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Weak-form market efficiency and corruption: a cross-country comparative analysis

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Abstract

Purpose – The economic and administrative conditions of countries normatively have an effect on the economy and level of market development. Moreover, it is of great importance for a healthy economy whether the public institutions and organizations are transparent and functioning in accordance with their purpose. The aim of this study is to show whether there is a relationship between transparency and market efficiency.

Design/methodology/approach – Correlation analysis has been conducted between prediction accuracy rates, which are obtained by seven different machine learning algorithms and Corruption Perception Index (CPI) levels.

Findings – It has been statistically shown that the indices of countries with low corruption levels are harder to predict, which, in turn, can be interpreted as having higher weak-form market efficiency. According to that, an intermediate negative correlation has been found between CPI scores and predictability levels of stock indices. Considering the findings, it can be interpreted that the markets of countries with relatively more transparent and well-functioning public sector have more weak-form market efficiency.

Research limitations/implications – The study can be extended with cutting-edge machine learning and deep learning techniques in future studies. There are very few studies which try to explain factors related to market efficiency. Thus, the authors claim that there is still room for further research in order to determine the factors related to market efficiency, implying that current literature is still far from explaining the causation behind the inefficiencies.

Practical implications – According to findings, the markets of countries with relatively more transparent and well-functioning public sector have more weak-form market efficiency. Based on these findings, in practice, it can be said that more successful predictions can be made using machine learning algorithms in countries with relatively lower CPI scores.

Originality/value – In literature, the factors related to market efficiency are still far from explaining the causation behind the inefficiencies. Thus, it has been investigated whether transparent and well-functioning public institutions and organizations have any relation with market efficiency.

Keywords Efficient market hypothesis, Corruption perception index, Machine learning, Stock market prediction

Paper type Research paper

JEL Classification — C45, C53, C58, G14, G17, G18

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1. Introduction

Capital markets are one of the most important institutions which undertake the task of allocation of capital required by companies on behalf of national economies. It is vital for capital markets to operate effectively in a healthy manner. Therefore, one of the most important economic indicators for national economies is the well-functioning capital markets where capital market instruments are exchanged. In order to develop our understanding for the mechanism and structure of capital markets, a large number of theories have been proposed such as capital asset pricing model (CAPM) of Sharpe (1964) and Fama-French three-factor model by Fama and French (1993). Such models aim to expand our understanding on how to invest in capital markets, yet there has been an increasing need for an explanation of the behavior of asset prices and their hard-to-predict nature. For this reason, asset pricing and price forecasting issues have always been important for financial economics literature and have kept their priority. In this context, different methods and theories have been proposed in order to forecast risky asset prices (see Rather *et al.* (2017) and Bahrammirzaee (2010) for review of such studies).

There are two major existing approaches, namely, fundamental analysis and technical analysis (TA) in finance literature to uncover overvalued or undervalued assets. Although there are different opinions about which of these approaches for estimating the prices of financial assets is superior (see Taylor and Allen, 1992 for a comparative study), it is common to utilize both methods at the same time in practice (Bettman *et al.*, 2009). The fundamental analysis is simply an attempt to make an inference about the intrinsic value of financial assets by examining financial reports of underlying companies. On the other hand, TA is an approach which tries to estimate the direction of future prices based on historical data. Furthermore, TA is one of the most widely used decision-making tool among millions of retail and institutional traders. Thus, researchers have questioned whether a successful trade strategy can be built upon TA indicators which can consistently beat market.

Market predictability is mostly a consequence of its efficiency put forward by Malkiel and Fama (1970) and following studies. It has been discussed extensively under efficient market hypothesis (EMH) and related discussions. The degree of efficiency of a given stock market consists of three levels: "weak-form market efficiency," "semi strong-form market efficiency" and "strong-form market efficiency." In a weak-form efficient market, which is the first level of market efficiency, past price movements should not be used for forecasting future prices. In other words, it is expected that there exists no pattern in asset prices. Therefore, in a weak-form efficient market, by analyzing past price movements, it would not be possible to predict future asset prices accurately at a statistically significant level, though fundamental analysis may still provide excess returns. However, according to a large number of studies, this is not the case (e.g. Lo *et al.*, 2000; Brock *et al.*, 1992) as there are predictable patterns in asset prices, which means using past data it is possible to earn excess return. In addition, with the recent developments in computational methods, it is shown that many approaches such as machine learning and evolutionary computational techniques are also successful in predicting such financial time series (see Yao and Tan, 2000).

There is a general consensus among market participants and scholars on developed markets being more efficient than emerging markets. Although Griffin *et al.* (2010) find that short-term reversal, post-earnings drift and momentum strategies earn similar returns in emerging and developed markets, there is still room for further research comparing underlying factors of market efficiency of developed and emerging markets with different experimental designs. Therefore, based on EMH's argument that future prices cannot be predicted using past price data, it is thought to be more difficult to predict future prices of developed capital markets with relatively higher market depth compared to less developed ones. As a result, in a weak-form efficient market, it is not possible to consistently make successful predictions or achieve positive returns by using the information available in a certain time period:

$$E[r_t|I_{t-1}] = 0. \tag{1}$$

Here, r_t is the percentage return from $t-1$ to t time period, and I_{t-1} is the information set available at time period $t-1$. Generally speaking, it is thought that the political and administrative conditions of the country in which the capital markets are located normatively have an effect on the economy and level of market development. There are various indicators that show the level of development of the country's economies. The leading ones among these indicators can be listed as GDP, GNP, GDP per capita. However, in addition to all these economic indicators, it is of great importance for a healthy economy whether the public institutions and organizations are transparent and functioning in accordance with their purpose as planned. Hence, the mission of identifying the needs of the national economies and bringing structural solutions to their problems is undertaken by the relevant institutions and organizations.

One of the most recent and sound attempt to make an explanation about factors related to market efficiency is proposed by Lo (2004) with adaptive market hypothesis (AMH) claiming that the degree of market efficiency is related to environmental factors characterized by market conditions. Since market conditions change over time, market participants should realize these changes rapidly and develop new strategies accordingly. However, it takes some of time for market participants to adapt to these changes. Therefore, there is a decrease in the efficiency levels of the markets during this period until the market participants adapt to new conditions, and the level of market efficiency increases with the improvement of their adaptation. For this reason, abnormal returns can be obtained until the majority of the participants adapt to the changes in market conditions. The time required for the market to refunction efficiently is related to dissemination speed of information to market participants about new situations and conditions. In other words, it depends on how quickly the participants can acquire information about this new situation and develop new strategies accordingly. Therefore, it is important that information about the markets is transparent, adequate and disseminated quickly.

It can be said that there are two important factors that affect the speed of information dissemination about the markets to the participants in a transparent manner: first, the policies followed by the market regulatory and supervisory institutions (market authorities), and, second, the expertise levels of the participants. Although the level of expertise of market participants is also expressed as a factor here, the roles of market regulatory and supervisory institutions are structurally more important. The reason is that, no matter how expert and professional the market participants, unless the supervisory and regulatory institutions operate in a healthy and transparent manner, the information on the changing conditions regarding the markets will not be disseminated to the vast majority of the participants at a sufficient speed and amount. As a result, there will be delays in the level of efficiency, and the periods of ineffectiveness of the markets will be extended. On the other hand, since the changes in today's economic and market conditions are very frequent and rapid, the delays in reaching the new conditions and related information in the markets can make this inefficient state almost permanent. For these reasons, market regulatory and supervisory institutions and authorities have an important role to play, and they must have a transparent and relevant functionality. In this sense, transparency as a dimension of the "degree of market efficiency is related to environmental factors characterizing market conditions" argument of AMH is examined in this study. We think that this study is an important effort to test whether there is a relationship between the transparency and purposeful functionality and the efficiency levels of the markets.

