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| [08] The Adoption of ICT in Small And Medium-sized Family Business. The Role of Younger Generation | 67 |
|---------------------------------------------------------------|
| Francesca Maria CESARONI |
| Domenico CONSOLI |
| Annalisa SENTUTI |

| [09] Issues and Challenges for the Romanian Insurance Market: Risk and Return Analysis | 81 |
|--------------------------------------------------------------------------------------------|
| Ingrid-Mihaela DRAGOTĂ |
| Dan-Oliver STAICU |

| [10] Renewables Energies Industry in the Current Investment Context | 97 |
|---------------------------------------------------------------------|
| Daniel MANAȚE |
| Ioan CUZMAN |
| Pavel FĂRCAȘ |

<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Laura Raisa MILOȘ</td>
</tr>
<tr>
<td>Carmen CORDUNEANU</td>
</tr>
</tbody>
</table>

| [12] Testing the Weak-Form Informational Efficiency of United Kingdom, United States of America and Japan’s Capital Markets | 111 |
|---------------------------------------------------------------------------------------------------------------|
| Otilia ȘĂRĂMĂT |
| Bogdan DIMA |

| [13] Accumulation of Human Capital and FDI Inflows in ASEAN-3 Countries (Malaysia, Thailand, Indonesia) | 123 |
|---------------------------------------------------------------------------------------------------------------|
| Heirsh SOLTANPANAH |
| Mohammad Sharif KARIMI |
1. Introduction

Efficiency of capital markets has important implications for the investors’ policy of investment. In efficient markets, all fundamental information about the intrinsic value of traded assets and information related to market characteristics, should be reflected in prices, without any distortions or omissions. So, prices of the assets will reflect markets’ best estimate for the risk and expected return of the asset, taking into account what is known about the asset at the time. Therefore, there will be no undervalued assets offering higher than expected return or overvalued assets offering lower than the expected return. All assets will be appropriately priced in the market offering optimal reward to risk.

In general terms, market efficiency means that prices "fully reflect all the available information" (Fama, 1970: 383). It was generally believed that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. The accepted view was that when information arises, the news spreads very quickly and is incorporated into the prices of securities without delay. Thus, neither technical analysis, which is the study of past stock prices in an attempt to predict future prices, nor even fundamental analysis, which is the analysis of financial information such as company earnings, asset values, etc., to help investors select "undervalued" stocks, would enable an investor to achieve returns greater than those that could be obtained by holding a randomly selected portfolio of individual stocks with comparable risk (Malkiel, 2003).

The goal of this paper is to empirically evaluate the informational efficiency for three major capital markets - United States of America, Japan and United Kingdom – in the context of actual real and financial turbulence.
The paper is structured as follows: the next section review the conceptual framework of Efficient Market Hypothesis, discussing some recent critics as this are synthesized by so called Adaptive Market Hypothesis. Section 3 describes the data and the methodology. Section 4 reports the results. Some conclusions are drawn and some further research directions are suggested in section 5.

2. Efficient Market Hypothesis (EMH): A Critical Evaluation

If a market is efficient, no information or analysis can be expected to result in out performance of an appropriate benchmark. The market is efficient if the reaction of market prices to new information is instantaneous and unbiased.

It seems that the term “efficient” was originally chosen partly because it provides a link with the broader economic concept of efficiency in resource allocation. The link between an asset market that efficiently reflects available information (at least up to the point consistent with the cost of collecting the information) and its role in efficient resource allocation may seem natural enough. Further analysis has made it clear, however, that an informational efficient asset market need not generate allocative or production efficiency in the economy more generally. The two concepts are distinct for reasons to do with the incompleteness of markets and the information-revealing role of prices when information is costly, and therefore valuable (Stiglitz, 1981).

Beechey et.al. (2000) argue that the efficient market hypothesis is usually the right place to start when thinking about asset price formation. Both academic research and asset market experience suggest, however, that it cannot explain some important and worrying features of asset market behaviour.

The EMH is a consistent with a model of markets in which no participants exert market power, new information is processed very rapidly, and prices reflect the unbiased to new information and are also randomly positive or negative.

Asset prices in an efficient market should fluctuate randomly through time in response to the unanticipated component of news (Samuelson, 1965). Prices may exhibit trends over time, in order that the total return on a financial asset exceeds the return on a risk-free asset by an amount commensurate with the level of risk undertaken in holding it. However, even in this case, fluctuations in the asset price away from trend should be unpredictable.

