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DISSERTATION

HOW EFFICIENT IS THE PORTUGUESE STOCK MARKET?

SÓNIA MELÂNIA OLIVEIRA VAZ

DECEMBER - 2012

Instituto Superior de Economia e Gestão
UNIVERSIDADE TÉCNICA DE LISBOA
DESDE 1911

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ORIENTATION:

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Abstract

This dissertation reports the results of tests on the weak-form market efficiency applied to six European market indexes (France, Germany, UK, Greece, Portugal and Spain) from January 2007 to January 2012. For this matter we use a serial correlation test, a runs test, an augmented Dickey-Fuller test and the multiple variance ratio test. In addition we also analyze if it would be possible to forecast the PSI-20 returns resorting data mining, more specifically using k-NN and Neural Network. Our findings show that from January 1997 to September 2008 France, Germany and Spain meet most of the criteria for the weak-form market efficiency hypothesis, a situation that occurs afterwards for all six European market indexes from September 2008 to January 2012. Regarding the forecast of PSI-20 returns we designed a strategy based on the forecast of k-NN and Neural Network and concluded that by implementing it we would obtain relevant higher returns than the ones achieved by a buy-and-hold strategy, which compromises the weak-form market efficiency.

Acknowledgements

This dissertation would not be possible without the support of my family and friends, who I would like to thank.

More specifically I would like to thank Jorge Moreira, master student at FEUP, who explained me how the Rapid Miner works and gave me some much needed help on understanding the designing of the data mining algorithms.

Also a thank you note for all the support given for my coworkers at PremiValor Consulting.

Finally it is important to thank the orientation of both Professor Raquel M. Gaspar and Professor António Costa, which was essential in this process.

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1. Introduction

The theory of market efficiency has been widely discussed in the financial literature over the years. However no undisputable conclusion has been reached. Being so, in this dissertation we choose to analyze the weak form market efficiency in six European indexes (France, Germany, UK, Greece, Spain and Portugal) from January 1997 to January 2012.

First, to fully understand this matter, we will do a literature review.

Then we will explain the methodology pursued which will be divided in two approaches. The first one is the classical efficiency tests, which concerns the correlations, runs test, unit root test and variance ratio test. The second one relies on the data mining approach using algorithms as W-ZeroR, k-NN and Neural Networks.

The chapter that follows concerns the performance of the six European indexes priory mentioned on the classical efficiency tests as well as an effort of forecasting the PSI-20 returns using the algorithms previously stated. In addition we will also develop a strategy that attempts to beat the market given the forecasts obtained by the algorithms.

Finally we will discuss all the results on a conclusion chapter.

2. Literature Review

According to LeRoy (1989) “at its most general level, the theory of efficient capital markets it just the theory of competitive equilibrium applied to asset markets” and its origin dated from the 1930s. In fact, Williams (1938) and Graham & Dodd (1934) stated that the fundamental value of any security is equal to the discounted cash flow of that security, which means the actual price should fluctuated around fundamental values. Being so, analysts began to recommend buying (selling) orders if securities were priced below (above) fundamental value.

After that, many other authors address the market efficiency hypothesis, as a random walk model, but it was with Samuelson (1965) that for the first time someone developed the link between capital market efficiency and martingales, which are in fact, as stated by LeRoy (1989), “a weaker restriction on asset prices that still captures the flavor of the random walk arguments”.

Also according to LeRoy (1989) “the dividing line between the ‘prehistory’ of efficient capital markets, associated with the random walk model, and the modern literature is Fama’s (1970) survey.” In here, Fama (1970) stated that “in an efficient market prices "fully reflect" available information” and present three categories to consider: weak form tests (which the concern is if past returns can predict or explain the future ones), semi-strong form tests (concerning how quickly prices adjust to the public information available, e.g. announcements of annual earnings, etc.) and strong form tests (to evaluate if an investor, or group of investors, have private information that is not entirely reflected in market prices). Later on, Fama (1991) proposes that weak form tests also covers “the more general area of *tests for return predictability*, which also includes the burgeoning work on forecasting returns with variables like dividend yields and interest rates”. In this article, he also proposes changing the title from semi-strong form test to *event studies* and from strong tests to *tests for private information*.

Therefore, the question we have to pose is if the analysis of past returns can provide us information about future returns. According to Jensen & Benington (1970) “the random walk and martingale efficient market theories of security price behavior imply that stock market trading rules based solely on the past price series cannot earn profits greater than those generated by a simple buy-and-hold policy”. However some analysts (technical analysts) believe that the past gives them clues about the future and operate in the basis of the psychology of the market.

Allen & Taylor (2002) affirm that "technical, or chartist, analysis of financial markets involves providing forecasts or trading advice on the basis of largely visual inspection of past prices, without regard to any underlying economic or 'fundamental' analysis" and Artus (1995) defends that there are two groups of investors: the fundamental ones and the technical ones. This author admits that technical investors will buy stocks due to an upward market movement (bull markets) and sell it if the market suffers from a descending movement (bear markets). Being so, if they are in a significant number, they will be able to influence the stock price, and consequently the market will operate according to their expectations.

As we shown, many were the authors that over the years refuted technical analysis as a way of achieving better results than with a buy and hold strategy. Even so in the sixty's Levy (1967, 1968) already claim to have achieved a trading rule that, on average, earn significantly more than the buy and hold strategy, which refutes the market efficiency hypothesis.

Nevertheless, as stated in Ferson et al (2005), "the empirical evidence for predictability in common stock returns remains ambiguous, even after many years of research". These authors analyze the Standard & Poor's stock index from 1885 to 2001 in order to make an indirect inference regarding the time-variation in expected stock returns, through the comparison of the unconditional sample variances with the estimates of expected conditional variances. Ferson et al (2005) then conclude concerning weak-form tests that "while the older historical data suggests economically significant predictability in the market index, there is little evidence of weak-form predictability in modern data" and "find small but economically significant predictability" concerning semi-strong form tests.

Smith & Ryoo (2003) tested the hypothesis of the stock market prices indexes follow a random walk for five markets (Greece, Hungary, Poland, Portugal and Turkey) using the multiple variance ratio test. In fact, according to Smith & Ryoo (2003) "in markets that are weak-form efficient, equity prices completely reflect all of the information contained in the past history of prices and do not convey information about future changes in prices. If they did convey such information there would be profit-making opportunities for investors and so markets would be imperfect". For this matter they used weekly data, beginning in the third week of April 1991 and ending in the last week of August 1998 and were able to conclude that only the Turkey market was efficient.

Worthington & Higgs (2004) also study the random walk and weak-form market efficiency in European markets, covering twenty European markets: 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). It is important to test this hypothesis because, as stated in Worthington & Higgs (2004) "the presence (or absence) of a random walk has implications for investors and trading strategies, fund managers and asset pricing models, capital markets and weak-form market efficiency, and consequently financial and economic development as a whole". To analyze if the markets chosen follow a random walk they made several tests as serial correlation coefficient, runs tests, Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root tests and multiple variance ratio (MVR). The conclusion was that only Germany, Ireland, Portugal, Sweden and the United Kingdom, regarding the developed markets, and Hungary, regarding the emerging markets, follow a random walk.

In addition Borges (2010) too assessed the random walk hypothesis for European countries (UK, France, Germany, Spain, Greece and Portugal) from January 1993 to December 2007, for both daily and weekly data, and by using runs test and variance ratio test concluded that the hypothesis of market efficiency is not rejected for Germany and Spain.

As seen before, the market efficiency has been related with the random walk and/or the martingale models. However with the development of new and more effective computational techniques, forecasting the financial data as a way of ascertain market efficiency has attracted special attention in recent years, and as we will see ahead, even though the focus is different they do not contradict each other and can in fact become complementary.

An example of these techniques is the genetic programming method, first developed by Koza (1992), and applied for example by Silva (2001) who tested the possibility to obtain an exceptional profitability, forecasting BVL Geral stock index evolution. The results show that this type of procedure can be used with some effectiveness in predicting the evolution of the index value, which can reveal the nonexistence of weak efficiency in the Portuguese stock market.

Another technique widely used is the data mining concept which employs algorithms as nearest neighbor[1] and neural networks. If "nearest neighbor forecasting models are attractive with their simplicity and the ability to predict complex nonlinear behavior" (Isfan et al, 2010), the neural networks, despite more complex, "represent one of the most powerful tools for non-parametric regression analysis" (Cabarkapa et al, 2010).

Hill et al (1996) evaluate traditional statistical models (as exponential smoothing, for example) and neural networks for time series forecasting and concluded that, regarding the quarterly and monthly data, the neural network model did significantly better forecasting than the traditional statistical.

Also McNelis (2005) examined how well neural network methods perform, using for that several examples as forecasting the automotive industry, the corporate bonds, the inflation, the credit card default and bank failure, and others.

Recently, Isfan et al (2010), forecast the Portuguese stock market using the Hurst exponent as well as nearest neighbor algorithm and artificial neural networks (ANN[2]) and they conclude that although neural networks were not "perfect in their prediction, they outperform all other methods".

3. Methodology

In this study we analyze the weak form market efficiency using two distinct approaches.

The first approach is the classical one as proposed by Worthington & Higgs (2004) and later used by Borges (2008, 2011), for the hypothesis of stock market indexes' returns following a random walk (or a martingale process, which is in practice less restrictive). Admitting that, the following tests will be done: correlations tests (with analysis of the

[1] This can also be written as k-NN.
[2] ANNs were often just called neural networks and, since the *RapidMiner 5.0* uses this terminology, from now on we will refer them just as neural networks.

autocorrelation, partial autocorrelation, joint correlation and a linear regression that allow us to conclude if yesterday's returns are statistically significant for today's returns), a runs test, the augmented Dickey-Fuller test to analyze the existence of an unit root and finally the multiple variance ratio test using different approaches. It is worth mentioning that the softwares *Eviews* and *SPSS* were a useful tool for those tests.

The second approach relies on the software *RapidMiner 5.0* to analyze if it is possible to predict the PSI-20 returns using several algorithms: W-ZeroR, k-NN and Neural Network.

3.1 Classical Efficiency tests

3.1.1 Correlations

We can define correlation as the degree of linear association between two variables as mentioned in Brooks (2002) and it is important to analyze the correlation of the returns because as stated by Borges (2008) "if the stock market indexes returns exhibit a random walk, the returns are uncorrelated at all leads and lags".

In this point we will analyze the folowing: the individual autocorrelation, the individual partial autocorrelation, joint correlation using the Ljung Box Q-statistic and finally the correlation on lag 1 with more detail.

The difference between the autocorrelation and partial autocorrelation lies in while the first is related to the moving average process, the second relates to the autoregressive process.