Since 1995, countries have being rated according to their perceived corruption levels of public sector based on views of experts and business executives by the Transparency International Organization [1]. These expert opinions are quantified and published annually under the name of the Corruption Perceptions Index (CPI). Accordingly, a score between 0 and 100 is given based on whether the public sector functions transparently and in accordance with its purpose. Countries with high transparency and less corruption have an increased CPI score, while countries with less transparency and corruption have a relatively lower CPI score. In this study, it is mainly investigated whether there is a relationship between the CPI score and the weak-form efficiency levels of the capital markets. The main motivation of the research is to reveal whether the capital markets of the countries whose public sector is transparent and functioning properly are also functioning efficiently (weak-form efficient).

In the literature, there is no study that directly investigates the relationship between the weak-form efficiency level of capital markets and the corruption levels of countries, as proposed here. According to the empirical survey on market efficiency by Lim and Brooks (2011), there are significant numbers of studies which are testing whether a market is weak-form efficient, but some of these studies emphasize the importance of the underlying factors that could lead to an efficient market. The aim of this study is to shed light partially to one of those underlying factors. Lim and Brooks (2011) also categorize the studies that research the factors affecting market efficiency in groups, such as "opening of domestic stock market to foreign investors, adoption of an electronic trading system, implementation of a price limits system, occurrence of a financial crisis, changes in regulatory framework, and technological advances." It would not be wrong to evaluate this study within the literature of "The Changes in Regulatory Framework."

CPI measures the level of healthy functioning of the administrative and public institutions and organizations of the countries. Therefore, the proper functioning of capital markets regulatory and supervisory institutions is directly or indirectly dependent on the general administrative conditions, structures and norms throughout the country under all conditions. Regulatory and supervisory institutions play a major role in sudden changes or deterioration in general economic, social, environmental or political conditions. Because when such conditions arise, extreme volatility may occur in the capital markets (Chowdhury, 2022). Under such conditions, it may become easier for manipulative behaviors to be observed. Insider trading and market manipulation is shown as one of the most important factors determining the efficiency level of activity in the capital markets. Insider trading can be prevented by the laws and controls of market regulatory agencies. Ojah *et al.* (2020) find that laws that effectively prevent insider trading improve stock market information dissemination so that market can operate more efficiently. Antoniou *et al.* (1997) indicate that the evolution in the regulatory framework of emerging markets will develop into efficient and effectively functioning markets over time.

On the other hand, market fairness is defined as another important market component along with market efficiency. A fair market has been linked to the inexistence of insider trading and manipulation (Aitken *et al.*, 2018). Manipulations' widely accepted definition in the relevant literature is simply release of false information about events that would have potential to move stock prices in any direction (Allen and Gale, 1992). Moreover, the development and employment of models that would effectively detect market manipulation by identifying suspicious trading behaviors would again lead to the formation of an efficient market environment under the governance of capital markets regulatory and supervisory institutions. In order to efficiently utilize current advanced models (such as Wang *et al.*, 2019) which can detect such manipulative trading behaviors by regulatory institutions, it is necessary to employ experts and qualified staff in these institutions.

Assuming that the efficiently functioning markets operate healthier than the inefficient ones, it would not be wrong to say that this study aligns with studies examining the relationship between the corruption levels of countries and the development of capital markets. Stock market development is a slightly vague term and may indicate different measures. For instance, Bolgorian (2011) tests whether there exists a relation between CPI score and stock market development which is measured by market capitalization (MC) divided by GDP, and finds that there exists a power law dependence between corruption and stock market development.

The study consists of five main sections. In the second section, the details of the methods, hypothesis and tests were shared. In the third section, data sets used in the analysis have been clarified. In the fourth section, analysis and findings have been presented, and, finally, in the fifth section, final inferences have been made and the results and findings have been interpreted.

2. Methodology

In this study, the prediction of a number of national stock exchange indices has been made via machine learning algorithms by using TA indicators as predictor variables in order to test market efficiency. The reason for adopting machine learning techniques is that they are known to be successful nonlinear classifiers (such as ANN and SVM with kernel trick), and they are known to handle time series prediction better than linear models. In this study, predictions made by machine learning techniques are based on the classification of time series. In other words, rather than predicting the future absolute price levels of the relevant time series, predictions have been made as classifications. This approach is also known as *time series directional prediction* (predicting that whether stock price goes up or down with respect to the previous day). This is due to the desire to have an economic interpretability of the predictions. Directional prediction success is indicated by the ratio of accurate direction predictions divided by total number of predictions. This ratio is also known as *hit rate*. Real valued prediction models and their evaluation methods such as root mean squared error (rmse) or mean absolute deviation (MAD) are not preferred because of their relatively difficult and uncertain economic interpretation. In their reference paper, de Oliveira *et al.* (2013) also quite clearly summarize the importance of directional predictions and emphasize that what really matters for decision-making is predicting directions of movements. However, RMSE is one of the most popular metric in evaluation stock market prediction models; accuracy is also widely preferred; likewise RMSE and most of the studies in the recent literature are based on classification-based prediction tasks (Kumbure *et al.*, 2022). Moreover, for the stock market direction prediction or classification task, accuracy is the only metric to be employed. Therefore, following the relevant literature, classification-based prediction is employed in this study too.

Directional predictions of closing prices with respect to previous trading day's closing price for the selected stock market indices have been made. Let $Y_{i,t}$ be the price direction of i th stock market index for time t, and $\widehat{Y}_{i,j,t}$ is the predicted price direction of i th stock market index by j th machine learning technique for time t with respect to $X_{i,t-1}$ which is a set of input features for i th stock market index of day $t-1$.

$$Y_{i,t} = \begin{cases} 1, \text{for } r_t > 0 \\ 0, \text{for } r_t \leq 1 \end{cases} \tag{2}$$

$\widehat{Y}_{i,j,t}$ is a function of $X_{i,t-1}$ such that $\widehat{Y}_{i,j,t} : \mathbb{R}^n \to \{0,1\}$ and $\widehat{Y}_{i,j,t} = f_j(X_{i,t-1})$. If $Y_{i,t} = \widehat{Y}_{i,j,t} = 1$, it is called true positive (TP); if $Y_{i,t} = \widehat{Y}_{i,j,t} = 0$ true negative (TN); $Y_{i,t} = 0, \widehat{Y}_{i,j,t} = 1$ false positive (FP); and $Y_{i,t} = 1, \widehat{Y}_{i,j,t} = 0$ false negative (FN). Then accurate rate is,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (3)$$

It is also worth to mention another necessity of directional predictions. We propose that statistically testing the accuracy level of predictions might be considered as an alternative way for testing weak-form market efficiency. In order to accomplish this task, we conduct one-sample t-tests on accuracy rates by analyzing if the predictions are different from random walk. Afterward, it is examined whether there is a relationship between CPI level of these countries and predictability of their capital markets.

It is also notable to summarize the significant contributions of the proposed study to the literature as follows: (I) the main contribution of this study is to show whether there is a relationship between transparency and market efficiency. For each of the seventy-three countries, it has been examined whether there is a relationship between the predictability of the national stock market indices and the corruption level of these countries. To achieve this goal, correlation analysis has been conducted between prediction accuracy rate (hit rate) and CPI level.

Predictions have been made for each of the seventy-three time series with seven distinct machine learning techniques. These techniques are artificial neural networks (ANN), naïve Bayes (NB), random forest (RF), Decision Tree (DT), support vector machines (SVM), K-nearest neighbors (KNN) and logistic regression (LR). Each of the stock market historical data of seventy-three countries has been split into the training and testing periods for eighty and twenty percent, respectively. Hyperparameters of employed prediction models are summarized in Table 1.

