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Financial Time Series: How Predictable are they?

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ABSTRACT

The goal of stock market forecasts is to predict how the stock value of a financial exchange will change in the future. Interest rates, politics, economic growth and many other factors affect the stock prediction. More accurate predictions lead investors to make more profit. Making decisions depends on the ability of foreseeing the stock market changes, consequently, digging out the role of randomness in financial time series behaviour and quantifying how predictable are financial time series is of great interest. This paper explores the limits of predictability on return's dynamics using different stock markets. To determine the theoretical maximum prediction Π_{max} accuracy for the returns, we solve a limited case of the Fano inequality while taking in consideration some previous studies suggestion to avoid an incorrect and overestimated results of 81%. The findings of this study showed that returns predictability could reach 66% by measuring the entropy of four major American and Chinese indices namely Nasdaq 100, S&P 500, SSE and SZSE 500.

KEYWORDS: *stock market, stock prediction, financial time series, predictability, returns*

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1. INTRODUCTION

There is considerable interest in stock return predictability. The literature, which has taken two strands, reflects the subject's appeal in terms of both practical and theoretical implications [1]. Some of these papers deals with the theoretical issues surrounding testing for stock market returns predictability [2, 3, 4, 5]. While other researches focus on the importance of stock return predictability to the economy [6, 7, 8]. There is a growing consensus from in-sample studies that there is a strong predictable component to stock returns [9]. Although there is significant evidence of in-sample predictability, several widely used predictors do not consistently produce out-of-sample predictability [7]. Significant improvement of the out-of-sample predictability has been demonstrated and supported by imposing theoretically grounded limits on forecasting regressions [10]. Additionally, a straightforward forecast using the mean of all economic factors can result in considerable out-of-sample gains [8].

Because there are so many factors that affect stock expectations, such as political events, economic conditions, and expectations among traders, predicting how the market will move is one of the most difficult tasks. Those variables and many others make the stock unstable, volatile and hence, extremely difficult to precisely anticipate [11]. The majority of researchers fundamental stimulus in the field of market prediction, is that it provides lucrative profit opportunities. Therefore, it should not come as a surprise that the predictability of stock returns is a topic on which a lot of research has been done, where many different economic factors being proposed as potential predictors. [12, 13, 14, 15]. Furthermore, a lot of studies that proposed and used different methods (such as: deep learning, neural networks…) and models to get the better possible predictions of the stock market returns [16, 17, 18, 19].

Due to the availability of sophisticated algorithms and crucial stock market information, returns forecast is becoming more accurate (on web: BBC, Bloomberg, and Yahoo Finance…). However, it's unclear how well these algorithms work in comparison to the ideal scenario. Finding out to what degree are they predictable would be interesting to know the limit of the best predictions that can be done. Accordingly, this paper investigates how predictable they are by adopting [20] analytical framework that has been extensively used different type of data and showed to be efficient [21, 22, 23, 24, 25, 26, 27, 28]. Unlike the other recent survey articles that emphasize analysing the prediction model or investigating the sources of the predictability [29, 30, 31], our aim is to explore how predictable are financial time series. Many reasons motivate this research such as the good empirical demonstrating that stock market returns are predictable based on previous returns [9].

Only monthly data serve as the basis for the study by [1]. Due to the data-frequency argument that was previously discussed, the question that emerges is whether their outcomes regarding predictability will endure when applied to a daily data collection, which contains more information than monthly data. In order to determine whether or not the results of a particular hypothesis test are reliable, it became then necessary to take into account using at least the data frequencies that are most frequently used. In our case, the returns are generally taken on daily frequencies [32, 33, 34]. According to some recent studies, daily price movements are statistically significantly less predictable than high-frequency price changes. [21]. To avoid predictability overestimation, we use daily data from four major American and Chinese indices: Nasdaq 100, S&P 500, SSE and SZSE 500.

The reminder for the paper is structured as follows: The methodology is presented in Section 2. The findings are described in Section 3, along with the study's conclusions and next research. Finlay, this paper is concluded with Section 4.