Fama (1970) argues that there are some market conditions that might help or hinder efficient adjustment of prices to information are in order. He believed that it is easy to determine sufficient conditions for capital market efficiency. Thus, if we consider a market in which there are no transactions costs in trading securities, all available information is costless available to all market participants, and all agree on the implications of current information for the current price and distributions of future prices of each security, in such a market the current price of a security obviously “fully reflects” all available information. But this kind of market, in which all information is freely available and investors agree on its implications is not descriptive of markets met in practice (Fama, 1970: 387).

The EMH for common stocks has received significant empirical support in the past, and as noted by Jensen (1978: 95), “there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis”.

The efficient market hypothesis is associated with the idea of a “random walk” which is a term loosely used in the finance literature to characterize a price series where all subsequent price changes represent random departures from previous prices (Malkiel, 2003). The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow’s price change will reflect only tomorrow’s news and will be independent of the price changes today. But news is by definition unpredictable and, thus, resulting price changes must be unpredictable and random. As a result, prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts.

Market efficiency is closely related to the “rational expectations” property analyzed by Muth (1961) and Lucas (1978).

In Lucas’s model, asset prices are a function of the current level of output, whose behavior over time is known by investors. Consumers make investment decisions based, in part, on their expectations of future prices. Rational expectations requires that the pricing function implied by consumer behavior (the true pricing function) is the same as the pricing function on which decisions are based (the perceived pricing function). Lucas shows that rational expectations can, and generally will, give rise to predictable variation in expected returns. Intuitively, changes in economic conditions will lead to changes in the discount rate and, consequently, predictable returns.

Leweelen and Shanken (2000) consider that estimation risk could be a third potential source of return predictabil-
The analyses undertaken by those two supports the idea that parameter uncertainty can significantly affect the time-series and cross-sectional behavior of asset prices. Prices in their model satisfy commonly accepted notions of market efficiency and rational expectations: investors use all available information when making decisions and, in equilibrium, the perceived pricing function equals the true pricing function. However, prices and returns violate standard tests of efficiency, suggesting that parameter uncertainty is likely to be important for characterizing an efficient market.

Lo and McInlay (2001) argue that EMH by itself is not a well-defined and empirically refutable hypothesis. To make it operational, one must specify additional structure, e.g., investors preferences, information structure, business conditions etc. However, a test of EMH could be seen as encompassing a test of several auxiliary hypotheses, and a rejection of such joint hypothesis tells us little about which aspect is inconsistent with the data. More importantly, tests of EMH may not be the most informative means of gauging the efficiency of a given market.

Grossman (1976) and Grossman and Stiglitz (1980) argue that perfectly informationally efficient markets are an impossibility, for if markets are perfectly efficient, the return to gathering information is nil, in which case there would be little reason to trade and markets would eventually collapse. Alternatively, the degree of market inefficiency determines the effort investors are willing to expend to gather and trade on information, hence a non-degenerate market equilibrium will arise only when there are sufficient profit opportunities, i.e., inefficiencies to compensate investors for the costs of trading and information gathering. The profits earned by this industrious investors may be viewed as economic rents that accrue to those willing to engage in such activities.

Supporters of the efficient market hypothesis can argue that many seeming violations of the hypothesis are instead examples of the ‘bad model’ problem. Under this interpretation, predictable excess returns represent compensation for risk, which is incorrectly measured by the asset-pricing model being used. While this is a logical possibility, it presumably applies with progressively less force the longer the violations remain unexplained using models based on the efficient market hypothesis.

Fama (1970) emphasizes that market efficiency must be tested jointly with a model for expected (normal) returns. The problem is that all models for expected returns are incomplete descriptions of the systematic patterns in average returns during any sample period. As a result, tests of efficiency are always contaminated by a bad-model problem.

The bad-model problem is less serious in event studies that focus on short return windows (a few days) since daily expected returns are close to zero and so have little effect on estimates of unexpected (abnormal) returns. But the problem grows with the return horizon.

Bad model problems are of two types. First, any asset pricing model is just a model and so does not completely describe expected returns. Second, even if there were a true model, any sample period produces systematic deviations from the models predictions, that is, sample-specific patterns in average returns that are due to chance.

Zhang (1999) argues that what is wrong in EMH is that it implies that if there are arbitrage opportunities, they would disappear instantly upon speculators’ action, and he pointed out the idea that arbitrage opportunities in general are represented by probabilities and though they are favorable in probabilistic sense, they are not riskless. To profit from such opportunities speculators would need large capital and bear certain risk. Thus this favorable probability is the speculators’ edge. Upon increased participation of speculators, this marginal probability would shrink, but never disappear. To make this favorable marginal probability disappear infinite capital is needed and the return per capital invested would diminish to zero. Zhang (1999) suggests that this marginal probability keeps the market competitive and dynamic, such that it is attractive to all participants, and a competitive market can keep its marginal probability low thanks to the fierce competition of the participants, and this makes him propose that the alternative of Marginally Efficient Market (MEM) to replace the EMH.