Each predictive model has been run sixty times with randomized training-testing splits and accuracy rates are obtained. Thus, when each index is predicted with seven machine learning algorithms, seven distinct samples with a size of sixty have been obtained composed of accuracy rates of each run. Then, the mean of each of these samples has been calculated. The accuracy rate used in the correlation analysis is the highest of means of these seven samples. In the remainder of the study, these values are referred to as *MaxMHR* standing for max-mean hit rate. For example, the mean hit rate values of Istanbul Stock Exchange's (Borsa Istanbul) main index for each technique have been obtained as 0.493, 0.518, 0.516, 0.527, 0.525, 0.509, and 0.529, respectively. Here, the accuracy rate to be used in the correlation analysis is 0.529, which is the value obtained by LR. In addition, t-test has been performed to test whether the mean of the accuracy rate sample of each technique is different

Prediction model	Hyper parameters	Programming language and package/library
ANN	Hidden layers = 10, output = 1, max iteration = 6,000, connection rate = 1.0, learning rate = 0.75	Python/libfann[a]
NB	threshold = 0.001, eps = 0	R/e1071[b]
RF	ntree = 500	R/randomForest[c]
DT	Default	R/rpart[d]
SVM	kernel = radial, degree = 3, coef0 = 0, cost = 1, nu = 0.5, cachesize = 40, tolerance = 0.001, epsilon = 0.1, cross = 0	R/e1071
KNN	k = 5, l = 0, prob = TRUE, use.all = TRUE)	R/class[e]
LR	Default	R/stats

Note(s): [a]https://github.com/libfann/fann, [b]https://cran.r-project.org/web/packages/e1071/index.html, [c]https://cran.r-project.org/web/packages/randomForest/index.html, [d]https://cran.r-project.org/web/packages/rpart/, [e]https://cran.r-project.org/web/packages/class/index.html
Source(s): Authors' own work

Table 1. Summary of employed prediction models

from random walk [2]. Our aim for performing the t-test is to show that some markets can be predicted with several techniques in a statistically significant way using only historical price data.

3. Experiments and research data

During the course of experiment design of a research of this nature, an important decision on gathering and organizing historical price data of the interested stock market indices arises. For the sake of maintaining a transparency in accessibility and research results reproducibility, publicly available daily historical data providing services have been preferred. For this regard, only the two financial data services available, respecting our criteria at the time of the research is being conducted, “Yahoo! Finance” and “Investing.com” financial data services, have been used to obtain the data. During the time of experiments, all of the publicly available data of the countries with an organized stock market have been reached. In this regard, a total of available 82 historical price data relating to different stock market indices have been downloaded from previously mentioned data services. Considering the low quality of some of the data, which is basically because of lacking proper open-high-low-close (OHLC) prices, some indices have been completely removed out of the scope of the experiments (Jamaica JSEM and Mauritius SEMDEX), and furthermore some data sets have been partially cropped for the same reason. Apart from that, although limited to only two indices, namely Ireland’s ISEQ20 and Philippines’ PSEi, indices which are available from both resources have been compared and consolidated. Moreover, indices which are representing a whole region by including a basket of stocks from different countries instead of stocks from a specific country, for instance Euronext100, have also been left out of the analysis. Finally, stock market indices belonging to a country whose CPI score is not available have been discarded from the scope of the study, thus resulting in 73 stock market indices subject to the analysis.

In Table 2, stock market indices subject to correlation analysis between CPI scores and hit rates obtained from time series predictions are listed. The available number of historical price data size is not the same for each stock market since the data policies of capital market regulators differ, and CPI scores used in correlation analysis are based on 2018 CPI scores [3].

One important aspect of time series prediction is learning the parameters for underlying machine learning algorithm for the data set and later testing with the unknown part of the same data. Therefore, in order to verify or test the accuracy of the predictions, each data set is divided into training and testing sets as 80% and 20%, respectively.

3.1 Preferred inputs for the machine learning models

For both predictive and classifier models dealing with time series data, whether it is recruiting a statistical time series analysis or a machine learning technique, one of the key factors for a successful model is the kind of inputs. Reaching a consensus on the inputs by each and every domain expert or practitioner is nearly impossible. Researchers and practitioners have embraced so many different kinds of inputs in a wide variety of combinations for their specific models. These inputs simply can be summarized as lagged (by auxiliary periods) time series of the original time series, derived inputs from previously held preparatory and preliminary analyses on the original data (e.g. principal component analysis (PCA)) or sometimes TA indicators especially when the application area is stock markets or financial indices.

Putting aside the trader/practitioner bias for preferring TA indicators as inputs, as they perceive them as a “natural” or “way to go” tool when dealing with past financial market data, it is intriguing to seek for more evidence whether there is a scientific/statistical ground for

Country	Market index	Source	Start	End	Data size
Argentina	MER	Yahoo	1.3.2000	1.1.2018	4402
Australia	AORD	Yahoo	1.3.2000	12.28.2017	4552
Austria	ATX	Yahoo	1.3.2000	12.29.2017	4458
Bahrain	BAX	Investing	3.24.2010	12.31.2017	1890
Belgium	BEL20	Investing	10.29.1991	8.3.2011	4999
Bosnia And Herzegovina	BIRS	Investing	12.24.2012	2.4.2019	1531
Brazil	BVSP	Yahoo	1.3.2000	12.29.2017	4456
Bulgaria	BSESOFIX	Investing	8.16.2011	2.4.2019	1851
Canada	GSPTSE	Yahoo	12.31.1999	12.29.2017	4549
Chili	IPSA	Yahoo	1.2.2002	12.29.2017	3987
China	SSE COMPOSITE INDEX	Yahoo	1.3.2000	1.29.2017	4483
Colombia	COLCAP	Investing	8.12.2011	12.28.2017	1556
Croatia	CROBEX	Investing	11.23.2007	2.4.2019	2790
Czech Republic	PX	Investing	1.17.2012	2.5.2019	1765
Denmark	OMX Copenhagen20	Investing	2.12.2001	2.5.2019	4496
Egypt	EGX30	Investing	5.24.2010	12.31.2017	1841
Estonia	Tallinn SE General	Investing	2.26.2002	2.5.2019	4263
Finland	OMX Helsinki25	Investing	3.9.2001	2.13.2018	4244
France	CAC40	Yahoo	1.3.2000	12.29.2017	4598
Germany	DAX	Yahoo	1.3.2000	12.29.2017	4571
Greece	FTSEAthex LargeCap25	Investing	1.3.2000	12.29.2017	4464
Hong Kong	HIS	Yahoo	1.3.2000	12.29.2017	4440
Hungary	BUX	Investing	3.7.2011	12.29.2017	1697
Iceland	Icex Main	Investing	1.9.2001	2.5.2019	4492
India	NIFTY50	Yahoo	9.17.2007	12.29.2017	2517
Indonesia	JKSE	Yahoo	1.4.2000	12.29.2017	4345
Ireland	ISEQ20	Yahoo	1.4.2000	12.29.2017	4550
Israel	TA125	Investing	1.3.2000	1.1.2018	4418
Italy	FTSE_MIB	Investing	1.3.2003	2.5.2019	4020
Japan	N225	Yahoo	1.4.2000	12.29.2017	4418
Jordan	Amman	Investing	11.9.2009	12.31.2017	4220
Kazakhstan	KASE	Investing	8.26.2014	2.6.2019	1085
Kenya	NSE25	Investing	2.9.2012	12.29.2017	1491
Kuwait	Premier Market	Investing	5.25.2010	2.5.2019	2175
Latvia	Riga General	Investing	8.30.2004	2.5.2019	3579
Lebanon	BLOM	Investing	1.3.2000	12.29.2017	4196
Malaysia	KLCI	Investing	5.20.2010	12.29.2017	1889
Mexico	MXX	Yahoo	1.3.2002	12.29.2017	4512
Morocco	Casablanca MASI	Investing	1.3.2002	12.29.2017	3993
Netherlands	AEX	Investing	9.1.1999	2.5.2019	4966
New Zealand	NZ50	Yahoo	1.2.2003	12.28.2017	3685
Nigeria	JSEM	Investing	1.30.1900	2.4.2019	1737
Norway	OSEBX	Investing	3.2.2001	12.29.2017	4226
Oman	MSM30	Investing	12.21.2000	1.1.2018	4228
Pakistan	KSE100	Investing	1.3.2000	1.1.2018	4445
Peru	S&P BVL	Yahoo	1.3.2000	12.29.2017	4362
Philippines	PSEIPS	Yahoo	1.3.2000	12.29.2017	4511
Poland	WIG20	Investing	2.23.2001	12.29.2017	4224
Portugal	PSI20	Investing	5.25.2010	2.5.2019	2232
Qatar	QE	Investing	3.14.2001	12.31.2017	4228
Romania	BET	Investing	5.17.2010	12.29.2017	1923
Russia	MOEX	Investing	1.5.2000	12.29.2017	4498
Saudi Arabia	TADAWUL TASI	Investing	1.12.2000	1.1.2018	4795
Serbia	BELEX 15	Investing	12.24.2012	2.5.2019	1541