A moving average model is a linear combination of terms in a white noise process[3] and using the notation presented in Brooks (2002), a moving average process of order q, MA(q), can be expressed as:

(1) $$y_t = \mu + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + ... + \theta_q u_{t-q}$$

Being u_t (t = 1, 2, …) the white noise process with $E(u_t) = 0$ and $var(u_t) = \sigma^2$

[3] Brooks (2002) states that «a white noise process is one with no discernible structure». So, the definition of a white noise process is $E(y_t) = \mu$ $var(y_t) = \sigma^2$ and $\gamma_{t-r} = \begin{cases} \sigma^2 & if\ t = r \\ 0 & otherwise \end{cases}$ where γ_{t-r} stands for the autocorrelation coefficient at lag t-r.

On the other hand, an autoregressive model is one in which the current value of a variable, y, depends only on the values that the variable had in previous periods, plus an error term. Using the notation expressed in Brooks (2002), an autoregressive model of order p, AR(p) can be written as:

(2) $$y_t = \mu + \varnothing_1 y_{t-1} + \varnothing_2 y_{t-2} + ... + \varnothing_p y_{t-p} + u_t$$

Where u_t is a white noise disturbance term.

Now that we clarify those concepts it is important to define the individual tests:

a) Regarding the autocorrelation the hypothesis will be

$H0: \theta_k = 0 \; for \; \forall k$
H1: if otherwise

And then we will reject H0 at 5% if $\left|\hat{\theta}_k\right| > 1{,}96 \times \frac{1}{\sqrt{T}}$

Where T is the number of observations

b) Regarding the partial correlation the hypothesis will be

$H0: \emptyset_{kk} = 0 \; for \; \forall k$
H1: if otherwise

And then we will reject H0 at 5% if $\left|\hat{\emptyset}_{kk}\right| > 1{,}96 \times \frac{1}{\sqrt{T}}$

In order to test for joint null correlations coeficienst, the hypothesis are the following:

H0: The data are independently distributed

H1: The data are not independently distributed

In this matter we aplly the Ljung Box Q-statistic joint test, expressed in Brooks (2002) as:

(3) $$Q(m) = T(T+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{T-k} \approx \chi^2_{(m)}$$

Where T is the sample size, m the maximum lag considered (in this thesis, m equals 100) and $\hat{\rho}_k$ is the sample autocorrelation coeficient.

Therefore we will reject the null hypotesis if Q-stat > $\chi^2_{(m)0,05}$ or if prob < 0,05.

At last our purpose is to analyze the lag 1 with more detail. In fact, as stated by Peña (2005), the confidence levels that we use to analyze if the autocorrelations are equal to zero, are asymptotic and not acurate enough for the firsts lags, being necessary further examination. Therefore, in order to do it, we raise the question "are the yesterday's returns staticaslly significant to today's returns?" which can be done through a linear regression:

(4) $$\Delta(\log(i)) = \beta_0 + \beta_1 \Delta(\log(i(-1)) + \varepsilon_t$$

where i referes to market index[4] and AR(1) an autoregressive of order 1.

3.1.2 Runs Test

The runs test is a non-parametric statistical test that determines if the elements of the sequence are mutually independent, as should happen under the weak-form efficient market hypothesis.

Following the methodology proposed in Borges (2010, 2011), we will classify a positive return (+) if the return is above media and a negative return (-) if the return is below media. Then, according to Borges (2010), "the runs test is based on the premise that if price changes (returns) are random, the actual number of runs (R) should be close to the expected number of runs (μ_R)" under the null hypothesis of the elements of the series are mutually independent. Also note that n_+ refers to the number of positive returns and n_- to the number of negative returns, which imply $n=n_++n_-$. Assuming large numbers of observations the following test will be made:

(5) $$Z = \frac{R - \mu_R}{\sigma_R} \approx N(0,1)$$

[4] For example $\Delta(\log(CAC\ 40)) = \beta_0 + \beta_1 \Delta(\log(CAC\ 40(-1))) + \varepsilon_t$

where $\mu_R = \frac{2n_+n_-}{n} + 1$ and $\sigma_R = \sqrt{\frac{2n_+n_-(2n_+n_- - n)}{n^2(n-1)}}$

3.1.3 Unit Root Tests

The unit root tests are used to determine whether a variable time series is non stationary, using for that purpose an autoregressive model. The first work on this matter was developed by Dickey and Fuller (Fuller, 1976; Dickey and Fuller, 1979), being the null hypothesis the series having a unit root versus the series being stationary.

According to Brooks (2002) the regression used for the Dickey-Fuller test is:

(6) $$\Delta y_t = \psi y_{t-1} + u_t$$

Where y_t represents the prices at time t, $\Delta y_t = y_t - y_{t-1}$ and u_t a white noise.

This will examine the null hypothesis of $\psi = 0$ against $\psi < 0$, being the test statistic defined as:

(7) $$\text{test stastistic} = \frac{\psi}{SE(\hat{\psi})}$$

However what we will take into account is the augmented Dickey-Fuller (ADF), which is an augmented version of Dickey-Fuller test and applies the following regression, using the notation presented in Brooks (2002):

(8) $$\Delta y_t = \mu + \lambda t + \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t$$

Where μ is a constant, λt is the coefficient for the trend and α_i are coefficients to be estimated. Note that imposing μ=0 and λt=0 corresponds to modeling a random walk, using only the constraint λt=0 corresponds to test for a random walk with drift and using no constraints means testing for a random walk with drift and a deterministic time trend. It is worth to mentioning that the null hypothesis of $\psi = 0$ against $\psi < 0$ remains and failing to reject the null hypothesis implies that we do not reject that the time series has the properties of a random walk.

3.1.4 Variance Ratio Tests

The variance ratio (VR) test allows to verify whether differences in a series are uncorrelated, by comparing variances of differences of the returns calculated over different lags.

The most common approach is the one developed by Lo and MacKinlay (1988, 1989) which tested the random walk hypothesis under two different null hypothesis: the first reliyng on homoskedastic increments and the second on heteroskedastic increments. Assuming y_t as the stock price at time t, where t = 1, …, T:

(9) $$\Delta y_t = \mu + \varepsilon_t$$

Where μ is an arbitrary drift parameter and ϵ_t the random disturbance term. Then, for the first hypothesis – the homoskedastic random walk hypothesis – Lo and MacKinlay (1988) assume that ϵ_t are i.i.d.[5] Gaussian with variance σ^2 and for the second hypothesis – the heteroskedastic random walk hypothesis – they assume a less restrictive theory that "offers a set of sufficient (but not necessary), conditions for ϵ_t to be a martingale difference sequence (m.d.s.)" (Quantitative Micro Software, LLC, 2009)

Using the notation presented in Quantative Micro Software, LLC (2009), we can define the mean of first difference and the scaled variance of the q-th difference respectively as:

(10) $$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T}(y_t - y_{t-1})$$

(11) $$\hat{\sigma}^2(q) = \frac{1}{Tq}\sum_{t=1}^{T}(y_t - y_{t-q} - q\hat{\mu})^2$$

With the correspondent Variance Ratio being

(12) $$VR(q) = \frac{\hat{\sigma}^2(q)}{\hat{\sigma}^2(1)}$$

[5] i.i.d. stands for independently and identically distributed.

where $\hat{\sigma}^2(q)$ is 1/q the variance of the qth difference and $\hat{\sigma}^2(1)$ is the variance of the first difference. Note that under the random walk hypothesis, we must have VR(q) = 1 for all q.

Then, the authors demonstrate that, under the i.i.d. assumption, the variance ratio z-statistic

(13) $$z_1(q) = \left(VR(q)-1\right) \times \left[\hat{s}^2(q)\right]^{-1/2}$$

is asymptotically N(0,1) where $\hat{s}^2(q) = \frac{2(2q-1)(q-1)}{3qT}$.

For the m.d.s. assumption, the authors propose a variance ratio z-statistic, which is robust under heteroskedasticity and follows the standard normal distribution asymptotically:

(14) $$z_2(q) = \left(VR(q)-1\right) \times \left[\hat{s}^2(q)\right]^{-1/2}$$

Where $\hat{s}^2(q) = \sum_{j=1}^{q-1} \left(\frac{2(q-j)}{q} \right)^2 \times \hat{\delta}_j$

and $\hat{\delta}_j = \dfrac{\left\{ \sum_{t=j+1}^{T} (y_{t-j} - \hat{\mu})^2 (y_t - \hat{\mu})^2 \right\}}{\left\{ \sum_{t=j+1}^{T} (y_{t-j} - \hat{\mu})^2 \right\}^2}$

The procedure above is, as stated by Borges (2010), "devised to test individual VR tests for a specific q-difference", however as we mentioned before, under the random walk hypothesis, we must have VR(q) equal to one for all q. Being so, we will analyze the joint variance ratio tests proposed by Chow and Denning (1993), which defined heteroskedastic test statistic as:

(15) $$CD = \sqrt{T} \max_{1 \le i \le m} \left| z_2(q_i) \right|$$

This test statistic follows the SMM[6] distribution with parameter m and T degrees of freedom, that is, SMM (α, m, T).

Kim (2006) also developed a VR test, but employing wild bootstrap. We will also explore Kim's methodology which consists in computing both individual and joint VR test statistics, conducting the three following stages:

1. Form a bootstrap sample of T observations $y_t^* = \eta_t y_t \ (t = 1, \ldots, T)$, where η_t is a random sequence with mean zero and variance one.
2. Calculate CD*, which is the CD statistic in Equation (16) from the sample generated in stage 1.
3. Repeat 1. and 2. sufficiently many times in order to form a bootstrap distribution of the test statistic CD*.

Another variance ratio approach that we will take into account is the one proposed by Wright (2000), that consists on a non-parametric alternative using ranks and signs. However in this thesis we will only adress the ranks alternative. Being so, given a sample of log returns $\{yt\}_{t=1}^{T}$ and letting r(y) be the rank of y_t among all T values, we can define the standardized rank (r_{1t}) and the van der Waerden rank scores (r_{2t}) as:

(16) $$r_{1t} = \frac{\left(r(y_t) - (T + \frac{1}{2})\right)}{\sqrt{\left((T-1)(T+1)\right)/12}}$$

(17) $$r_{2t} = \frac{\Phi^{-1} r(y_t)}{T+1}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function.

It is important to mentioned that, as stated in Wright (2000), if the data are highly non-normal, the Wright tests can be more powerful than others (as the Lo and MacKinlay VR test, for example).

[6] SMM stands for Studentized Maximum Modulus.

3.2 RapidMiner (data mining) approach

Data mining began in the 80s and is an interdisciplinary field of computer science. Can be defined, as stated in Han and Kamber (2006), to «the process of discovering interesting knowledge from large amounts of data stored in databases, data warehouses, or other information repositories». It is also important to point out, quoting Han and Kamber (2006), that «data mining is considered one of the most important frontiers in database and information systems and one of the most promising interdisciplinary developments in the information technology» and its applications covers various domains, as financial data analysis, retail industry, telecommunication industry and others. Regarding financial data analysis, it is said in Han and Kamber (2006) that this area has complete data that is also reliable and with high quality, which facilitates the data mining.

Under the assumption of the efficient market hypothesis of which a market price fully reflects all available information, any attempt of forecasting the market should not be possible.