Financial market efficiency is an important topic in the world of Finance. While most financiers believe the markets are neither 100% efficient, nor 100% inefficient, many disagree where on the efficiency line the world’s markets fall.

It can be concluded that in reality a financial market can’t be considered to be extremely efficient, or completely inefficient. The financial markets are a mixture of both, sometimes the market will provide fair returns on the investment for everyone, while at other times certain investors will generate above average returns on their investment.

2.1. Forms of market efficiency

According to Fama (1965) the information could be separated in three categories, to which three levels of the informational efficiency degree correspond: weak, semi-strong and strong.

Weak form efficiency states that prices of the securities instantly and fully reflect all information contained in the recors of past prices. This means future price movements cannot be predicted by using past prices. The corollary is that there is no point in performing technical analysis. The implication of weak-form efficiency is the random walk hypothesis, which indicates that successive price changes are random and serially independent.
In **semi-strong-form efficiency**, it is implied that share prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information. Semi-strong-form efficiency implies that neither fundamental analysis nor technical analysis techniques will be able to reliably produce excess returns. To test for semi-strong-form efficiency, the adjustments to previously unknown news must be of a reasonable size and must be instantaneous. To test for this, consistent upward or downward adjustments after the initial change must be looked for. If there are any such adjustments it would suggest that investors had interpreted the information in a biased fashion and hence in an inefficient manner.

In general, semi-strong form tests of efficient markets model are concerned if whether current prices fully reflect all obviously publicly available information. Each individual test, however, is concerned with the adjustment of security prices to one kind of information generating event (stock splits, announcements of financial reports by firms, new security issues etc). Thus, each test only brings supporting evidence for the model, with the idea that by accumulating such evidence the validity of the model will be established.

In fact, however, though the available evidence is in support of the efficient market model, it is limited to a few major types of information generating events.

**Strong form efficiency** states that asset prices fully reflect all of the public and inside information available. Therefore, no one can have advantage on the market in predicting prices since there is no data that would provide any additional value to the investors. The strong form tests imply that no market participant can enjoy excess trading profits due to monopolistic access to information, and in addition that all analysis is useless. The testing of this statement is based on different investment groups that may have access to important private information. This includes the top management of a company, investment specialists, advisors and mutual fund managers. If one or more of these groups earn above average profits, the strong form hypothesis will not be valid.

### 2.2. Empirical evidences

Information efficiency of capital markets has been the subject of an important stream of literature. In addition to the information set one also needs to specify a model of market equilibrium in order to be able to test any propositions about the capital market efficiency.

Bollerslev and Hodrick (1992) realized a selective survey of the voluminous literature on tests for market efficiency. The ideas discussed include standard autocorrelation tests, multi-period regression tests and volatility tests. The formulation and estimation of models for time varying volatility were also considered. They argued that dependence in second-order moments plays an important role in implementing and understanding tests for market efficiency. All of the reported test statistics and model estimates were calculated with monthly data on value-weighted NYSE stock prices and dividends. Their survey illustrated how a present value model for NYSE price index that accounts for the time-varying uncertainty in dividend growth rates can actually explain most of the rejections of market efficiency on the basis of the different tests discussed above. In particular, the conditional mean and variance of monthly NYSE dividend growth rates both have a distinct seasonal pattern, whereas annual dividend growth rates show little serial correlation and appear homoskedastic. Using simulation methods, they show how incorporating this predictable monthly time variation into a model with stochastic discount rates provides a reconciliation of the actual empirical findings in tests for market efficiency with the present value relationship.

The results illustrate the importance of explicitly recognizing the presence of a time-varying risk premium in tests for market efficiency.

Ryoo and Smith (2002) examined the random walk hypothesis for the Korean stock market over the period from March 1988 to December 1998. There were five regimes of daily price limits during the period they have studied. They used a sample of 55 actively traded stocks selected to cover a wide range of industries and with a marked number of limit moves and test the random walk hypothesis under each price limit regime. They have observed that the system of price limits prevents equity prices from following a random walk process and so results in the market being inefficient, but as the daily price limits were increased, the proportion of stock prices following a random walk increased to. So, their final conclusion was that the stock market as a whole approaches a random walk as price limits are relaxed.