(*continued*)

Table 2.
List of stock market data

Country	Market index	Source	Start	End	Data size
Singapore	STI	Yahoo	11.23.2000	1.2.2018	4340
Slovakia	SAX	Investing	8.15.2011	2.4.2019	1860
Slovenia	BLUE CHIP SBITOP	Investing	4.5.2006	2.5.2019	3201
South Africa	FTSE JSET40	Investing	1.13.2000	2.13.2018	4530
South Korea	KOSPI	Yahoo	1.4.2000	1.2.2018	4438
Spain	IBEX35	Yahoo	1.3.2000	12.29.2017	4568
Sri Lanka	JSE	Yahoo	1.3.2000	12.29.2017	4305
Sweden	OMX	Yahoo	12.31.1999	12.29.2017	4585
Switzerland	SSMI	Yahoo	12.31.1999	12.29.2017	4591
Taiwan	TWII	Yahoo	1.4.2000	12.29.2017	4436
Thailand	SET	Investing	3.18.2011	12.29.2017	1658
Tunisia	TUN INDEX	Investing	3.2.2009	2.5.2019	2467
Turkey	XU100	Yahoo	1.3.2000	12.29.2017	4471
Ukraine	UX	Investing	1.9.2008	12.28.2017	2456
United Arab Emirates	ADX GENERAL	Investing	7.2.2001	12.28.2017	4276
United Kingdom	FTSE 100	Investing	1.3.2001	12.29.2017	4292
USA	DJI	Yahoo	12.31.1999	12.29.2017	4529
Venezuela	BURSATIL	Investing	12.9.2011	2.5.2019	1715
Vietnam	HoChiMinh VNIVN	Investing	7.31.2000	12.29.2017	4194

Table 2.

Source(s): Authors' own work

employing TA indicators as inputs. There is an ongoing debate on the TA's usefulness and scientific foundations. Neely *et al.* (2014) find that technical indicators have statistically and economically significant predictive power. Plenty of papers argue that TA is at least useful in practical manner, although TA is not claimed as a scientific method in any sense. There is a much wider consensus that TA is simply a set of tools that are derived during trading history of first organized stock/commodity markets. One of the earliest notable TA efforts goes back to the first ages of organized commodity trading such as Japan's rice markets where the use of candlesticks first appeared. As the organized markets have developed and increased in number, the pioneering effort in explaining market price dynamics, namely Dow theory, and its successors, has been adopted by many traders.

When decision-making procedures of retail traders are examined, one can clearly realize that vast majority of retail traders do use TA. TA is in such a widespread adoption that its use is not limited with retail traders, but even professional traders who are managing hedge funds are also using it in their practical decision-making process or perceive it as a viable tool (Menkhoff, 2010). Informally referred as "chartism," TA still seems to be the dominating decision-making tool in financial investment. The main reason for this popularity is because the vast majority of investors and retail traders have no other way to estimate market direction or sentiment unlike institutional investors who can afford costly market researches, demand and production predictions or other research like meteorological estimates in agro-commodities case which requires very big budgets.

In this context, the question is whether these price patterns always exist in historical charts, and if they do, how could they be recognized without visual interference of a human expert arises. Furthermore, also a corresponding question stems that if these patterns are present in the price charts, whether it is possible for TA indicators to detect and exploit these patterns for determining the direction of the market. Another important aspect may be considered as the source of these patterns and their relations with TA. Patterns may be a *natural phenomenon* arising as a result of human psychology, as well as they may very well be caused by the collective actions of the market participants. In other words, patterns may be related to the actions of the traders who take decisions by the help of TA indicators, hence they do actually arise since other traders act beforehand assuming those patterns were going to arise. In other words, occurrence of those patterns is either natural or as a result of *self-fulfilling prophecy*. Determining the exact reason of occurrences of patterns is beyond the scope of the study; nonetheless, examining successfully exploitation of these patterns in practice is thought to be involved by the experiment design and the empirical models followed throughout this paper.

In this regard, during the consideration of which set of TA indicators would be an acceptable and useful input sets to machine learning models, we have followed a strategy based on the widespread usage and adoption of these indicators. Moreover, based on the idea, a concise yet inclusive approach should include TA indicators belonging to different classes of indicators which are thought to handle different aspects of a financial time series data. To this aim, different TA indicators which belong to *momentum*, *volatility* and *overlap studies* (i.e. moving average-based TA indicators) families have been included to the input set.

TA indicators selected from momentum family are RSI (Relative Strength Index) and Stochastics oscillator (Stoch %K and Stoch %D), both of which are from the most preferred indicators and are available by default in any TA analysis software. Another important class of TA indicators is volatility family of indicators from which we have included ATR (average true range) into our analysis. Finally, from the family of TA indicators called overlap studies, we have preferred to include EMA (exponential moving average) and SAR (parabolic SAR), which are highly popular and widely available. The utilized technical indicators are summarized in Table 3.

During the computation of selected TA indicators, TA-Lib [4] library and its Python programming language interface [5] have been used. Machine learning algorithms have been coded in Python and R programming languages; to be more precise only ANN has been coded in Python by using Fast Artificial Neural Network Library (FANN) [6], and for the rest "e1071" R packages [7].

4. Analysis and findings

Capital markets can be predicted to a certain extent by using some methods without human intervention (Qi, 1999). These results can be cited as evidence that markets are not weak-form efficient. Machine learning methods have become a serious competitor to classical time series estimation methods ("Box–Jenkins based approaches") in terms of being able to handle nonlinearity at different levels regardless of whether the data have certain statistical properties. In fact, in recent surveys, it is regularly claimed that machine learning techniques

Technical indicators	Parameters
Momentum Indicators	
RSI	time period: 14
Stochastics (%K, %D)	fastk_period: 5 slowk_period: 3 slowk_matype: 0 slowd_period: 3 slowd_matype: 0
Volatility indicators	
ATR	time period: 14
Overlap studies	
EMA	time period: 30
Parabolic SAR	acceleration: 0.02 maximum: 0.2

Source(s): Authors' own work

Table 3. Description of selected technical indicators

are even unrivaled at obtaining accurate results in complex time series which are extremely difficult to separate into their structural components. If the aforementioned methods can be used as a tool for predictability of markets, it is possible to compare the predictability of different markets and to obtain a measure of the efficiency of these markets. Considering the conditions which directly affect the efficiency of the markets, the transparency and governance quality might be considered as explanatory factors.