Being so, we will analyze if it is possible to forecast the PSI-20 returns using several algorithms as W-Zeror, k-NN and neural network present in the Software *RapidMiner 5.0,* which is the world-leading open-source system for data mining.

3.2.1 W-ZeroR

W-ZeroR is defined by Witten et al (1999) as the most primitive learning scheme in Weka[7]. In fact, this algorithm as stated in Witten et al (1999) "predicts the majority class in the training data for problems with a categorical class value, and the average class value for numeric prediction problems", or in other words, predicts the average if we have a numerical class and predicts the mode if we have a nominal class.

Although W-ZeroR is a simple algorithm, it will be useful for determining a baseline performance as a benchmark for other learning schemes. For instance, if other learning schemes perform worse than W-ZeroR this indicates some overfitting.

[7] Weka stands for Waikato Environment for Knowledge Analysis and it is open-source data mining software in Java.

3.2.2 K-NN

K-NN lists the top 10 data mining algorithms according to Wu, et al. (2008), which demonstrate how powerful this algorithm can be even though its simplicity. In fact it is generally defined as a non parametric lazy learner because as mentioned, for example, in Han and Kamber (2006), k-NN is «based on learning by analogy». Indeed, what it does is verify the nearest neighbors (k) for the training set and then attributes the dominant class, by vote, where this class is the most common. The distance of the nearest neighbors is specified in accordance with the Euclidean distance, that is:

(18) $$d(x_1, x_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2}$$

In conclusion, we present the following figure, adapted from Wu, et al. (2008) that summarizes the k-NN method.

Input: D, the set of k training objects, and test object $z = (x_1, y_1)$

Process: Compute $d(x_1, x_2)$, the distance between z and every object, $(x_2, y_2) \in D$
Select $D_z \subseteq D$, the set of k closest training objects to z.

Output: $y_1 = \underset{v}{argmax} \sum_{(x_t, y_t) \in D_x} I(v = y_i)$

Figure 1: The k-nearest neighbor classification algorithm

3.2.3 Neural Network

According to Han and Kamber (2006), neural networks are, as well as k-NN, «distance-based mining algorithm» and its name (neural networks) translate on being a set of interconnected basic units (neurons).

As we can see on Figure 2, which we adapted from Han and Kamber (2006), the neurons are grouped into three types of layers: input, hidden and output.

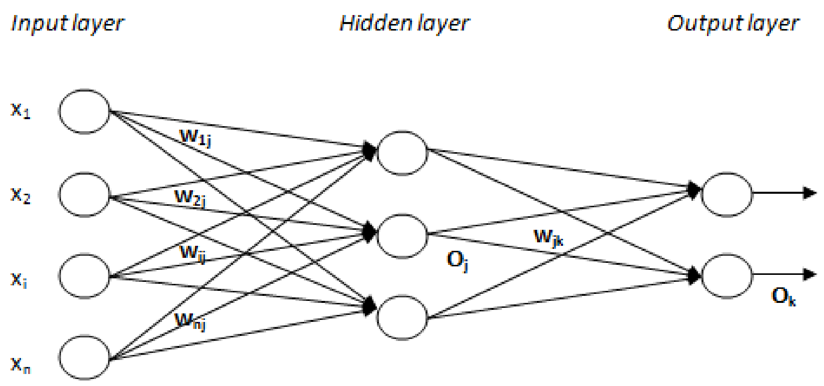


Figure 2. A multilayer feed-forward neural network

As described by Han and Kamber (2006) and Cabarkapa, et al. (2010), the input layer receives the input data from external environment and then sends the inputs weighted to the hidden layer, where the information is processed. Then the outputs of the hidden layer units can be imputed into another hidden layer (although the most common procedure is using only one hidden layer) or weighted and sent to the output layer neurons. In here, the network output will be compared to the desired output resulting on the network error. Afterward, the network will take this error into account by adjusting the values of connection weights between the neurons. This process will then be repeated for a given number of iterations until the network finds the output closest to the desirable output, which is, in practice, the network output presented to the user.

4. The Data

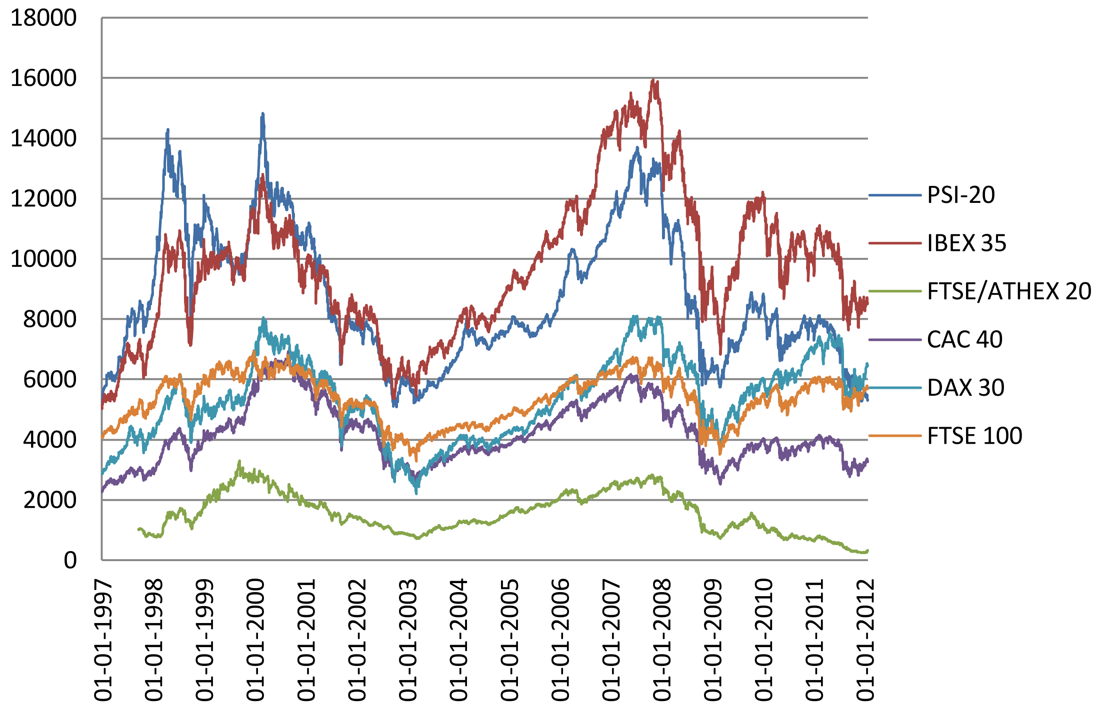
Our data will be the daily closing values for France, Germany, UK, Greece, Spain and Portugal stock market indexes[8]. Then we converted the price series into series of returns because as mentioned in Brooks (2002) it is preferable to do it like that because, among other advantages, the use of returns has the added benefit of being unit free. The choice of these countries is due firstly to compare our results with the ones presented in Borges (2008, 2010) and secondly because according to International Monetary Fund (2011) all of these European countries are on the IMF advanced economies list, however France,

[8] The stock market indexes are, respectively, CAC 40, DAX 30, FTSE 100, FTSE ATHEX 20, IBEX 35 and PSI 20.

Germany and UK stand also in G7 group, being therefore relevant to compare the results of these countries with the ones of Greece, Spain and Portugal.

The source of all data is Datastream and the period of analysis is from 01/01/1997 to 31/01/2012. During this period of time, we assist at some financial crisis namely the April 15th 2000, September 11th 2001 and more recently the subprime crisis leading Lehman Brothers to bankruptcy at September 15th 2008.

This way, we will make a cut in the sample at the time of the bankruptcy of Lehman Brothers, that is, we will apply the empirical tests to a first period from January 1st 1997 to September 12th 2008 and then compare those results with the ones on the following period of time: September 15th 2008 to January 31st 2012. In fact, with this, we intent to show has stated in Lim et al (2008) that after a financial crisis the stock markets improve their efficiency. It is also important to cover the period from September 2008 to January 2012 because not only gives an updated approach to this thesis but also because this period of time was not yet covered by previous studies.



Source: Datastream

Figure 3. Stock Market Indexes - Closing Prices - 1997 to 2012

Table I. Descriptive statistics of returns

	France CAC 40	Germany DAX 30	UK FTSE 100	Greece FTSE ATHEX 20	Spain IBEX 35	Portugal PSI 20
Panel A: Data from 01/01/97 to 12/09/08						
Observations	3053	3053	3053	2864	3053	3053
Mean	0,0002	0,0003	0,0001	0,0002	0,0003	0,0002
Median	0,0001	0,0007	0,0000	0,0000	0,0005	0,0000
Maximum	0,0700	0,0755	0,0590	0,0868	0,0672	0,0694
Minimum	-0,0768	-0,0887	-0,0589	-0,0960	-0,0784	-0,0959
Std. Dev.	0,0140	0,0154	0,0115	0,0168	0,0138	0,0108
Skewness	-0,1311	-0,2515	-0,1705	6,0737	-0,2019	-0,5775
Kurtosis	5,6876	6,0380	5,5241	6,6198	5,8693	9,1730
Jarque-Bera	927**	1206**	825**	1566**	1068**	5015**
JB p-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Panel B: Data from 15/09/08 to 31/01/12						
Observations	882	882	882	882	882	882
Mean	-0,0003	0,0001	0,0001	-0,0018	-0,0003	-0,0005
Median	0,0000	0,0004	0,0000	-0,0016	0,0000	0,0001
Maximum	0,1059	0,1080	0,0938	0,1637	0,1348	0,1020
Minimum	-0,0947	-0,0734	-0,9266	-0,0980	-0,0959	-0,1038
Std. Dev.	0,0194	0,0186	0,0162	0,0273	0,0196	0,0158
Skewness	0,1882	0,2139	-0,0795	0,3545	0,3093	0,0950
Kurtosis	7,7236	7,8095	9,2906	5,5002	8,3697	10,1365
Jarque-Bera	824**	856**	1454**	248**	1072**	1871**
JB p-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

Notes: The JB p-value refers to the p-value of Jarque-Bera test used to determine whether the returns are normally distributed based on the null hypothesis of skewness being equal to zero and kurtosis equal to three.
** Null hypothesis rejection significant at the 1% level.

In the first period of time, Panel A, the daily returns are negatively skewed in all countries, excepting Greece, which mean that in this 5 countries (France, Germany, UK, Spain and Portugal) large negative returns tend to be larger than the higher positive retuns. However if we consider the Panel B then we conclude that all indexes, except UK[9], have positive skewness.

Since the level of kurtosis is greater that 3, the excess of kurtosis is positive for all countries and period of time, indicating that all the distribution of returns are leptokurtic, as expected from previous empirical evidence.

To test if the returns are normally distributed we will apply the Jarque-Bera test:

[9] Although not statistically significant.

(19) $$JB = n\left(\frac{s_k^2}{6} + \frac{(k-3)^2}{24}\right) \approx \chi^2_{(2)}$$

where s_k means skewness and *k* kurtosis.

being the null hypothesis:

H0: normal distribution,
skewness is zero and kurtosis is three.