The weak form market efficiency of Asian capital markets was studied by Whorthington and Higgs (2006). So, they examined for random walks daily returns for ten emerging (China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Sri Lanka, Taiwan and Thailand) and five developed markets (Australia, Hong Kong, Japan, New Zealand and Singapore), using serial correlation coefficient and runs tests, augmented Dickey-Fuller, unit root tests and multiple variance ratio tests. The results for the tests of serial correlation were in broad agreement, conclusively rejecting the random walks in the daily returns of all the markets studied. Contrary to the serial correlation tests, the unit root tests concluded that unit roots, as necessary conditions for a random walk were nearly all logs of the price series, so the unit root tests suggest weak form efficiency in all markets, with the exception of Australia and Taiwan. The results from the more stringent variance ratio tests indicated that none of the emerging markets was characterised by random walks and hence are not weak-form efficient, while only the developed markets in Hong Kong, New Zealand and Japan were consistent with the most stringent random walk criteria.
Cooray (2003) tested the random walk hypothesis for the stock markets of the U.S., Japan, Germany, the U.K., Hong Kong and Australia, using unit root tests and spectral analysis, which is a method of testing for oscillatory movements in a time series and enables identifying any cyclical or seasonal patterns in stock prices. For this study were used monthly data of stock market indices of these six countries mentioned above, during April 1991 to March 2003. The results based upon the augmented Dicky-Fuller (1979) and Phillips-Perron (1988) tests and spectral analysis find that all markets exhibit a random walk. While the multivariate cointegration tests based upon the Johansen Juselius (1988, 1990) methodology indicates that all six markets share a common long run stochastic trend, the vector error correction models suggest a short run relationship between the US, Germany, Australia and the rest of the markets implying that these countries can gain in the short run by diversifying their portfolios.

Chen (2008) tested the random walk hypothesis of the Euro/U.S. Dollar exchange rate using the data from January 1999 to July 2008. He used three variance ratio tests in his research: Lo –MacKinlay’s (1988) conventional variance ratio test, Chow – Denning’s (1993) simple multiple variance ratio test and Wright’s (2000) non-parametric ranks and signs based variance ratio test. The results of all those three variance ratio tests consistently indicate that the null hypothesis of random walk cannot be rejected. Therefore, the Euro/ U.S. Dollar exchange rate market is regarded as weak-form efficient.

Taylor (2000) investigated the predictability of long time series of stock index levels and stock prices, by using both statistical and trading rule methodologies. The trading rule analysis used a double moving-average rule and the methods of Brock, Lakonishok and Le Baron (1992). Thus, he studied the FTA, FTSE-100, DJIA and S&P-500 indices, prices for twelve UK stocks and indices derived from these stock prices. From the statistical analysis resulted that the index and price series were not random walks, and the trading rule analysis generally confirmed this conclusion. However, he observed that small transaction costs would eliminate the profitability of the moving-average rule. Standard ARMA-ARCH models were estimated for time series of returns and there were used bootstrap methods to decide if the models could explain the observed trading statistics. The conclusion was that the models provided a reasonable description, but, the trading rule methodology suggested that sometimes, the standard models failed to describe the dynamics of the indices and prices.

Borges (2008) studied the weak-form market efficiency applied to stock market indexes of France, Germany, UK, Greece and Spain. The used data were daily closing values of stock markets, chosen as representative for each of those markets. The period observed was between 1 January 1993 and 31 December 2007, during which the markets were very volatile, especially in the case of Greece. From the daily closing prices she computed monthly data and thus, from country samples of around 3880 daily observations, were generated 180 monthly observations for the whole period. She applied the empirical tests - a serial correlation test, a runs test, an augmented Dikey-Fuller (1979) test and the multiple variance ratio test proposed by Lo and MacKinlay (1988) - to the whole 15-year period, but also to a smaller period of five years, from 1 January 2003 to 31 December 2007, because they considered that the testing of different periods has the advantage of allowing for structural changes, so that the market may follow a random walk in some period while in other periods that hypothesis may be rejected. Overall, she found convincing evidence that monthly prices and returns follow random walks in all six countries. Daily returns were not normally distributed, because they are negatively skewed and leptokurtic. She concluded that France, Germany, UK and Spain meet most of the criteria for a random walk behavior with daily data, but that hypothesis is rejected for Greece and Portugal, due to serial positive correlation. However, she argues that the empirical tests show that these two countries have also been approaching a random walk behavior after 2003.

Karemera et. al. (1999) examined the stochastic properties of local currency- and US dollar-based equity returns in 15 emerging capital markets, by using the multiple variance-ratio test of Chow and Denning (1993). Their technique was based on the Studentized Maximum Modulus distribution and provided a multiple statistical comparison of variance-ratios, with control of the joint-test’s size. They found that the random walk model is consistent with the dynamics of returns in most of the emerging markets analyzed, which contrasts many random walk test results documented with the use of single variance-ratio techniques. Further, a runs test suggested that most of the emerging markets are weak-form efficient. Overall, their results suggested that investors are unlikely to make systematic nonzero profit by using past information in many of the examined markets, thus, investors should predicate their investment strategies on the assumption of random walks. Additionally, their results suggested exchange rate matters in returns’ dynamics determination for some of the emerging equity markets they have analyzed.