If the predictability of the markets can be measured up to a certain level, the existence of the relationship between market efficiency and the measures showing the transparency and corruption level of the environment is worth investigating; hence, it is the main motivation of this study. As the result of our analyses, it has been put forth that there is a moderate inverse, statistically significant linear relationship between CPI score and predictability.

In Table 4, the mean hit rates of sixty runs for each technique are included in the row of the relevant country. The maximum of the average hit rate values of the techniques in these rows are also included in the last column. Accordingly, MaxMHR indicates the most successful machine learning technique in predicting the relevant index. Hitrate values in italics indicate the highest one.

Since each of the indices in the study is subject to various conditions (economic, political, demographic, etc.) of the country, different market dynamics are in question. In this context, it would be useful to show the predictability of the relevant index of the average hit rate values obtained by the different techniques used in the study. For this purpose, the average accurate prediction rates obtained for each national index with seven different techniques are shown in Figure 1 via the violin plot. In Figure 1, each line consists of seven points.

On another note, comparative performances of machine learning techniques on the same data are also of interest. In Figure 2, each box-whisker plot consists of seventy-three data points. If we make a comparison over the medians, it could be seen that the relatively more successful techniques are NB, DT and LR. Although very high hit rates could be observed in auxiliary runs, these could be ruled out as outliers. In both interquartile range and median values, ANN has been found to be the weakest technique. This is thought to be due to the use of a simple feed forward neural network in a fixed architecture here.

There are studies showing that financial markets can be predicted with outstanding accuracy when ANN is hybridized with other techniques or when ANN-based deep learning algorithms such as RNN and LTSM are used (see for example Qiu and Song, 2016). However, it has been shown that the idea that financial markets can be easily predicted over simple feed forward ANN architectures is a “public hype.”

A one-sided t-test is required to demonstrate that the mean accuracy rates (π) are statistically different from the random walk (0.5). For this purpose, the p values calculated for this test and whether at least one of the p values is statistically significant ($\alpha \leq 0.05$) is given in Appendix Table A1.

In order to test the main hypothesis of this research, a correlation analysis has been held for determining the existence of a relationship between CPI score and MaxMHRs of each country. As shown in Table 5, MaxMHR and CPI score have a correlation coefficient of −0.34, which corresponds to an intermediately negative correlation.

This outcome is thought to be a fundamental finding supporting the main objective of this paper. As a further analysis, three more correlation analyses have been conducted, the first being the correlation between CPI score and MaxMaxHR. The motivation behind this analysis is to see whether there is an even stronger correlation between CPI and the most successful runs that are the highest hit rates. It can be seen from Table 5, correlation coefficient between CPI score and MaxMaxHR is −0.55 as expected. MaxMaxHR represents the highest forecast accuracy that could be achieved for a market. Therefore, it could be concluded that the highest hit rate that could be obtained for countries with a higher CPI score would be lower than those with a lower CPI score. The other two correlation analyses have

Nations	ANN	NB	RF	DT	SVM	KNN	LR	MaxMHR
Argentina MERV	0.4918	0.5126	0.5122	*0.5335*	0.5308	0.5132	0.5289	0.5335
Australia AORD	0.4945	*0.5308*	0.5142	0.5291	0.5231	0.5091	0.5302	0.5308
Austria ATX	0.5030	0.5296	0.5124	0.5263	*0.5339*	0.5068	0.5261	0.5339
Bahrain BAX	0.5103	*0.5282*	0.5276	0.5015	0.5121	0.5222	0.5207	0.5282
Belgium BEL20	0.5081	0.5206	0.5128	0.5169	0.5213	0.5012	*0.5260*	0.5260
Bosnia Herzegovina BIRS	0.5082	0.5372	0.5639	0.5576	*0.5806*	0.5364	0.5474	0.5806
Brazil BVSP	0.5024	0.5128	0.5098	0.5116	*0.5211*	0.5001	0.5103	0.5211
Bulgaria BSESOFIX	0.5123	0.5238	0.5212	0.5234	0.5112	0.5031	*0.5352*	0.5352
Canada GSPTSE	0.5069	0.5306	0.5166	*0.5386*	0.5372	0.4999	0.5369	0.5386
Chilean IPSA	0.5086	0.5221	0.5292	0.5360	0.5374	0.5040	*0.5431*	0.5431
China SSE Comp	0.4677	0.5301	0.5203	*0.5408*	0.5354	0.5102	0.5317	0.5408
Colombia COLCAP	0.4763	0.5038	0.5143	0.5075	*0.5196*	0.5060	0.5187	0.5196
Croatia Crobex ZSE	0.4983	0.5025	0.5173	*0.5189*	0.5180	0.4948	0.5130	0.5189
Czech Republic PX	0.5078	0.5180	*0.5283*	0.5056	0.5194	0.5023	0.5248	0.5283
Denmark OMX20	0.4979	0.5146	0.5172	*0.5250*	0.5189	0.5034	0.5189	0.5250
Egypt EGX30	0.5083	0.5227	0.5243	0.5271	0.5355	0.5059	*0.5370*	0.5370
Estonia Tallinn SE General	0.4917	*0.5474*	0.5242	0.5338	0.5394	0.5177	0.5453	0.5474
Finland OMX25	0.5125	0.5053	0.5099	0.5204	*0.5240*	0.4995	0.5239	0.5240
France CAC40	0.5102	0.5102	*0.5158*	0.5132	0.5138	0.5030	0.5151	0.5158
Germany DAX	0.5051	0.5165	0.5073	*0.5271*	0.5256	0.4985	0.5235	0.5271
Greece FTSEAthex25	0.5103	0.5167	0.5179	0.5242	0.5310	0.5097	*0.5328*	0.5328
Hong Kong HSI	0.5045	0.4946	0.5038	0.4990	0.5045	0.5068	*0.5089*	0.5089
Hungary BUX	0.4896	0.5089	*0.5254*	0.5111	0.5120	0.4995	0.5128	0.5254
Iceland ICEX Main	0.4977	0.5328	0.5286	0.5216	*0.5440*	0.5219	0.5396	0.5440
INDIA NIFTY50	*0.5172*	0.4948	0.5087	0.5100	0.5107	0.4949	0.5104	0.5172
Indonesia JKSE	0.5062	0.5505	0.5362	*0.5539*	0.5509	0.5095	0.5533	0.5539
Ireland ISEQ	0.5063	*0.5315*	0.5218	0.5208	0.5254	0.5132	0.5277	0.5315
Israel TA125	0.4905	0.5258	0.5063	0.5215	*0.5282*	0.5004	0.5212	0.5282
Italy FTSE MIB	0.4929	0.5143	0.5000	*0.5196*	0.5144	0.4961	0.5185	0.5196
Japan N225	*0.5267*	0.5032	0.5019	0.5100	0.4993	0.5007	0.5066	0.5267
Jordan Amman	0.4991	0.5394	0.5347	0.5338	0.5422	0.5301	*0.5428*	0.5428
Kazakhstan KASE	0.4900	0.5147	0.5332	0.5268	*0.5368*	0.5334	0.5223	0.5368
Kenya NSE25	0.5998	0.5635	0.5784	0.5662	*0.6041*	0.5519	0.6047	0.6047
Kuwait Premier Market	0.5216	0.5451	0.5292	0.5400	0.5462	0.5156	*0.5525*	0.5525
Latvia Riga General	0.5250	0.5149	0.5164	0.5227	0.5259	0.5160	*0.5328*	0.5328
Lebanon BLOM	0.5026	0.5258	0.5315	0.5271	*0.5398*	0.5296	0.5363	0.5398
Malaysia KLCI	0.4984	0.5160	*0.5293*	0.5167	0.5180	0.5099	0.5190	0.5293
Mexican MXX	0.4979	0.5259	0.5316	0.5289	*0.5388*	0.5188	0.5304	0.5388
Moroccan Casablanca MASI	0.4961	0.5416	0.5426	0.5439	*0.5534*	0.5320	0.5499	0.5534
Netherlands AEX	0.5132	*0.5218*	0.5102	0.5186	0.5172	0.4943	0.5213	0.5218
New Zealand NZ50	0.5025	0.5492	0.5323	0.5559	0.5569	0.5156	*0.5584*	0.5584
Nigeria JSEM	0.5146	*0.5604*	0.5441	0.5479	0.5501	0.5353	0.5598	0.5604
Norway OSEBX	0.5008	0.5357	0.5210	0.5386	*0.5423*	0.5179	0.5418	0.5423
Oman MSM30	0.4888	0.5597	0.5708	0.5643	0.5777	0.5483	*0.5806*	0.5806
Pakistan KSE100	0.5068	0.5529	0.5537	0.5591	*0.5656*	0.5401	0.5629	0.5656
Peru S&PBVL	0.5231	0.5491	0.5318	0.5483	*0.5599*	0.5267	0.5574	0.5599
Philippine PSEIPS	0.5050	0.5172	0.5173	0.5232	*0.5354*	0.5118	0.5281	0.5354
Poland WIG20	0.5121	0.5192	0.5079	0.5116	0.5071	0.4984	*0.5240*	0.5240
Portugal PSI20	*0.5193*	0.5043	0.5131	0.4980	0.5099	0.5037	0.5113	0.5193
Qatar QE	0.5136	0.5625	0.5515	0.5557	0.5615	0.5259	*0.5738*	0.5738
Romania BET	0.5364	0.5163	*0.5432*	0.5191	0.5131	0.5340	0.5184	0.5432
Russia MOEX	0.4863	0.5187	0.5204	0.5206	0.5293	0.5136	*0.5302*	0.5302

