429	0.000000	0
100,000	0.50	4,000	300	30	123.333	0.000000	0

Note: $IPR is the Dollar value of IPR

These examples show that estimation theory in financial accounting is a fundamental ingredient in correcting financial reporting data. Now, financial analysts now have a complete set of data to work with when making earnings forecasts and other decisions. Our finding does not dispute that of others.

Additional Evidence Concerning Estimation Theory and Methods

Estimation and timing of the recognition and matching of costs and revenues is dependent on the underlying analysis of data that corroborates its use. Although one cannot examine all data but only samples of data previously analyzed by Berger, Ofek, and Swary (1996). In their study, they obtained data from the International Brokers Estimate System (IBES) that have forecasts of earnings and growth in earnings. In Table 4, we provide their descriptive information on the sample information obtained. The information obtained describes the distribution of PVCF for three separate forecasting methods. In analyzing these data, one calculates the skewness coefficient and presents the results in the expanded table. The analytics indicates the symmetry in the distributions of the PVCF data.

A previous study by Berger, Ofek, and I. Swary(1996)the distribution of the sample data for rates of return is probably close to a symmetrical one and, in turn, likely to be distributed similar to a normal distribution process. If not exactly normally distributed, there are many ways one can estimate the distribution of the PVCF data, bringing more credibility to the process. One last point concerning the distribution of PVCF of Berger concerns the kurtosis in the sample data in Berger's study. Westtfall (2014) notes, "it's only an unambiguous interpretation in terms of the tail extremity; i.e., either existing outliers (for the sample kurtosis) or propensity to produce outliers (for the kurtosis of a probability distribution).' The logic is simple: Kurtosis is the average (or expected value) of the standardized data raised to the fourth power. Any standardized values that are less than 1 (i.e., data within one standard deviation of the mean, where the "peak" would be) contribute virtually nothing to kurtosis, because raising a number that is less than one to the fourth power makes it closer to zero. The only data values (observed or observable) that contribute to kurtosis in any meaningful way are those outside the region of the peak, stated differently, hypothesis that the unit root exists indicate the existence of unit roots for all the time series under study. We present the estimates for the parameters of the model equation in this table as well. All of the p-values were large (at least .066) indicating the existence of unit roots. This verifies the notion that these time series are not completely random and do have properties for modeling at least for periods up to 300 trading days

Table 2

Modeling Results

Firm	Degree of Differencing	Significant AR Terms	Significant MA Terms	Constant	Portmonteau Q-Statistic at Lag 5	Prob	Inverted Roots
abv							
adrx							
ahc	1	1,5	1,5	No	2.8895	0.089	AR,MA
aig	1	1	1,5	No	3.0814	0.214	AR,MA
ald	1	1,2	1	No	1.8043	0.406	AR,MA
amat	1	2,5	5	No	3.1869	0.203	AR,MA
bmy	1	5	5	No	4.0972	0.251	AR,MA
c	1	1,5	1,5	No	5.0889	0.405	AR,MA
cat	1	ns	ns	No			Not Sig.
cers	1	5	5	No	4.514	0.211	AR,MA
cmcsk	1	5	5	No	1.5404	0.585	AR,MA
cohr	1	1,5	1,5	No	3.5575	0.059	AR,MA
cost	1	5	5	Yes	1.3975	0.706	AR,MA
csco	1	2		No	2.05	0.727	Not Sig.
cvs	1	5	5	No	3.6537	0.16	AR,MA
cvx	1	5	5	No	0.8472	0.838	AR,MA
cytc	1	1,5	1,2,5	No	3.3958	0.065	AR,MA
dj	1	5	5	No	3.4545	0.327	AR,MA
f	1	1,5	5	No	7.8642	0.02	AR,MA
fbf	1	1,5	1,5	No	3.6668	0.056	AR,MA
fdc	1	1,2	1,2	No	8.5996	0.126	AR,MA
fnm	1	5	5	Yes	5.0324	0.169	AR,MA
fox	1	1,5	1,5	No	1.3745	0.241	AR,MA
fre	1	2	2	No	2.4747	0.48	AR,MA
g	1	2,5	2,5	No	3.8452	0.05	AR,MA
ge	1	5	5		2.733	0.435	AR,MA
hal	1	1	1,2	Yes	0.5318	0.616	AR,MA
has	1	1,5	1,5	No	4.5879	0.032	AR,MA
hb	0	1	1	No	3.7181	0.29	MA
hd	1	5	5	No	1.4391	0.571	AR,MA
hlt	1	5	5	No	4.4449	0.217	AR,MA
hpq	1	5	5	No	7.0516	0.07	AR,MA
intc	1	1	1	No	6.0289	0.052	AR,MA