H1: non-normal distribution

As presented at Table I, the JB p-value are all very close to zero, which implies that the null hypothesis is strongly rejected for any usual level for every stock market index for both periods, and therefore stock market indexes' returns are not normally distributed.

It is also necessary to mention that in Appendix A1 and A2 there are the comparison with the histograms of the stock indexes' returns and the Normal Distribution for the corresponding period of time.

5. Results

In this chapter we will present the results on the tests referred in the Methodology.

Additionally we will present a table that summarizes the results of the performed classical efficiency tests, answering the question "Is the random walk hypothesis rejected?" for each one.

5.1 Classical Efficiency tests

5.1.1 Correlations

The results for the tests on autocorrelation, partial correlation and Ljung-Box Q-statistic probability are expressed on Table II.

Table II. Autocorrelation, Partial Autocorrelation and Joint correlation (Ljung-Box Q-statistic probability)

	France			**Germany**			**UK**			**Greece**			**Spain**			**Portugal**		
	CAC 40			**DAX 30**			**FTSE 100**			**FTSE ATHEX 20**			**IBEX 35**			**PSI 20**		
Panel A: Data from 01/01/97 to 12/09/08																		
Lag	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*
1	-0,008	-0,008	0,648	-0,023	-0,023	0,201	-0,030	-0,030	0,101	0,120	0,120	0,000	-0,001	-0,001	0,954	0,115	0,115	0,000
2	-0,013	-0,013	0,701	-0,005	-0,005	0,427	-0,032	-0,033	0,054	0,008	-0,006	0,000	-0,027	-0,027	0,334	0,030	0,017	0,000
3	-0,060*	-0,060*	0,009	-0,018	-0,018	0,448	-0,060*	-0,083*	0,000	0,020	0,020	0,000	-0,041*	-0,041*	0,062	0,035	0,030	0,000
4	0,000	-0,002	0,021	0,016	0,015	0,485	0,020	0,014	0,000	0,008	0,003	0,000	0,014	0,013	0,095	0,048*	0,041*	0,000
5	-0,040*	-0,041*	0,006	-0,022	-0,021	0,431	-0,036*	-0,041*	0,000	0,008	0,007	0,000	-0,009	-0,011	0,148	0,007	-0,005	0,000
10	-0,009	-0,014	0,008	-0,019	-0,017	0,072	-0,032	-0,028	0,000	0,027	0,032	0,000	0,024	0,026	0,034	0,035	0,035	0,000
15	0,045*	0,047*	0,001	0,013	0,016	0,013	0,025	0,022	0,000	0,003	0,004	0,000	0,046*	0,048*	0,010	0,062*	0,053*	0,000
25	-0,022	-0,002	0,002	0,004	0,001	0,020	0,017	0,015	0,000	0,047*	0,042*	0,000	0,008	0,007	0,012	0,059*	0,055*	0,000
50	0,041*	0,051*	0,002	0,043*	0,047*	0,004	0,022	0,028	0,000	-0,005	-0,007	0,000	0,012	0,024	0,001	0,006	0,007	0,000
100	-0,004	-0,004	0,001	-0,005	0,009	0,003	-0,011	-0,013	0,000	-0,048*	-0,042*	0,000	0,002	0,007	0,011	0,018	0,005	0,000
Panel B: Data from 15/09/08 to 31/01/12																		
Lag	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*	*AC*	*PAC*	*Prob*
1	-0,021	-0,021	0,537	0,027	0,027	0,427	-0,009	-0,009	0,779	0,033	0,033	0,325	0,048	0,048	0,158	0,054	0,054	0,107
2	-0,089*	-0,089*	0,026	-0,085*	-0,086*	0,030	-0,096*	-0,096*	0,016	-0,062	-0,063	0,114	-0,087*	-0,089*	0,013	-0,052	-0,055	0,081
3	-0,077*	-0,081*	0,006	-0,042	-0,038	0,035	-0,089*	-0,092*	0,002	-0,005	-0,001	0,224	-0,066	-0,058	0,006	-0,051	-0,045	0,063
4	0,088*	0,077*	0,001	0,065	0,061	0,015	0,138*	0,128*	0,000	0,026	0,022	0,293	0,033	0,032	0,009	0,019	0,021	0,107
5	-0,059	-0,070*	0,000	-0,041	-0,052	0,017	-0,082*	-0,099*	0,000	0,010	0,008	0,411	-0,058	-0,073*	0,006	-0,049	-0,056	0,084
10	0,003	0,005	0,000	0,046	0,041	0,035	0,017	0,032	0,000	0,016	0,011	0,250	-0,012	-0,010	0,011	-0,026	-0,012	0,012
15	-0,038	-0,044	0,000	-0,022	-0,020	0,118	-0,062	-0,062	0,000	0,015	0,022	0,199	-0,064	-0,063	0,006	0,013	-0,004	0,005
25	0,029	0,041	0,003	0,039	0,053	0,105	0,050	0,043	0,000	0,010	0,021	0,575	-0,003	-0,002	0,005	0,002	0,015	0,013
50	-0,061	-0,061	0,000	-0,056	-0,055	0,003	-0,048	-0,063	0,000	0,017	0,006	0,681	-0,066	-0,050	0,001	0,000	0,012	0,083
100	0,007	-0,011	0,009	0,012	0,001	0,065	-0,005	-0,006	0,002	0,024	0,017	0,700	0,008	0,010	0,019	0,012	0,025	0,463

Notes: AC refers to the Autocorrelation (r_k), PAC to the Partial Autocorrelation ($\widehat{\emptyset}_{kk}$) and Prob to the p-value of the Ljung-Box Q-statistic.

Null hypothesis of individual uncorrelation is rejected if $|r_k|$ or $|\widehat{\emptyset}_{kk}|$ greater than 0,035 (or greater than 0,037 for Greece's index) given Panel A; and greater than 0,066 considering Panel B. Whenever this occurs we marked it as *.

In terms of Ljung-Box Q-statistic probability (Prob), each time the Prob is lower than 0,05, we reject the null hypothesis of joint zero correlation (at that lag).

Recall that if $|r_k| > 1,96 \times \frac{1}{\sqrt{T}}$ then the null hypothesis that the true value of the coefficient at lag k is zero is rejected. This means that, for the first period, the critical value is 0,035 for all countries except Greece, which is 0,037 and for the second period, the critical value is 0,066 for all market indexes[10].

Given the Panel A of Table II, the null hypothesis of joint zero correlation in France is rejected as from lag 3, in Germany as from lag 15 and in UK as from lag 3. There are also some evidence of correlation (AC and PAC) in France at lags 3, 5, 15 and 50; in Germany at lag 50 and in UK at lags 3 and 5. We can also conclude that we reject the null hypothesis of joint zero correlation for all lags in Greece and Portugal. Cosidering Spain, there are evidence of joint zero correlation of returns in the first lags, however from lag 10 there are evidence of joint correlation.

Observing the Panel B, at lag 100, the joint zero correlation is rejected for CAC 40, FTSE 100 and IBEX 35.

The last step concerning correlations, will be attending to a greater analysis at lag 1 because, as mentioned before, the first lags require a greater exigency. In order to correct it, ARCH[11] type test has been accounted for. Being so, note that the results presented at Table III are the ones achieved after removing the heteroskedasticity.

Table III. Are yesterday's returns statistically significant for today's returns?

	France CAC 40	Germany DAX 30	UK FTSE 100	Greece FTSE ATHEX 20	Spain IBEX 35	Portugal PSI 20
Panel A: Data from 01/01/97 to 12/09/08						
C	0,0006	0,0008	0,0004	0,0441	0,0008	0,0006
AR(1)	-0,0169	-0,0198	-0,0230	0,1108	0,0010	0,1155
p-value	0,3910	0,3225	0,2330	0,0000**	0,9613	0,0000**
Panel B: Data from 15/09/08 to 31/01/12						
C	0,0006	0,0009	0,0007	-0,0005	0,0004	0,0003
AR(1)	-0,0016	0,0180	0,0001	0,0321	0,0462	0,0511
p-value	0,9678	0,6599	0,9971	0,3318	0,1891	0,1233

Notes: This is an individual significance test with null hypothesis being AR(1) equal to zero.
** Null hypothesis rejection significant at the 1% level.

[10] This relies on the fact that T = 3052 for all market indexes in the first period, excepting the Greece one, where T=2863 and T=881 for all market indexes in the second period of time.
[11] ARCH means autoregressive conditionally heteroskedastic.

As we have seen previously in the correlograms and now on table III, yesterday's returns were only statiscally significant for today's returns in Greece and Portugal for the first period of time (Panel A). However, for the second period of time, Panel B, all indexes show that there are no correlation at lag 1.

5.1.2 Runs Test

We will now present on table IV the runs test results being the mean of the returns the reference value. Recall that given the nature of this test, the results do not depend on the normality of returns.

Analyzing the table below, for the Panel A, the number of runs is significantly less than the expected number of runs (μ_R) in Greece and Portugal, showing also here, that the stock market indexes' of these two countries have positive serial correlation, implying even a rejection of the null hypothesis at 1% level. On the contrary, the other four stock market indexes have a number of runs higher than the expected runs, which can also lead to a rejection of the null hypothesis (as occur for France at a 5% level) because it implies a mean-reverting behavior.

Given Panel B, data from 15/09/08 to 31/01/12, the number of runs is higher than the expected number of runs for Germany and UK. For the other countries, with the number of runs being less than the expected, only Greece and Portugal reject the null hypothesis (but now at a 5% level).

Table IV. Runs Test

	France	**Germany**	**UK**	**Greece**	**Spain**	**Portugal**
	CAC 40	**DAX 30**	**FTSE 100**	**FTSE ATHEX 20**	**IBEX 35**	**PSI 20**
Panel A: Data from 01/01/97 to 12/09/08						
Mean	0,0002	0,0003	0,0001	0,0002	0,0003	0,0002
n_-	1532	1473	1541	1495	1500	1550
n_+	1520	1579	1511	1368	1552	1502
μ_R	1527,0	1525,2	1526,9	1429,7	1526,6	1526,6
Number of Runs	1596	1556	1532	1300	1564	1425
Z	2,499*	1,118	0,186	-4,858**	1,356	-3,68**
Asymp. Sig. (2-tailed)	0,012	0,264	0,852	0,000	0,175	0,000

Panel B: Data from 15/09/08 to 31/01/12						
Mean	-0,0003	0,0001	0,0001	-0,0018	-0,0003	-0,0005
n_-	428	434	443	431	414	413
n_+	453	447	438	450	467	468
μ_R	441,1	441,4	441,5	441,3	439,9	439,8
Number of Runs	424	442	450	406	416	403
Z	-1,157	0,04	0,574	-2,381*	-1,618	-2,49*
Asymp. Sig. (2-tailed)	0,247	0,968	0,566	0,017	0,106	0,013

Notes: We tested as test value the mean of the stock indexes' returns. The runs test assumes as a null hypothesis the elements of the series are mutually independent.
* Null hypotehsis rejection significant at the 5% level.
** Null hypothesis rejection significant at the 1% level.