Chan et al. (1992) studied the relationships among the stock markets in Hong Kong, South Korea, Singapore, Taiwan, Japan and the United States, by using unit root and cointegration tests. In this study, all the stock prices were analyzed both individually and collectively to test for international market efficiency. They found unit roots in stock prices and the higher-order cointegration tests indicated that there is no evidence of cointegration among the stock prices. Their finding suggested that the stock prices...
in major Asian markets and United States were weak-form efficient individually and collectively in the long run.

Cheung and Coutts (2001) concluded that the Hang Seng Index on the Hong Kong Stock Exchange follows a random walk model and, consequently, the index is weak-form efficient, after they have examined the random walk hypothesis for this index by using variance ratio tests with both homoscedastic and heteroscedastic error variances.

Worthington and Higgins (2003) have tested random walks and weak-form efficiency in European equity markets. They have studied the daily returns for sixteen developed markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom) and four emerging markets (Czech Republic, Hungary, Poland and Russia). Their results shown that among the developed markets, only Germany, Ireland, Portugal, Sweden and the United Kingdom satisfy the most stringent random walk criteria with France, Finland, the Netherlands, Norway and Spain meeting at least some of the requirements of a strict random walk. Among the emerging markets, only Hungary satisfies the strictest requirements for a random walk in daily stock returns. The results of their analysis are consistent with the evidence regarding developed markets is less conclusive with some markets following random walks while others do not.

### 3. Data and methodology

A fragmentary approach to the empirical evaluation of EMH consists in the identification of market prices behaviour as random-walk processes. The “random walk” model states that the prices in the financial markets evolve accordingly to a random-walk (with or without drift). Therefore, identifying trends or patterns of price changes in a market couldn’t be used to predict the future value of financial instruments.

For drawing the sample study, we obtained data from three developed capital markets, namely United Kingdom, United States and Japan, on the DJI indexes, the FTSE 100 and Nikkei 225 over the period 1995-2010.

The main statistic characteristics of the indexes are reported in Table 1. It can be noticed that the indexes display a non-normal distribution with clear fat-tails effects. More exactly, the distribution of DJI and FTSE 100 indexes is left tailed while Nikkei 225 is right tailed. In the mean time, DJI have a peaked distribution (leptokurtic) relative to the normal one while for FTSE 100 and Nikkei 225 this is flat (platykurtic) relative to the normal.

<table>
<thead>
<tr>
<th></th>
<th>DJI</th>
<th>FTSE100</th>
<th>NIKKEI225</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>9486.69</td>
<td>5103.81</td>
<td>14154.51</td>
</tr>
<tr>
<td>Median</td>
<td>10110.02</td>
<td>5203.75</td>
<td>14156.87</td>
</tr>
<tr>
<td>Maximum</td>
<td>14093.08</td>
<td>6930.20</td>
<td>22667.00</td>
</tr>
<tr>
<td>Minimum</td>
<td>3832.08</td>
<td>2954.20</td>
<td>7054.98</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>2219.10</td>
<td>967.71</td>
<td>3799.44</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.65</td>
<td>-0.22</td>
<td>0.15</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.05</td>
<td>1.94</td>
<td>1.92</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>265.02</td>
<td>204.63</td>
<td>196.88</td>
</tr>
<tr>
<td>Probability</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Observations</td>
<td>3732</td>
<td>3732</td>
<td>3732</td>
</tr>
</tbody>
</table>

A common example of a nonstationary series is the random walk:

\[ y_t = y_{t-1} + \varepsilon_t \]  \hspace{1cm} (1)

where \( \varepsilon_t \) is a stationary random disturbance term. The series \( y_t \) has a constant forecast value, conditional on \( t \), and the variance is increasing over time. The random walk is a difference stationary series since the first difference of \( y_t \) is stationary:

\[ y_t - y_{t-1} = (1-L)y_t = \varepsilon_t \]  \hspace{1cm} (2)

A difference stationary series is said to be integrated and is denoted as \( I(d) \) where \( d \) is the order of integration. The order of integration is the number of unit roots contained in the series, or the number of differencing operations it takes to make the series stationary. For the random walk above, there is one unit root, so it is an \( I(1) \) series. Similarly, a stationary series is \( I(0) \).

Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test.