(*continued*)

Table 4.
Mean hit rates of each technique and MaxMHRs

Nations	ANN	NB	RF	DT	SVM	KNN	LR	MaxMHR
Saudi Arabia Tadawul TASI	0.5052	0.5426	0.5430	*0.5677*	*0.5677*	0.5329	0.5605	0.5677
Serbia Belex15	0.4873	0.5146	0.5110	0.5033	*0.5401*	0.5002	0.5193	0.5401
Singapore S68SI	0.4829	0.5577	0.5418	*0.5616*	0.5587	0.5200	0.5614	0.5616
Slovakia SAX	0.5277	0.5866	0.5638	0.5969	0.5955	0.5337	*0.6093*	0.6093
Slovenia BlueChip SBITOP	0.5016	0.5250	0.5274	0.5288	*0.5289*	0.5260	0.5251	0.5289
South Africa FTSEJSET40	0.5139	0.5199	0.5185	0.5274	*0.5312*	0.5154	0.5270	0.5312
South Korea KOSPI composite	0.5055	0.5190	0.5212	0.5260	0.5247	0.5192	*0.5331*	0.5331
Spain IBEX35	0.4967	0.5158	0.5005	*0.5207*	0.5074	0.5037	0.5162	0.5207
Sri Lanka CSE	0.5674	0.5706	0.5583	0.5730	*0.5818*	0.5386	0.5791	0.5818
Sweden OMX	0.5105	0.5114	0.5037	0.5185	*0.5220*	0.5032	0.5172	0.5220
Switzerland SSMI	0.5087	0.5251	0.5156	*0.5313*	0.5256	0.4896	0.5311	0.5313
Taiwan TWII	0.5059	0.5120	0.5155	*0.5181*	0.5177	0.5002	0.5175	0.5181
Thailand SET	0.5182	0.5309	0.5196	0.5217	0.5324	0.5078	*0.5469*	0.5469
Tunisia Tunindex	0.5521	0.5620	0.5362	0.5546	*0.5741*	0.5342	0.5682	0.5741
Turkey XU100	0.4935	0.5175	0.5158	0.5271	0.5246	0.5085	*0.5286*	0.5286
Ukraine UX	0.4978	0.5059	*0.5151*	0.5009	0.5009	0.5091	0.5145	0.5151
United Arab Emirates ADX	0.5076	0.5402	0.5329	0.5284	*0.5582*	0.5239	0.5499	0.5582
United Kingdom FTSE100	0.5084	0.5120	0.4979	0.5158	*0.5209*	0.4858	0.5204	0.5209
USA DJI	0.4943	0.5130	0.5103	*0.5267*	0.5233	0.5001	0.5248	0.5267
Venezuela Bursatil	0.5332	0.6159	0.6429	0.6460	*0.6489*	0.6193	0.6383	0.6489
Vietnam HoChiMinh VNIVN	0.4815	*0.5505*	0.5215	0.5452	0.5488	0.5353	0.5497	0.5505

Table 4.

Source(s): Authors' own work

been held between the mentioned hit rates (MaxMHR and MaxMaxHR) and a ratio which is the average of CPI and market capitalization per GDP (MCAP.GDP.CPI).

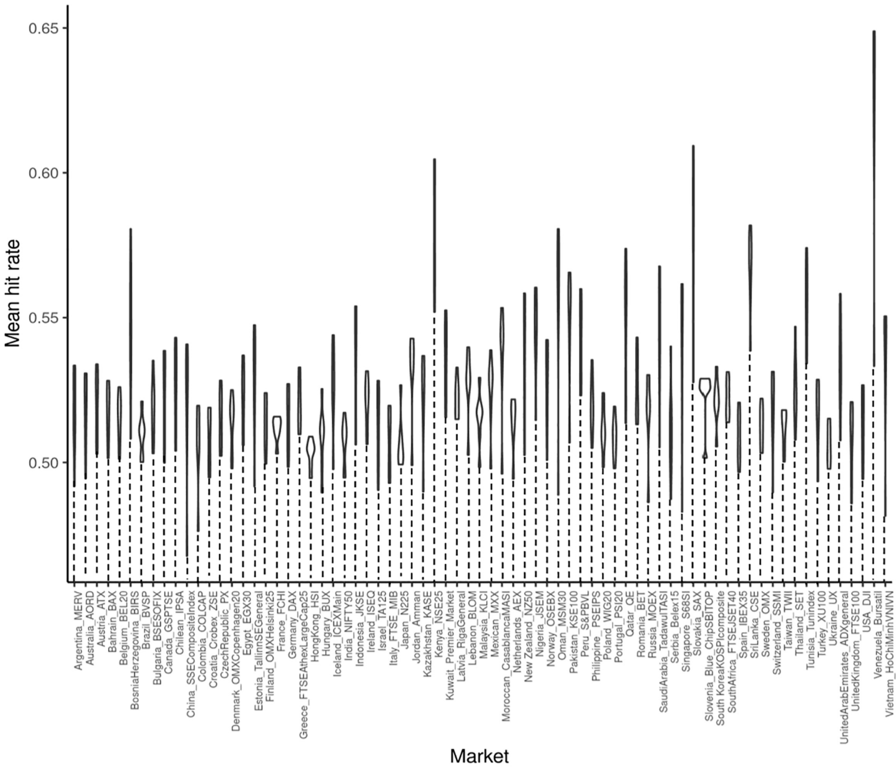
Before computing the average of CPI and market cap per GDP, these two variables have been normalized. According to outcomes of correlation analysis, an important difference has not been found compared to others.