5.1.3 Unit Root Tests

Observing Table V the null hypothesis of a unit-root is not rejected for any index or period, indicating, according to the Augmented Dickey-Fuller test, that the random walk hypothesis can not be discarded.

Table V. Unit Root Tests

	France CAC 40	Germany DAX 30	UK FTSE 100	Greece FTSE ATHEX 20	Spain IBEX 35	Portugal PSI 20
Panel A: Data from 01/01/97 to 12/09/08						
ADF t-statistic	-2,1382	1,8460	-2,1127	-1,8099	-1,8493	-1,9331
p-value	0,2297	0,3584	0,2397	0,3760	0,3568	0,3172
included observations	3052	3052	3049	2862	3052	3051
number of lags	0	0	3	1	0	1
Panel B: Data from 15/09/08 to 31/01/12						
ADF t-statistic	-2,7504	-1,5660	-1,6756	-1,8994	-2,1175	-1,3364
p-value	0,0661	0,4996	0,4434	0,3327	0,2379	0,6142
included observations	881	881	881	881	879	879
number of lags	0	0	0	0	2	2

Notes: ADF t-statistic refers to the Augmented Dickey-Fuller t-statistic, used to determine if the stock market indexes have a unit-root.

5.1.4 Variance Ratio Tests

Our fourth test is the Variance Ratio (VR) test, which according Lo and MacKinlay (1989), provides an added advantage because is a more reliable test than testing for correlations or unit roots.

For VR test we will present three approaches: the first is VR test robust under heteroskedasticity proposed by Lo and MacKinlay (1988); the second approach is the wild bootstrap sugested by Kim (2006); and the third approach is the VR test based on ranks and signs[12], as proposed by Wright (2000).

In order to facilitate comparisons with other recent studies, we selected the lags 2, 5, 10 and 30.

[12] Although Wright's methodology proposes two alternatives: a rank test and a sign test, in this thesis we chose to perform the rank VR test.

Table VI. Variance ratio test for lags 2, 5, 10, 30 as well as joint variance ratio test

	France CAC 40		Germany DAX 30		UK FTSE 100		Greece FTSE ATHEX 20		Spain IBEX 35		Portugal PSI 20	
Panel A: Data from 01/01/97 to 12/09/08												
Lag	*VR(q)*	*Prob.*	*VR(q)*	*Prob*	*VR(q)*	*Prob*	*VR(q)*	*Prob.*	*VR(q)*	*Prob*	*VR(q)*	*Prob*
2	0,9838	0,4751	0,9852	0,5163	0,9774	0,3339	1,1201	0,0001	0,9836	0,5043	1,1089	0,0007
5	0,9175	0,1077	0,9715	0,5873	0,8609	0,0076	1,1620	0,0226	0,9338	0,2352	1,2474	0,0002
10	0,8254	0,0278	0,9335	0,4120	0,7646	0,0035	1,1043	0,3209	0,8959	0,2255	1,3709	0,0002
30	0,8400	0,2626	0,9849	0,9163	0,7077	0,0412	1,0567	0,7430	1,3346	0,8182	1,7686	0,0000
Joint VR test (1)		0,1068		0,8805		0,0140*		0,0006**		0,6401		0,0001**
Joint VR test (2)		0,0740[(a)]		0,7740		0,0100*		0,0000**		0,5100		0,0010**
Joint VR test (3)		0,0010**		0,1020		0,0010**		0,0000**		0,1720		0,0000**
Panel B: Data from 15/09/08 to 31/01/12												
Lag	*VR(q)*	*Prob.*	*VR(q)*	*Prob*	*VR(q)*	*Prob*	*VR(q)*	*Prob.*	*VR(q)*	*Prob*	*VR(q)*	*Prob*
2	0,9756	0,6132	1,0421	0,3216	0,9973	0,9549	1,0619	0,9549	1,0385	0,4404	1,0546	0,2907
5	0,8386	0,1461	0,9825	0,8616	0,8757	0,2576	1,0252	0,2576	0,9237	0,4817	0,9993	0,9953
10	0,7790	0,2075	0,9544	0,7724	0,8160	0,2912	1,0704	0,2912	0,8145	0,2730	0,9168	0,6362
30	0,6245	0,2282	0,8814	0,6737	0,6090	0,2084	1,2000	0,2084	0,7849	0,4658	0,8246	0,5753
Joint VR test (1)		0,4685		0,7882		0,6073		0,4940		0,7207		0,7469
Joint VR test (2)		0,2920		0,6650		0,4470		0,3770		0,5650		0,5890
Joint VR test (3)		0,3800		0,5030		0,1970		0,4040		0,0800[(a)]		0,1520

Notes: Recall that VR(q), in theory, tends to equal one.

Joint VR test (1) refers to the Chowm-Denning joint VR test using the Lo and MacKinlay approach, joint VR test (2) uses the Kim approach and joint VR test (3) uses the rank-variance test developed by wright.

Although formally we are not considering a null hypothesis rejection significant at the 10% level, we think it is important, for a better analysis, to take it into account and therefore mark it with [(a)] when occurs.

* Null hypothesis rejection significant at the 5% level.

** Null hypothesis rejection significant at the 1% level.

Analyzing Table VI - Panel A, we observe that the VR(q) are higher than one in Greece and Portugal for all selected lags, indicating that variances grow more that proportionally with time. For these countries the null hypothesis is rejected at 1% level for all tests. We can also see that Spain shows on lag 30 a VR(q) higher than one, however this event is not statistically relevant and the null hypothesis is not rejected for any of the three tests. In Germany the null hypothesis is also not rejected for any of the joint VR test. Regarding UK, the null hypothesis of the joint VR test is rejected at a 5% level for the Lo and MacKinlay approach as well as for the Kim approach, in addition to a rejection at 1% level for the Wright approach. At last, France shows no rejection in terms of the joint VR test concerning the Lo and MacKinlay approach but in terms of the Kim approach already demonstrate some possibility of rejection (null hypothesis rejection significant at the 10% level), leading to a rejection at 5% level when considering the Wright approach (recall that this test can be more robust than the other).

Analyzing the Panel B, we can see some improvements in terms of market efficiency because there is no rejection (at 1% and 5% level) of the null hypothesis for any stock market index. However it is important to point that for Wright approach in Spain, the null hypothesis could be rejected at a 10% level.

5.1.5 Summary of Tests Results

In the Table VII we summarized the previous test results, where it is clear that all stock market indexes, excepting Spain, improved their efficiency after the financial crisis.

Analyzing Panel A, we achieved similar conclusions to the ones in Borges (2008, 2010) and report that the random hypothesis is rejected, in every test excepting the ADF, for both FTSE ATHEX 20 and PSI 20. Regarding Panel B (the period not yet covered by previous studies) this hypothesis is now only rejected for the Runs test concerning Greece’s index; and for the Ljung Box Q-statistic test and Runs Test concerning Portugal’s index. It is also worth mentioning that, for the Panel B, the random walk hypothesis is not rejected for any test regarding DAX 30 index.

As for the IBEX 35, the only index that did not improved its efficiency, although in Panel A it is apparently the best (random walk only rejected at a 5% level for the Ljung Box Q-statistic), given Panel B, for the Ljung Box Q-statistic the random walk is now rejected at a 1% level and if we want to be thorough, we can also refer that the random walk can be rejected at a 10% level concerning the Wright VR test.

Table VII. Summary of Previous Test Results: Is the random walk hypothesis rejected?

	France	Germany	UK	Greece FTSE	Spain	Portugal
	CAC 40	**DAX 30**	**FTSE 100**	**ATHEX 20**	**IBEX 35**	**PSI 20**
Panel A: Data from 01/01/97 to 12/09/08						
Serial correlation Tests						
Correlation at lag 1	NO	NO	NO	YES**	NO	YES**
Ljung Box Q-statistic test (at lag 25)	YES**	YES**	YES**	YES**	YES*	YES**
Runs Test	YES	NO	NO	YES**	NO	YES**
Augmented DickeyFuller	NO	NO	NO	NO	NO	NO
Joint VR test (1)	NO	NO	YES	YES**	NO	YES**
Joint VR test (2)	NO[(a)]	NO	YES	YES**	NO	YES**
Joint VR test (3)	YES*	NO	YES**	YES**	NO	YES**
Panel B: Data from 15/09/08 to 31/01/12						
Serial correlation Tests						
Correlation at lag 1	NO	NO	NO	NO	NO	NO
Ljung Box Q-statistic test (at lag 25)	YES**	NO	YES**	NO	YES**	YES*
Runs Test	NO	NO	NO	YES*	NO	YES*
Augmented DickeyFuller	NO	NO	NO	NO	NO	NO
Joint VR test (1)	NO	NO	NO	NO	NO	NO
Joint VR test (2)	NO	NO	NO	NO	NO	NO
Joint VR test (3)	NO	NO	NO	NO	NO[(a)]	NO

Notes: We choose to present the results of Ljung Box Q-statistic at lag 25 because it represents approximately one month.

Joint VR test (1) represents the Chow and Denning Joint Variance Ratio test using the Lo and MacKinlay approach; Joint VR(2) the Kim approach and VR(3) the Wright approach.

[(a)] Represents the cases in which the null hypothesis would be rejected at 10% level.

*Null hypothesis rejection at a 5% level.

** Null hypothesis rejection at a 1% level.

5.2 RapidMiner (data mining) approach

As mentioned before we will resort the Software RapidMiner 5.0 attempting to obtain reliable forecasting of PSI-20 returns with the algorithms W-ZeroR, k-NN and Neural Network. But first we will explain each of the 5 steps with the following example:

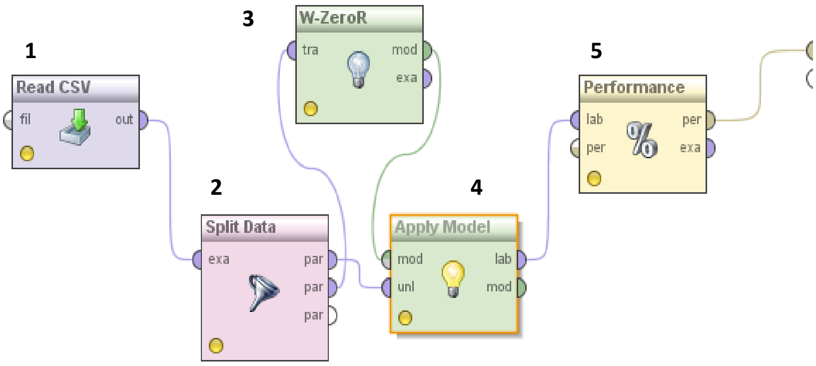


Figure 4. Example of a RapidMiner process

1. In order that the software read the data it was necessary first to place it in a CSV format. In this point it was also necessary to define the PSI-20 returns as "label".
2. In the "split data" box we chose to define that 70% of the data will work as train and 30% as test. In here we also had to define the sampling type as "linear sampling"
3. This represents the operator that runs the algorithm. In this example we presented the W-ZeroR algorithm and although the layout will be the same either with k-NN either with Neural Network, we had to make some specific adjustments depending on the algorithm in question.
4. This feature serves only to apply the model.
5. With the operator "Performance" we chose as measures the Root Mean Squared Error (RMSE), Absolute Error and Root Relative Squared Error (RRSE).