Unit root tests can be used to determine if trending data should be first differenced or regressed on deterministic functions of time to render the data stationary. Moreover, economic and finance theory often suggests the existence of long-run equilibrium relationships among nonstationary time series variables.

Various unit root tests suggests that overall the evolutions of the considered developed markets indexes can be fairly
described as unit root with drift processes (Table 2). Among these, Kwiatkowski et. Al. (1992) and Bierens and Guo (1993) implies as null trend stationarity against unit root with drift while Bierens (1993) and Breitung (2002) assumes that the series are unit roots with drifts.

With some notable exceptions, especially for Bierens-Guo tests (Type 6) and, in a certain measure for Nikkei 225, these are converging to depict the image of all the markets’ indexes being \( I(1) \) variables.

4. Results

In order to evaluate the relevance of random walk hypothesis for the considered set of data we are applying the so-called Lo and Mackinlay (1988; 1989) overlapping Variance Ratio Test on time series forms by the Hurst exponent of the indexes. The Variance Ratio Test examines the predictability of the time series by comparing variances of differences of data computed over different intervals. If the data are assumed to follow a random walk, the variance of a \( -q \) period difference should be \( q \) times the variance of the one-period difference. Evaluating the empirical evidence for or against this restriction is the basis of the variance ratio test. More exactly, if there is a time series \( \{Y_t\} = \{Y_1, Y_2, ..., Y_T\} \) satisfying:

\[
\Delta Y_t = \mu + \varepsilon_t
\]  

where \( \mu \) is an arbitrary drift parameter then the key properties of a random walk that are of interest for the test can be described as \( E(\varepsilon_t) = 0 \) for all \( t \) and \( E(\varepsilon_t\varepsilon_{t-j}) = 0 \) for any positive \( j \).

The estimators for the mean of first difference and the scaled variance of the \( q \)-th difference are defined as:

\[
\hat{\mu} = \frac{1}{T} \sum_{i=1}^{T} (Y_i - \hat{Y}_{i-1})
\]

\[
\sigma^2(q) = \frac{1}{Tq} \sum_{i=1}^{T} (Y_i - Y_{i-q} - q\hat{\mu})^2
\]

and the corresponding variance ratio:

\[
VR(q) = \frac{\hat{\sigma}^2(q)}{\hat{\sigma}^2(l)}
\]

The variance estimators may be adjusted for bias, as suggested by Lo and MacKinlay, by replacing \( T \) in equation (4) with \( (T-q+1) \) in the no-drift case, or with \( (T-q+1)(1-q/T) \) in the drift case.

Lo and MacKinlay (1988) show that the variance ratio z-statistic:

\[
z(q) = (VR(q) - 1) \cdot \left[ \hat{\delta}(q) \right]^{1/2}
\]

is asymptotically N(0,1) if the estimator \( s^2 \) is properly chosen.

Under the i.i.d.(independent identically distribution) hypothesis we have the estimator,

\[
\hat{\delta} = \frac{2(2q-1)(q-1)}{3qT}
\]

while under the m.d.s. assumption we may use the kernel estimator,

\[
\hat{\delta}(q) = \sum_{j=1}^{q-1} \left( \frac{2(q-j)}{q} \right)^{\frac{1}{2}} \hat{\delta}_j
\]

Table 2

<table>
<thead>
<tr>
<th></th>
<th>KPSS Null: Trend stationarity against unit root with drift</th>
<th>Bierens-Guo (Type 5) Null: Trend stationarity against unit root with drift</th>
<th>Bierens-Guo (Type 6) Null: Trend stationarity against unit root with drift</th>
<th>Bierens DHOAC Null: Unit root with drift against trend stationarity</th>
<th>Breitung Null: Unit root with drift against trend stationarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJI</td>
<td>0.97 (reject / reject)</td>
<td>1560.49 (reject / reject)</td>
<td>24.05 (reject / reject)</td>
<td>DHOAC(1,1)=0.42 DHOAC(2,2)=0.45 (accept/accept)</td>
<td>0.42 (accept/accept)</td>
</tr>
<tr>
<td>FTSE 100</td>
<td>0.68 (reject / reject)</td>
<td>1882.12 (reject / reject)</td>
<td>27.74 (reject / reject)</td>
<td>DHOAC(1,1)=0.39 DHOAC(2,2)=0.56 (accept/accept)</td>
<td>0.26 (accept/accept)</td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>0.76 (reject / reject)</td>
<td>181.67 (reject / reject)</td>
<td>10.65 (accept / reject)</td>
<td>DHOAC(1,1)=0.58 DHOAC(2,2)=0.68 (accept/accept)</td>
<td>0.31 (accept/accept)</td>
</tr>
</tbody>
</table>