All of the computed *t*-statistics of correlation coefficients are statistically significant, and corresponding *p*-values and confidence intervals are given in Table 6.

5. Conclusion

Stock markets may exhibit some degree of inefficiency occasionally. Market inefficiency has been tried to be revealed by researchers via proving inexistence of the weak-form efficiency. In this paper, we have examined seventy-three national stock indices predictability via seven machine learning techniques. Financial markets produce time series that are difficult to predict. The markets are directly related to the economic condition of the country in which they operate, and to the transparency and efficiency of regulatory institutions. The idea that countries with more efficient markets have more transparent and well-functioning supervisory and regulatory institutions has been tested in this research.

Contemporary approach is to predict these highly nonlinear and difficult-to-predict time series by means of several techniques which are branded under the name of umbrella term machine learning. These techniques are known to predict financial time series with higher



Note(s): Each dot represents mean hit-rate of 60 runs of a specific model on a specific market. (Vertical dotted lines have been placed on the plot for pivotal purposes.)

Source(s): Authors own work

Figure 1. Box plot showing mean hit rates market-wise

accuracy rates compared to conventional statistical time series forecasting methods. Thus, it is natural to think that the testing market efficiency can be carried out using the prediction successes of machine learning methods. Moreover, the success level of the same technique on different markets can be associated with the factors that determine the efficiency of the relevant market.

The aim of this study is to determine whether there is a relationship between weak-form market efficiency and corruption levels of seventy-three countries. Weak-form market efficiency and corruption levels have been measured by the predictability levels of the main stock indices and CPI scores, respectively. For the sake of accessibility and reproducibility, the publicly available data of these indices have been obtained from free sources for the study. The proposed empirical study employing seven fundamental machine learning algorithms has been carried out in accordance with the aforementioned experimental design. Finally, it has been statistically shown that the indices of countries with low corruption levels is harder to predict, which, in turn, can be interpreted as having higher weak-form market efficiency. According to that, there is an intermediate negative correlation found between CPI scores and predictability levels of stock indices. Considering the findings, it can be interpreted that the markets of countries with relatively more transparent and well-functioning public sector have more weak-form market efficiency. Therefore, it can be thought that the improvements

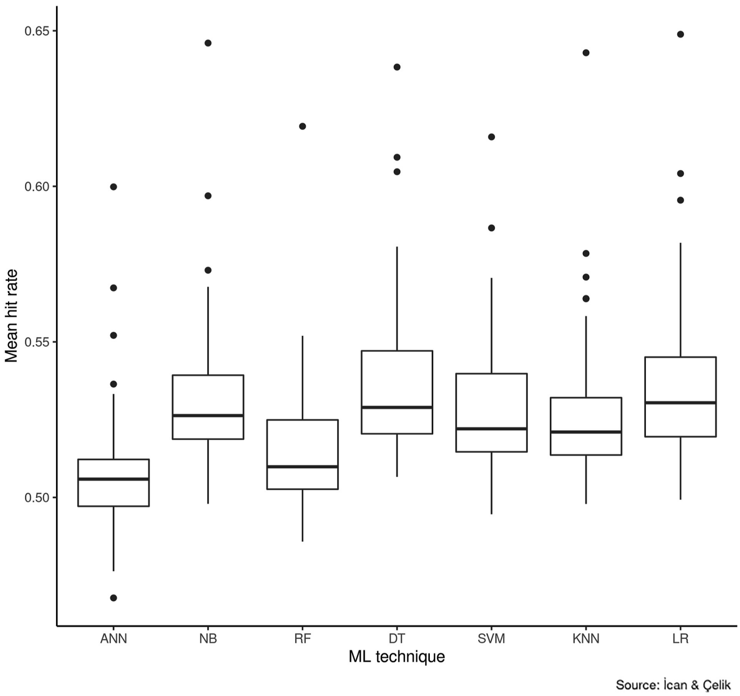


Figure 2.
Box plot showing performances of ML techniques

Note(s): Each dot represents mean hit-rate of sixty runs of a specific model on a specific market

Source(s): Authors own work

Table 5.
Correlation analysis results

	CPI Score	MCAP.GDP.CPI	MaxMHR	MaxMaxHR
CPI Score	1			
MCAP.GDP.CPI	0.80934	1		
MaxMHR	−0.34185	−0.36371	1	
MaxMaxHR	−0.55102	−0.52138	0.84441	1

Source(s): Authors' own work

Table 6.
Confidence intervals, t statistics and p values for correlation coefficients

Variables	t statistic	p value	95% confidence interval
MAXMHR and CPI score	−3.0652	0.003075	−0.5302189, −0.1213280
MAXMHR and MCAP.GDP.CPI	−3.29	0.001562	−0.5479291, −0.1458485
MAXMAXHR and CPI Score	−5.5639	4.384e−07	−0.6932090, −0.3675487
MAXMAXHR and MCAP.GDP.CPI	−5.1484	2.249e−06	−0.6709658, −0.3310230

Source(s): Authors' own work

to be made in this sense within the public sector will contribute partially, but not completely, to market efficiency.

Overall, we have developed a genuine experiment design based on machine learning algorithms' prediction abilities. We think that this approach can be extended with cutting edge machine learning and deep learning techniques in future studies. Moreover, although there is a vast literature concerning market efficiency, we have come across very few studies which try to explain factors relate to market efficiency. Thus, we claim that there is still room for further research in order to determine the factors related to market efficiency, implying that current literature is still far from explaining the causation behind the inefficiencies.

Notes

1. https://www.transparency.org/en/the-organisation
2. Suppose you toss a fair coin each time before market price movement to predict the direction. If heads shows up, you predict the direction of the next price movement as upward, and otherwise downward. Let $P(upwad)$ and $P(downward)$ be the probabilities of upward and downward movements, respectively. Then $P(true\ prediction) = P(upwad)0.5 + P(downward)0.5 = 0.5$.
3. https://www.transparency.org/en/cpi/2018
4. https://www.ta-lib.org/
5. https://mrjbq7.github.io/ta-lib/
6. https://github.com/libfann
7. https://cran.r-project.org/web/packages/e1071/index.html