At this point it is relevant to explain each performance measurer. Regarding RMSE is the square root of the sum of the difference regarding predicted returns compared to the test data. The Absolute Error is merely the sum of the difference between the predicted returns compared to the test data. As to RRSE, it represents the variation coefficient between the standard deviation of the predicted returns and the standard deviation of the original test data; being so, in an ideal fit, RRSE should be equal to zero.

It is also worth mentioning that not only we maintain the same subdivision of the period under analysis but we also apply two forecast approaches: the first concerns directly if PSI-20 past returns can predict the future ones and therefore uses only the PSI-20 returns as inputs; for the second approach we aggregate the returns into 4 classes (class 1 for returns lower than -5%, class 2 for returns between -5% and zero, class 3 for returns between zero and 5% and class 4 for returns greater than 5%).

In the next sub-chapters we will present the results of forecasting with the three chosen algorithms (W-Zeror, k-NN and Neural Network) for each period of time and taking into account the two approaches mentioned above.

Additionally we will also present a strategy that we design and implement using the best estimates of the k-NN and the Neural Net to find out if we can obtain greater results than the ones achieved using a buy and hold strategy.

5.2.1 W-ZeroR

As mentioned before, the W-ZeroR has in here the purpose of give us a forecasting benchmark. Being so is expected that the k-NN and the Neural Network have lower RMSE, absolute error and RRSE than the ones presented on Table VIII.

Table VIII. Performance of the algorithm W-ZeroR

Root Mean Squared Error	Absolute Error	Root Relative Squared Error
Panel A: Results using only the PSI-20 returns as inputs with data from 01/01/97 to 12/09/08		
0,009	0,006 +/- 0,007	1,000
Panel B: Results aggregating the PSI-20 returns in classes with data from 01/01/97 to 12/09/08		
0,009	0,006 +/- 0,007	1,000
Panel C: Results using only the PSI-20 returns as inputs with data from 15/09/08 to 31/01/12		
0,014	0,011 +/- 0,009	1,004
Panel D: Results aggregating the PSI-20 returns in classes with data from 15/09/08 to 31/01/12		
0,014	0,011 +/- 0,009	1,004

Since W-ZeroR predicts the average of a numerical series, and the mean of the PSI-20 returns is approximately 0%, aggregating the PSI-20 returns in classes does not translate, in here, in an evident advantage. Also, is without surprise that we achieve the following forecasting results:

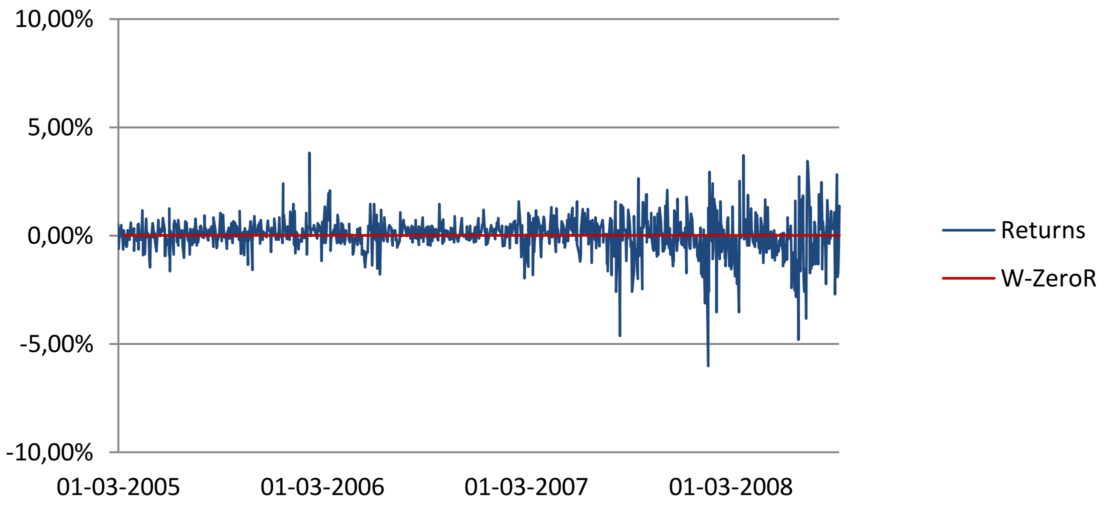


Figure 5. PSI-20 forecasting results with W-ZeroR: data from 01/01/97 to 12/09/08

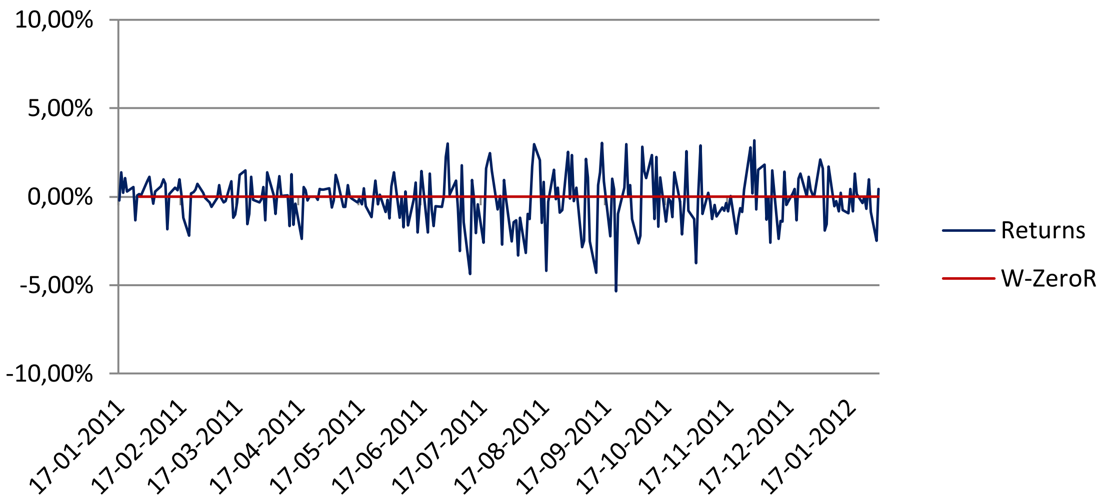


Figure 6. PSI-20 forecasting results with W-ZeroR: data from 15/09/08 to 31/01/12

5.2.2 K-NN

Table IX. Performance of the algorithm k-NN

k	Root Mean Squared Error	Absolute Error	Root Relative Squared Error
Panel A: Results using only the PSI-20 returns as inputs with data from 01/01/97 to 12/09/08			
1	0,011	0,009 +/- 0,007	1,226
2	0,010	0,007 +/- 0,007	1,086
3	0,009	0,007 +/- 0,007	1,047
4	0,009	0,006 +/- 0,007	1,005
5	0,009	0,006 +/- 0,007	1,002
10*	0,009	0,006 +/- 0,007	1,000
15	0,009	0,006 +/- 0,007	1,015

Panel B: Results aggregating the PSI-20 returns in classes with data from 01/01/97 to 12/09/08			
1	0,008	0,005 +/- 0,006	0,875
2*	0,006	0,004 +/- 0,005	0,723
3	0,008	0,006 +/- 0,005	0,840
4	0,008	0,006 +/- 0,005	0,923
5	0,008	0,006 +/- 0,005	0,929
10	0,008	0,006 +/- 0,005	0,880
15	0,007	0,005 +/- 0,005	0,782
Panel C: Results using only the PSI-20 returns as inputs with data from 15/09/08 to 31/01/12			
1	0,014	0,011 +/- 0,009	1,013
2	0,015	0,012 +/- 0,009	1,056
3	0,014	0,011 +/- 0,009	1,002
4*	0,014	0,011 +/- 0,009	1,000
5	0,014	0,011 +/- 0,009	1,016
10	0,014	0,011 +/- 0,009	1,014
15	0,014	0,011 +/- 0,009	1,005
Panel D: Results aggregating the PSI-20 returns in classes with data from 15/09/08 to 31/01/12			
1	0,013	0,010 +/- 0,007	0,891
2	0,015	0,013 +/- 0,008	1,078
3	0,013	0,011 +/- 0,008	0,922
4	0,01	0,008 +/- 0,006	0,719
5*	0,01	0,008 +/- 0,006	0,672
10	0,01	0,008 +/- 0,005	0,687
15	0,011	0,010 +/- 0,006	0,807

Note: The K that for each panel provides the best performance is marked with an *.

Given the nature of the k-NN algorithm, determining the good value of *k* is done experimentally, as stated in Han and Kamber (2006), so we have to test which results we would obtain given different neighbors (*k*), then we marked the *k* that provided the best performance, that is, the minimum error at those three criterions.

It is also important to point out that, for this algorithm, aggregating the PSI-20 returns in classes comes as an advantage for prediction purposes.

The next two figures express the optimal results using classes for both periods of time.