Notes: Bierens DHOAC and Breitung tests computed based on 100 replications with the errors draw from the normal distribution with zero mean and variances the squared OLS residuals (bootstrapping). The conclusions are drawn for 5% and 10% critical regions.
where:

\[
\delta_j = \frac{\sum_{i=j+1}^{T}(y_{i-j} - \hat{\mu})^2}{\left\{ \sum_{i=j+1}^{T}(y_{i-j} - \hat{\mu})^2 \right\}^{\frac{3}{2}}}
\]  

(9)

The test is first performed for homoskedastic random walks using the wild bootstrap distribution to evaluate statistical significance. Such an approach is based on the strong assumption that \( \varepsilon_t \) is i.i.d. Gaussian but the normality assumption is not strictly necessary. Three different alternatives are considered:

1) the Hurst exponent series are random walks so that the variances are computed for differences of the data;

2) these series are assumed to follow an exponential random walk so that the innovations are obtained by taking log differences or, alternatively,

3) the series contains the random walk innovations themselves.

Kim (2006) offers a wild bootstrap approach to improving the small sample properties of variance ratio tests, as it was found that the wild bootstrap tests have desirable size properties and exhibit higher power than their alternatives in most cases. The approach involves computing the individual (Lo&MacKinlay, 1988) and joint (Chow&Denning, 1993) variance ratio test statistics on samples of observations formed by weighting the original data by mean 0 and variance 1 random variables, and using the results to form bootstrap distributions of the test statistics. The bootstrap \( p \) values are computed directly from the fraction of replications falling outside the bounds defined by the estimated statistic. Kim’s simulations indicate that the test results are generally insensitive to the choice of wild bootstrap distribution.

Wright (2000) proposes modifying the usual variance ratio tests using standardized ranks of the increments, \( \Delta Y_t \).

Letting \( r(\Delta Y_t) \) be the rank of the \( \Delta Y_t \) among all \( T \) values, he defines the standardized rank \( r_{\Delta Y_t} \) and van der Waerden rank scores \( r_{\Delta Y_t} \):

\[
r_{\Delta Y_t} = \frac{r(\Delta Y_t) - \frac{T + 1}{2}}{\sqrt{(T - 1)(T + 1)/12}}
\]

(10)

\[
r_{\Delta Y_t} = \Phi^{-1}(r(\Delta Y_t)/(T + 1))
\]

(11)

In cases where there are tied ranks, the denominator in \( r_{\Delta Y_t} \) may be modified slightly to account for the tie handling.

The Wright variance ratio test statistics are obtained by computing the Lo and MacKinlay (1988) homoskedastic test statistic using the ranks or rank scores in place of the original data.

Under the i.i.d. null hypothesis, the exact sampling distribution of the statistics may be approximated using a permutation bootstrap.

Wright (2000) also proposes a modification of the homoskedastic Lo and MacKinlay (1988) statistic in which each \( \Delta Y_t \) is replaced by its sign. This statistic is valid under the m.d.s. null hypothesis, and under the assumption that \( \mu = 0 \), the exact sampling distribution may also be approximated using a permutation bootstrap.

In order to evaluate the Hurst exponent we are using the Detrended Fluctuation Analysis DFA (see for instance Liu et al. 1999) which has been argued to have several advantages over other methods.

For this methodology, the evaluation of Hurst exponent is divided in five steps.

Step 1. Get the cumulative production \( \{y(k)\} \) as follows:

\[
y(k) = \sum_{i=1}^{k} (x_i - \langle x \rangle), \quad (k = 1, 2, ..., N)
\]

(12)

where, \( \{x_i\} \) is the time series and \( \langle x \rangle = \sum_{i=1}^{N} x_i/N \) is the average of the series \( \{x_i\} \).

Step 2. Divide the series \( \{y(k)\} \) into \( N_s = \text{int}(N/s) \) sub-interval \( v_j (j = 1, 2, ..., N_s) \), which are consecutive and non-overlapping. Then the length for each interval \( v_j \) is \( s \).

As \( N \) may not be the integer multiple of \( s \), the series \( \{y(k)\} \) should be divided from the opposite end again to make sure no information is lost. Then, there are \( 2N_s \) sub-intervals.

Step 3. Fit the trend \( p^n_j(k) \) with the least-square fits method as follows:

\[
p^n_j(k) = b_{j0} + b_{j1}k + b_{j(m-1)}k^{m-1} + b_{jm}k
\]

(13)

where \( m = 1, 2, ..., \) is the order of the detrended trend. The analysis method with value \( m \) is tenoted by DFAm.