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jdsu	1	5	5	No	3.441	0.328	AR,MA
jnj	1	3		No	0.9781	0.913	AR
jpm	1	5	5	No	2.1627	0.539	AR,MA
klac	1	1,5		No	5.1381	0.077	AR
ko	1	5		No	0.8214	0.936	AR
l	1	2	2	No	3.4767	0.324	Not Sig.
lmt	1		5	No	4.074	0.396	MA
low	1		1,2,3,4,5	Yes	Large	0.001	MA
mcd	1	5	1,5	No	1.4499	0.229	AR,MA
mdt	1	5	1,5	No	4.1625	0.125	AR,MA
medi	1	5	5	No	7.6297	0.054	AR,MA
msft	1	5	1,5	No	1.739	0.419	AR,MA
mwd	1	1	1	No	4.6859	0.196	AR,MA
nok	1		1,5	No	2.7719	0.428	MA
orcl	1	1,5	1,5	No	3.1834	0.074	AR,MA
pfe	1	2	2	No	3.2473	0.355	Not Sig.

TABLE 3

Augmented Dickey-Fuller

NULL Hyp.: Unit Root Exists

Firm	Test Statistic	P-Value	Dep. Variable	Constant
abv	-1.6913	0.753	-0.02	0.3745
adrx	-2.3914	0.3832	-0.0356	2.7438
ahc	-1.5343	0.515	-0.0139	0.9455
aig	-1.4229	0.5712	-0.0156	1.0587
ald	-2.2835	0.4413	-0.0346	0.7945
amat	-1.5511	0.8097	-0.0196	0.434
bmy	-2.7759	0.2075	-0.0364	2.2662
c	-0.19186	0.6423	-0.0281	1.3073
cat	-1.8671	0.669	-0.0259	1.3968
cers	-0.5172	0.8219	-0.0175	1.0159
cmcsk	-2.6395	0.2631	-0.0462	1.8387
cohr	-2.4908	0.3325	-0.0446	1.5441
cost	-2.0954	0.5458	-0.0313	1.3419
csco	-2.7003	0.2373	-0.0485	0.899
cvs	-1.9278	0.6374	-0.0233	0.7218
cvx	-2.5564	0.3009	-0.0473	4.1983
cytc	-2.387	0.3856	-0.0321	0.9914
dj	-1.4483	0.8447	-0.0143	0.7399
f	-2.0567	0.5673	-0.0245	0.464

fbf	-0.8376	0.8065	-0.0085	0.2291
fdc	-1.9145	0.3254	-0.023	0.8545
fnm	-2.9493	0.0411	-0.0556	4.3061
fox	-2.7559	0.066	-0.0434	0.9953
fre	-3.1425	0.0246	-0.0637	4.0843
g	-2.18945	0.2106	-0.0273	0.8826
ge	-2.0038	0.2852	-0.0195	0.6416
hal	-2.2353	0.1943	-0.0172	0.2584
has	-1.5499	0.507	-0.0192	0.2853
hb	-2.0644	0.2595	-0.0288	1.622
hd	-0.9401	0.7745	-0.0084	0.3122
hlt	-1.484	0.5406	-0.0146	0.1754
hpq	-1.8181	0.3713	-0.0175	0.2914
intc	-0.7634	0.8273	-0.0073	0.1516
jdsu	-1.1805	0.3773	-0.0143	0.0579
jnj	-2.3418	0.1596	-0.0307	1.7557
jpm	-1.1995	0.6755	-0.0131	0.3774
klac	-1.3362	0.6133	-0.0156	0.6891
ko	-1.8349	0.3632	-0.0203	1.009
l	-1.5054	0.5297	-0.0141	0.1437
lmt	-1.2072	0.6722	-0.0081	0.5228
low	-1.895	0.3345	-0.0237	0.9893
mcd	-0.5245	0.883	-0.0073	0.175
mdt	-2.2155	0.2013	-0.0324	1.4178
medi	-1.3453	0.609	-0.0141	0.4367
msft	-2.0488	0.266	-0.0255	1.4095
mwd	-2.1357	0.2309	-0.0278	1.3086
nok	-1.4534	0.556	-0.0147	0.243
orcl	-1.8146	0.373	-0.0165	0.1836
pfe	-1.1151	0.7106	-0.0131	0.4647

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