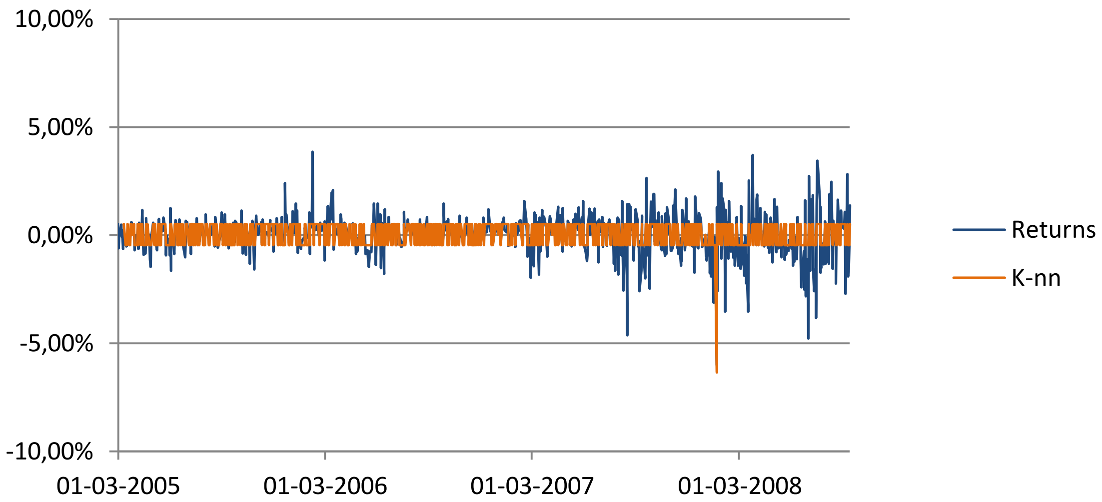


Figure 7. PSI-20 forecasting results with k-NN: data from 01/01/97 to 12/09/08

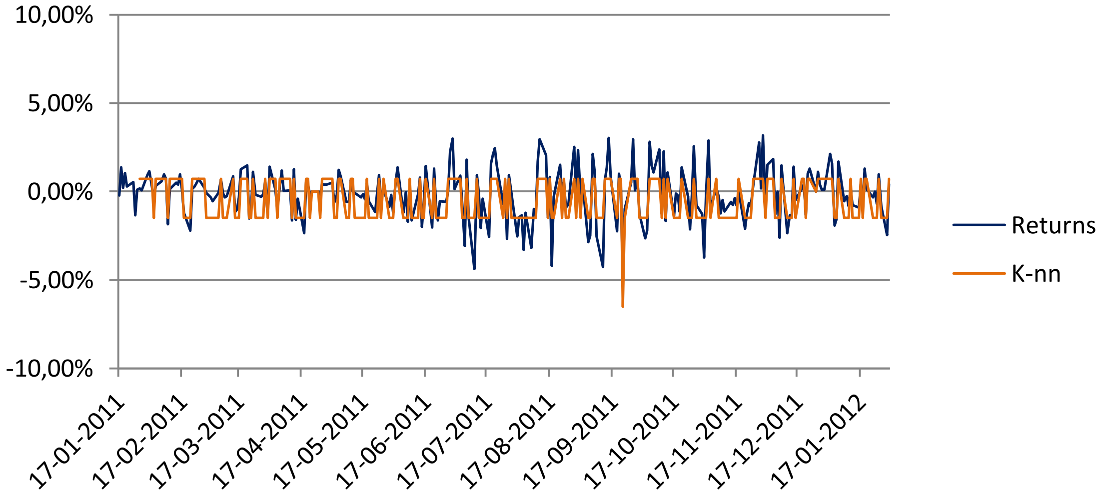


Figure 8. PSI-20 forecasting results with k-NN: data from 15/09/08 to 31/01/12

5.2.3 Neural Network

Table X. Performance of the algorithm Neural Net

	Root Mean Squared Error	Absolute Error	Root Relative Squared Error
Panel A: Results using only the PSI-20 returns as inputs with data from 01/01/97 to 12/09/08			
	0,009	0,006 +/- 0,007	1,007
Panel B: Results aggregating the PSI-20 returns in classes with data from 01/01/97 to 12/09/08			
	0,006	0,004 +/- 0,005	0,711
Panel C: Results using only the PSI-20 returns as inputs with data from 09/15/08 to 01/31/12			
	0,014	0,011 +/- 0,009	1,014

Panel D: Results aggregating the PSI-20 returns in classes with data from 09/15/08 to 01/31/12		
0,009	0,007 +/- 0,006	0,645

Analyzing the table above, we can retain that, regarding the Panel B and D, forecasting using the Neural Network, gives us the best performance so far. However, if we consider the Panel A and C, we can observe that the W-ZeroR algorithm had a better performance, which indicates, for these Panels some overfiting. For conclusion, we will present the results of the best forecasting using this algorithm.

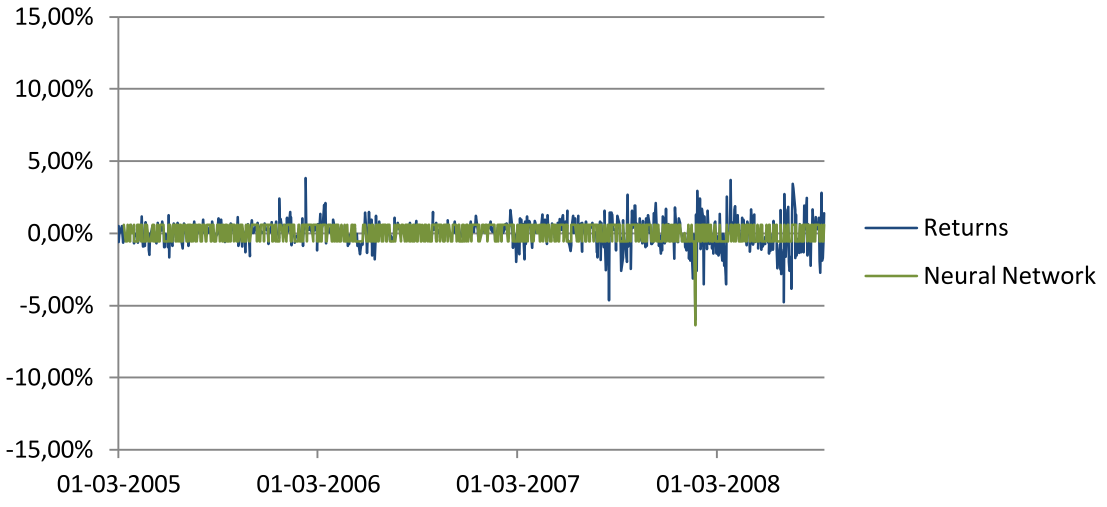


Figure 9. PSI-20 forecasting results with Neural Network: data from 01/01/97 to 12/09/08

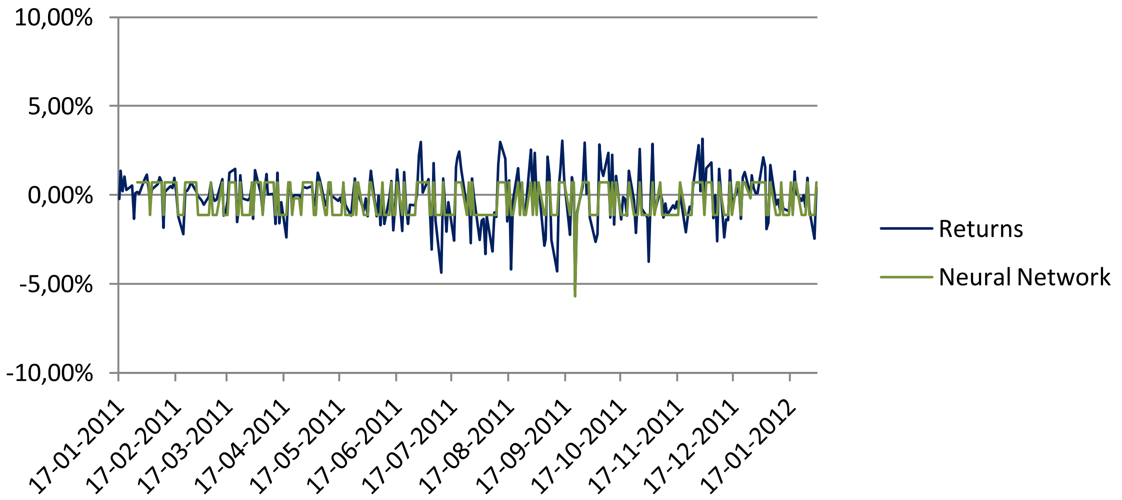


Figure 10. PSI-20 forecasting results with Neural Network: data from 15/09/08 to 31/01/12

5.2.4 Can we beat the market?

As earlier mentioned we will attempt to beat the market, using the best estimates of k-NN and Neural Network.

Before we explain how we intend to do it, recalls that for the algorithms operate, our initial data was split in order to 70% work as train and 30% as test. Being so, the data we will now use concerns only those 30% which means that, the strategy is made with respect to the data from 10/03/2005 to 12/09/2008, for the first period; and data from 26/01/2011 to 31/01/2012, for the second period.

In order to implement the strategy, first we defined the average of the returns predicted either by k-NN either by Neural Network. Then, we calculated the moving average for 5 days and defined as a strategy to buy the index if the moving average was below the average primarily calculated and to sell it if it was above. Finally we computed the return we would obtain with this strategy and compare it with a buy and hold strategy. The results were the ones presented at Table XI and assume as an assumption that there are no transaction costs.

We also present in the Appendix A3 the histograms respecting the moving average for 5 days of the real PSI-20 returns, the k-NN prediction and the Neural Network prediction concerning the first period of time (10/03/2005 to 12/09/2008); and in Appendix A4 the same histograms but now with respect to the second period of time (26/01/2011 to 31/01/2012).

Table XI. Results of implementing the algorithms strategy

Real returns from a buy and hold strategy	Real returns from a strategy using k-NN predictions	Real returns from a strategy using Neural Network predictions
Panel A: Data from 10/03/2005 to 12/09/2008		
5,96%	39,18%	39,15%
Panel B: Data from 26/01/2011 to 31/12/2012		
-37,28%	-11,52%	-11,52%

Looking at the Table XI, we can conclude that the real returns that we would obtain using either the k-NN strategy either the Neural Network strategy are substantially higher that the ones we would obtain using a buy and hold strategy.

6. Conclusions

In order to conclude this thesis is worth mentioning, regarding the Classical Efficiency tests that all the indexes under analysis improve its efficiency after the subprime crisis, with exception of the IBEX 35. It is also important to mention that, after the subprime crisis, the DAX 30 did not reject the random walk hypothesis (or martingale process) for any of the tests.

Based on the premise that if the market is efficient than it should not be possible to forecast it, we introduced the algorithms as a complement of the classical tests for the PSI-20 returns. This allows us to design a strategy based on the k-NN and on the Neural Network predictions, and we conclude that would be possible to obtain significantly higher earnings by the implementation of this strategy than using a simple buy-and-hold strategy. Being so, this shows that the PSI-20 is not yet totally efficient, in fact as priory confirmed by the classical tests.

In terms of other possible lines of research we believe it would be interesting to repeat the tests mentioned in this dissertation, in a few years, to verify on the one hand if the six European indexes chosen improve its efficiency, and on the other hand if it is possible to obtain profits with the algorithms predictions. This will be useful because as mentioned before, the techniques based on data mining will improve with time. Another suggestion made is to consider transaction costs when designing the strategy "can we beat the market?".

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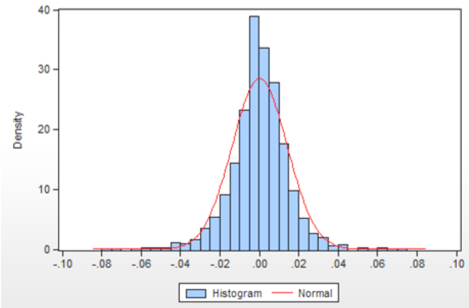
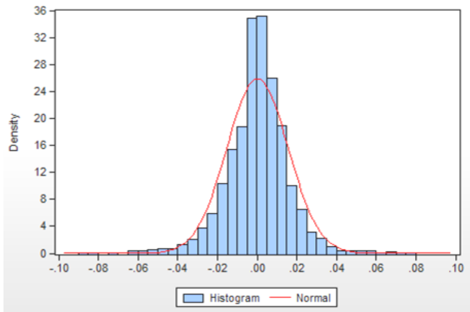
Appendixes

A1. Histograms of the stock indexes' returns from 01/01/1997 to 09/12/2012 and its comparison with the Normal Distribution.