Calculate the cumulative deviation series in every interval, where the trend has been eliminated:

\[
y^n_j(i) = y(k) - p^n_j(k).
\]

Calculate the variance of the \( 2N_s \) sub-intervals:

\[
F^2(j, s) = \left\langle y^n_j(i)^2 \right\rangle = \frac{1}{s} \sum_{i=1}^{s} \left\langle y((j-1)s + i) - p^n_j(i) \right\rangle^2
\]

(14)

for \( j = 1, 2, ..., N_s \), and
\[ F^2(j, s) = \{y_j^2(i)\} \]
\[ = \sum_{i=1}^{s} \left[ y(N - (j - N_s)s + i) - p^m_y(i) \right]^2 \]  
for  \( j = N_s + 1, N_s + 2, \ldots, 2N_s \).  

Step 4. Calculate the average of all variance and the square root, we then get the fluctuation of DFA \( F(s) \):

\[ F(s) = \left[ \frac{1}{2N_s} \sum_{j=1}^{2N_s} F^2(j, s) \right]^{1/2} \]  

Step 5. Repeat from step 2 to step 4 with different \( s \) such that \( s(N/4) > s \geq 2m + 2 \), and then calculate the corresponding value of \( F(s) \). If \( F(s) \) and \( s \) satisfy the linear relationship in the double logarithmic curve:

\[ \log F(s) = \log C + a \log s \]  
there are fluctuations in the form of power law: \( F(s) = Cs^a \).

Using the linear least-square regression we can get the slope \( a \), which is the DFA scaling exponent [1]. The results are reported in Table 3.

### Table 3: Lo and MacKinlay Variance Ratio Tests

<table>
<thead>
<tr>
<th></th>
<th>DJI</th>
<th>FTSE 100</th>
<th>Nikkei 225</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A) Random walk</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint Tests</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max (</td>
<td>z</td>
<td>) (at period 8)</td>
<td>3.35</td>
</tr>
<tr>
<td>Wald (Chi-Square)</td>
<td>29.84</td>
<td>35.14</td>
<td>15.95</td>
</tr>
<tr>
<td><strong>B) Exponential Random walk</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint Tests</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max (</td>
<td>z</td>
<td>) (at period 9)</td>
<td>4.14</td>
</tr>
<tr>
<td>Wald (Chi-Square)</td>
<td>35.14</td>
<td>37.90</td>
<td>15.34</td>
</tr>
<tr>
<td><strong>C) Random walk innovations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint Tests</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max (</td>
<td>z</td>
<td>) (at period 16)</td>
<td>200.99</td>
</tr>
</tbody>
</table>

**Notes:** Null Hypothesis: A) The index is a random walk; B) The (log) index is a random walk; C) The cumulated index is a random walk; Computed using: Rank scores; Included observations: 3731 (after adjustments); Standard error estimates assume no heteroskedasticity; Lags specified as grid: min=2, max=16, step=1; Test probabilities computed using permutation bootstrap: 10000; Random generator: Knuth; Tie handling: Random
According to these results, the Hurst exponent series cannot be fairly treated as random walks, exponential random walks or containing random walks innovation for none of the considered indexes.

The unit root analysis suggests that overall, the trend stationarity hypothesis can be rejected in favor of unit root with drift processes. In the mean time, the failure of describing the Hurst exponent as a random walk, suggests that the indexes are imperfectly adjusted under the impact of informational shocks and displays some rigidities in their formation mechanisms.

5. Conclusions and Further Research

The purpose of this study was to evaluate the weak-form of three major capital market’s informational efficiency. Our results suggest that the Hurst exponent for the prices series cannot be described as random walk (with different versions) processes.

We are interpreting such results as rejecting the Efficient Market Hypothesis for the considered markets. Of course, there can be identified some limitations of our proposed analysis. Among this, the estimated levels of the Hurst exponent are sensitive to the choice of methodology; the Lo and MacKinlay approach is a test of the long run variance and thus allows the treatment of the short run adjustments in the series. The data set is limited and no structural break-points are identified in the behavior of indexes during different subperiods of the observed time span; the interactions between indexes are ignored; the Adaptive Market Hypothesis is just mentioned, but no analytical developments are considered. Thus, some possible further research can be developed by evaluating the results robustness to the changes of the methodology evaluating the Hurst exponent; considering a longer data set and performing subperiods evaluations; developing a more sound framework, able to explain in greater details the mechanisms of market’s partial informational inefficiency; identifying the specificities of such framework in the case of emerging markets with various structural, functional and institutional imperfections.

Despite this caveats, we consider that such results can better highlight the intrinsic markets adjustment’s mechanisms to the various informational shocks and allows a better understanding of transactional decisions in the context of an uncertain business environment.

Bibliography