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Appendix

Nations	ANN	NB	RF	DT	SVM	KNN	LR	RESULT
Argentina MERV	0.6864	0.2283	0.2351	*0.0239*	*0.0341*	0.2182	*0.0435*	TRUE
Australia AORD	0.6292	*0.0321*	0.1965	*0.0401*	0.0826	0.2919	*0.0347*	TRUE
Austria ATX	0.4301	0.0390	0.2300	0.0587	0.0218	0.3428	0.0600	TRUE
Bahrain BAX	0.3460	0.1381	0.1435	0.4773	0.3204	0.1961	0.2123	FALSE
Belgium BEL20	0.3052	0.0965	0.2100	0.1437	0.0893	0.4696	0.0505	FALSE
Bosnia Herzegovina BIRS	0.3885	0.0986	0.0133	0.0228	0.0026	0.1034	0.0502	TRUE
Brazil BVSP	0.4441	0.2236	0.2788	0.2453	0.1050	0.4969	0.2695	FALSE
Bulgaria BSESOFIX	0.3187	0.1819	0.2090	0.1857	0.3341	0.4527	0.0895	FALSE
Canada GSPTSE	0.3385	0.0330	0.1592	0.0102	0.0126	0.5027	0.0132	TRUE
Chilean IPSA	0.3149	0.1072	0.0499	0.0213	0.0177	0.4109	0.0076	TRUE
China SSEComp	0.9731	0.0364	0.1124	0.0074	0.0174	0.2719	0.0290	TRUE
Colombia COLCAP	0.7966	0.4475	0.3089	0.3960	0.2463	0.4175	0.2560	FALSE
Croatia Crobex ZSE	0.5312	0.4525	0.2081	0.1869	0.1985	0.5960	0.2700	FALSE
CzechRepublic PX	0.3860	0.2511	0.1459	0.4171	0.2349	0.4665	0.1774	FALSE
Denmark OMX20	0.5490	0.1911	0.1523	0.0674	0.1289	0.4204	0.1293	FALSE
Egypt EGX30	0.3761	0.1940	0.1776	0.1509	0.0881	0.4105	0.0795	FALSE
Estonia TallinnSEGeneral	0.6856	0.0029	0.0792	0.0246	0.0109	0.1521	0.0042	TRUE
Finland OMX25	0.2335	0.3781	0.2831	0.1183	0.0818	0.5110	0.0822	FALSE
France CAC40	0.2691	0.2690	0.1696	0.2127	0.2017	0.4273	0.1807	FALSE
Germany DAX	0.3785	0.1593	0.3296	0.0511	0.0614	0.5366	0.0785	FALSE
Greece FTSEAthex25	0.2697	0.1601	0.1431	0.0750	0.0322	0.2814	0.0253	TRUE
HongKong HSI	0.3940	0.6256	0.4098	0.5228	0.3946	0.3437	0.2983	FALSE
Hungary BUX	0.6480	0.3730	0.1768	0.3423	0.3310	0.5073	0.3198	FALSE
Iceland ICEXMain	0.5556	0.0250	0.0435	0.0979	0.0043	0.0953	0.0090	TRUE
INDIA NIFTY50	0.2217	0.5923	0.3491	0.3283	0.3160	0.5906	0.3208	FALSE
Indonesia JKSE	0.3588	0.0015	0.0166	0.0008	0.0014	0.2891	0.0009	TRUE
Ireland ISEQ	0.3351	0.5022	0.0747	0.2865	0.3375	0.1800	0.2047	FALSE
Israel TA125	0.7135	0.0634	0.3547	0.1014	0.0472	0.4906	0.1040	TRUE
Italy FTSE MIB	0.6558	0.2095	0.5009	0.1339	0.2082	0.5865	0.1479	FALSE
Japan N225	0.0568	0.4250	0.4552	0.2768	0.5166	0.4834	0.3476	FALSE
Jordan Amman	0.5216	0.0113	0.0221	0.0253	0.0073	0.0405	0.0066	TRUE
Kazakhstan KASE	0.6148	0.3348	0.1676	0.2183	0.1425	0.1659	0.2588	FALSE
Kenya NSE25	0.0003	0.0148	0.0036	0.0118	0.0002	0.0377	0.0002	TRUE
Kuwait Premier Market	0.1856	0.0308	0.1134	0.0487	0.0277	0.2594	0.0148	TRUE
Latvia RigaGeneral	0.0910	0.2131	0.1906	0.1137	0.0834	0.1964	0.0403	TRUE
Lebanon BLOM	0.4538	0.1261	0.0804	0.1145	0.0385	0.0940	0.0535	TRUE
Malaysia KLCI	0.5242	0.2686	0.1295	0.2601	0.2436	0.3519	0.2318	FALSE
Mexican MXX	0.5502	0.0606	0.0293	0.0415	0.0101	0.1300	0.0343	TRUE
Moroccan CasablancaMASI	0.5869	0.0096	0.0082	0.0067	0.0013	0.0359	0.0025	TRUE
Netherlands AEX	0.2040	0.0854	0.2600	0.1217	0.1395	0.6389	0.0905	FALSE
New Zealand NZ50	0.4454	0.0039	0.0404	0.0013	0.0010	0.1992	0.0008	TRUE
Nigeria JSEM	0.2945	0.0127	0.0515	0.0382	0.0319	0.0959	0.0135	TRUE
Norway OSEBX	0.4807	0.0193	0.1116	0.0127	0.0071	0.1492	0.0077	TRUE
Oman MSM30	0.7418	0.0003	0.0000	0.0001	0.0000	0.0026	0.0000	TRUE
Pakistan KSE100	0.3420	0.0008	0.0007	0.0002	0.0000	0.0085	0.0001	TRUE
Peru S&PBVL	0.0867	0.0019	0.0304	0.0022	0.0002	0.0577	0.0004	TRUE
Philippine PSEIPS	0.3824	0.1508	0.1506	0.0824	0.0170	0.2400	0.0463	TRUE
Poland WIG20	0.2419	0.1331	0.3243	0.2508	0.3406	0.5380	0.0822	FALSE
Portugal PSI20	0.2085	0.4282	0.2914	0.5342	0.3393	0.4382	0.3181	FALSE
Qatar QE	0.2159	0.0001	0.0014	0.0006	0.0002	0.0666	0.0000	TRUE

(*continued*)

Table A1. $p-values$ for $H_1: \pi > 0.5$ and whether at least one tech significantly predicts

Nations	ANN	NB	RF	DT	SVM	KNN	LR	RESULT
Romania BET	0.0780	0.2632	0.0464	0.2281	0.3045	0.0928	0.2365	TRUE
Russia MOEX	0.7741	0.1528	0.1322	0.1294	0.0542	0.2281	0.0491	TRUE
Saudi Arabia TadawulTASI	0.3740	0.0043	0.0040	0.0000	0.0000	0.0212	0.0001	TRUE
Serbia Belex15	0.6704	0.3060	0.3504	0.4549	0.0815	0.4969	0.2506	FALSE
Singapore S68SI	0.8425	0.0004	0.0071	0.0001	0.0003	0.1206	0.0002	TRUE
Slovakia SAX	0.1450	0.0005	0.0073	0.0001	0.0001	0.0989	0.0000	TRUE
Slovenia BlueChipSBITOP	0.4687	0.1038	0.0833	0.0736	0.0725	0.0953	0.1031	FALSE
South Africa FTSEJSET40	0.2198	0.1337	0.1514	0.0629	0.0407	0.1958	0.0659	TRUE
South Korea KOSPIcomposite	0.3721	0.1301	0.1045	0.0609	0.0711	0.1273	0.0248	TRUE
Spain IBEX35	0.5795	0.1702	0.4885	0.1060	0.3285	0.4106	0.1643	FALSE
Sri Lanka CSE	0.0000	0.0000	0.0003	0.0000	0.0000	0.0121	0.0000	TRUE
Sweden OMX	0.2623	0.2464	0.4113	0.1321	0.0916	0.4225	0.1499	FALSE
Switzerland SSMI	0.2992	0.0644	0.1728	0.0291	0.0610	0.7350	0.0299	TRUE
Taiwan TWII	0.3635	0.2385	0.1781	0.1416	0.1465	0.4942	0.1491	FALSE
Thailand SET	0.2560	0.1321	0.2397	0.2167	0.1213	0.3885	0.0453	TRUE
Tunisia Tunindex	0.0107	0.0031	0.0550	0.0079	0.0005	0.0655	0.0013	TRUE
Turkey XU100	0.6519	0.1479	0.1733	0.0533	0.0711	0.3055	0.0440	TRUE
Ukraine UX	0.5362	0.4040	0.2663	0.4845	0.4851	0.3535	0.2748	FALSE
United Arab Emirates ADX	0.3530	0.0231	0.0514	0.0796	0.0019	0.1176	0.0066	TRUE
United Kingdom FTSE100	0.3122	0.2422	0.5482	0.1785	0.1114	0.7963	0.1162	FALSE
USA DJI	0.6346	0.2174	0.2674	0.0546	0.0812	0.4978	0.0683	FALSE
Venezuela Bursatil	0.1112	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	TRUE
Vietnam HoChiMinhVNIVN	0.8398	0.0033	0.1241	0.0075	0.0043	0.0289	0.0037	TRUE

Table A1.

Source(s): Authors' own work

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