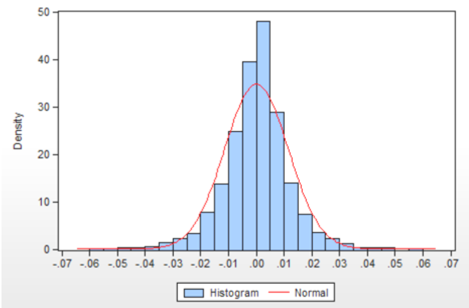
CAC 40



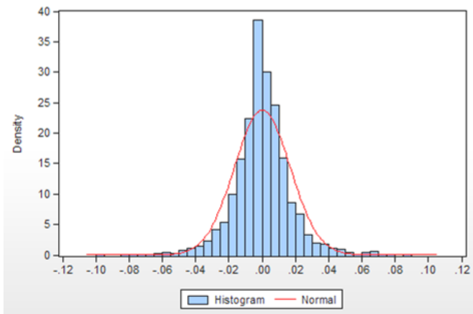
DAX 30



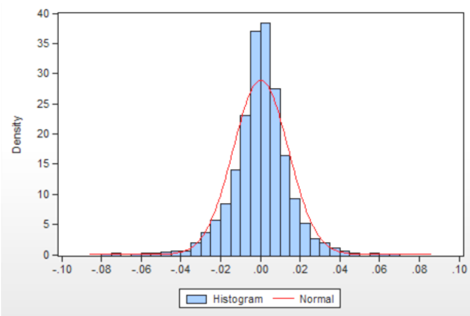
FTSE 100



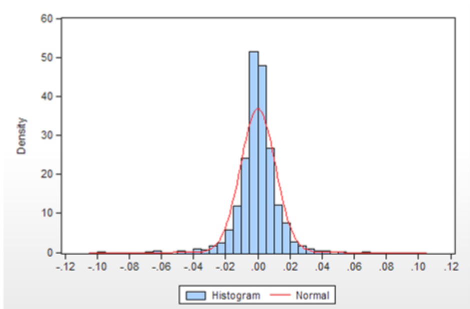
FTSE ATHEX 20



IBEX 35

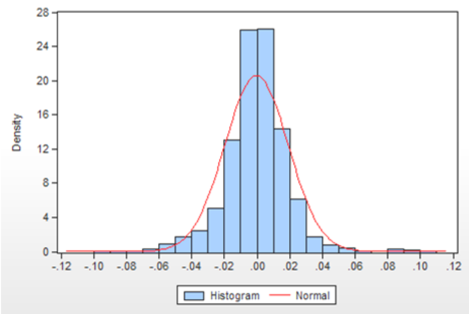


PSI 20



A2. Histograms of the stock indexes' returns from 09/15/1997 to 01/31/2012 and its comparison with the Normal Distribution

CAC 40



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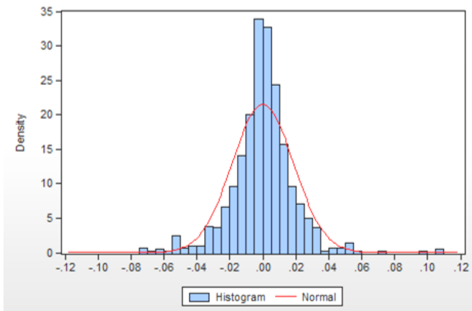

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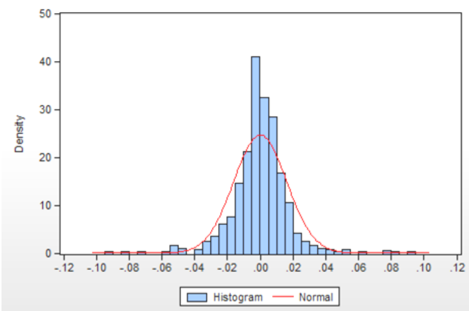
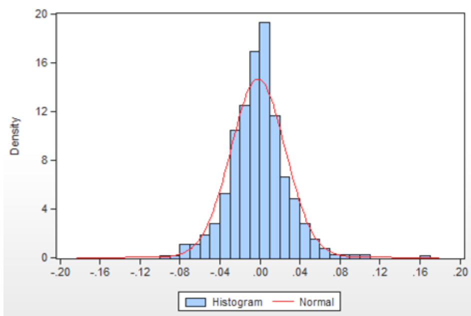
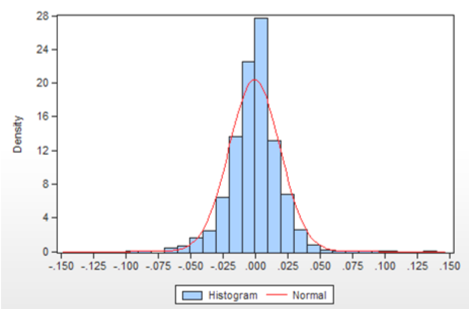


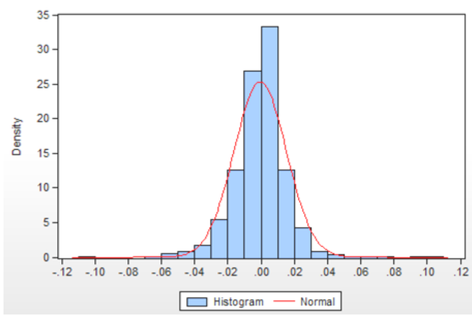
FTSE ATHEX 20



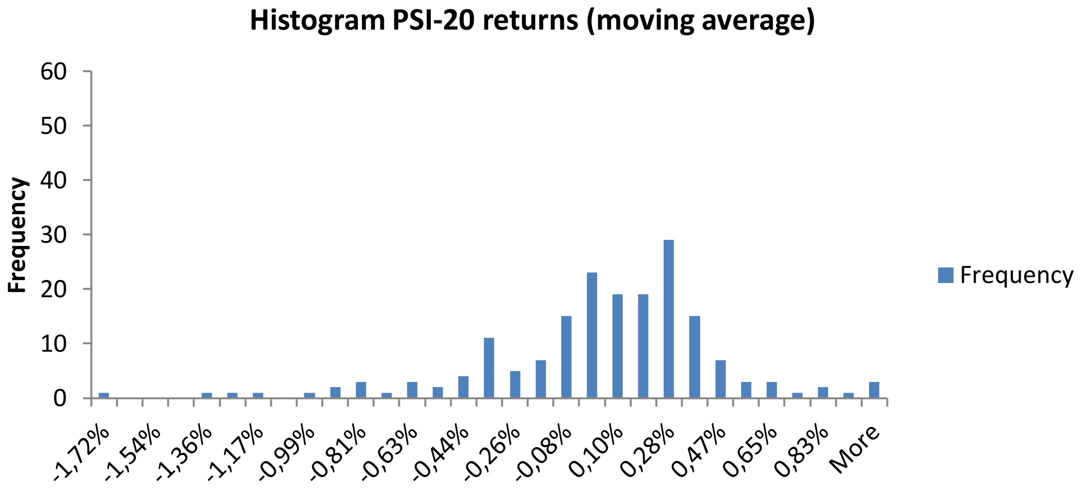
IBEX 35

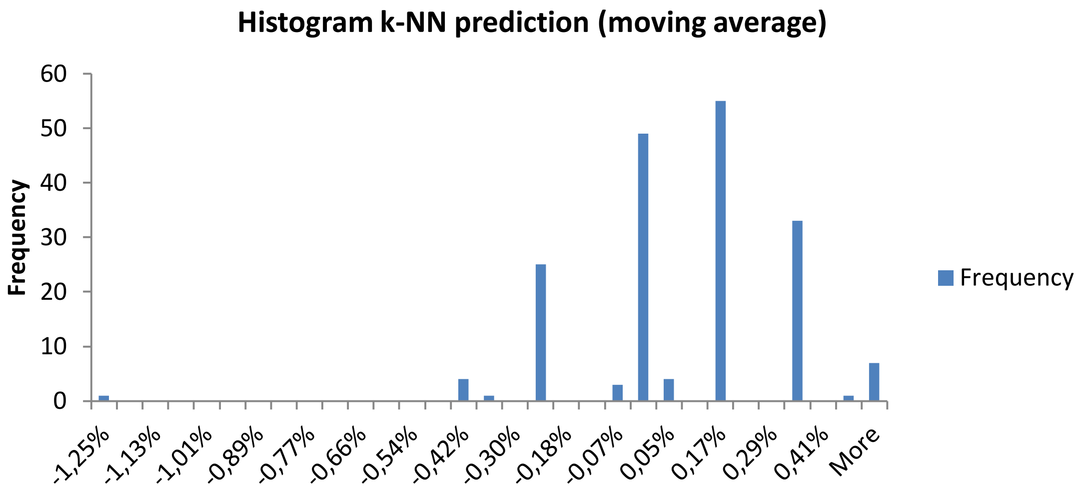


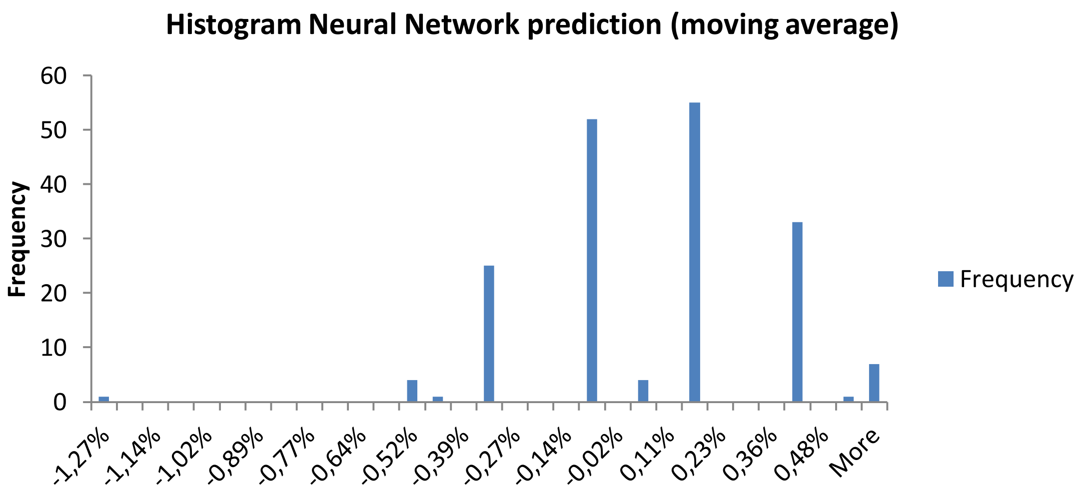
PSI 20



A3. Moving average for 5 days of the real PSI-20 returns, the k-NN prediction and the Neural Network prediction. Data from 10/03/2005 to 12/09/2008







A4. Moving average for 5 days of the real PSI-20 returns, the k-NN prediction and the Neural Network prediction. Data from 26/01/2011 to 31/12/2012