2. Methodology

Entropy is a concept that has been usually used to measure the predictability. Low entropy denotes strong certainty and information availability, while high entropy indicates low predictability. The predictability of time series can be calculated by using entropy rates, which quantify the level of uncertainty in random variables. We expanded the analytical framework suggested by SONG. Et al [20], which is closely followed in examining the predictability of other types of time series, in order to determine the role of randomness in time series behaviour and the extent to which financial time series changes are predictable. In order to obtain accurate estimates of our time series predictability, this study will take into consideration some modifications due to some imprecise descriptions in their publication, which according to [35] findings led to some overestimations.

SONG et al. [20], used the real entropy in their work, which depends on the order in which nodes were visited as well as visitation frequency. Considering a historical sequence $T = \{X_1, X_2, \dots, X_n\}$, to assess the sequence's information capacity.:

$$S = -\sum_{T' \subset T} P(T')\log_2 P(T') \dots (1)$$

where $P(T')$ identifies the probability that a subsequence T' will be found in the trajectory T.

Methods for estimating entropy can be divided into two categories:

- Maximum likelihood estimators:

These estimators cannot be used to analyze mid- and long-term relationships, which are crucial in economics and finance. As a result, these techniques are waning in popularity, hence we are not using them in this research.

- Estimators based on data compression algorithm:

Such as the estimator based on the Lempel-Zif compression (LZ) and which shows in many previous studies its usefulness and precision even for a limited sample size.

Since the direct calculation of the actual entropy takes too long, it is impractical for real-time series. One of the estimators based on the LZ estimators that has been demonstrated to have superior statistical qualities in comparison to earlier estimators based on the same technique is defined as:

$$'S^{est} = (\frac{1}{n}\sum_i \Lambda_i)^{-1}\ln(n) \dots (2)$$

Where:

n = the length of time series

Λ_i = the smallest length L at which the sequence commencing at location "i" and having length L does not appear to be a continuous series from time 1 to "$i-1$".

Example:

For time series: $T = \{0,1,1,0,0,1,0,1,0,1,1,0,0\}$,

When $i = 6$:

$\Lambda_6 = 3$

To obtain the upper limits for human mobility pattern Π_{max}, Song et al have solved the following Fano's inequality:

$\Pi \leq \Pi_{max} \dots (3)$

And Π_{max} is given by:

$$H = -[\Pi_{max}\log_2\Pi_{max} + (1-\Pi_{max})\log_2(1-\Pi_{max})] + (1-\Pi_{max})\log_2(m-1) \dots (4)$$

Where:
$$H = \lim_{n\to\infty} S(X_1, X_2, \dots, X_n) \dots (5)$$

And m indicates how many different places were seen in T

According to Xu, P et. al [35], some explanation in [20] were ambiguous for the following reasons:
- Eq. 2 doesn't explicitly provide the logarithm base.
- Determining Λ_i is a puzzle if each subsequence beginning at position "i" is a continuous subsequence of $\{X_1, X_2, \dots, X_{i-1}\}$.

To clarify the descriptions and avoid the misunderstanding, which lead to an overestimation of the predictability, it has been suggested that:
- In order to prevent the error brought on by unmatched bases, the two logarithm bases in equations 1 and 2 should be identical. To obtain S^{est} in bits, taking the logarithm bases down to base 2 has been suggested [36], hence we estimate the entropy by:

$$S^{est} = \left(\frac{1}{n}\sum_i \Lambda_i\right)^{-1} log_2(n) \dots (6)$$

- The unified explanation of Λ_i is determine by:

$$\Lambda_i = 1 + k_{(i)}^{max} \dots (7)$$

Where:
$k_{(i)}^{max}$ = length of the longest continuous sub-sequence of the sequences $\{X_1, X_2, \dots, X_{i-1}\}$ beginning at position "i".

Every sub-sequence beginning at position "i" appearing as a sub-sequence of $\{X_1, X_2, \dots, X_{i-1}\}$ in this scenario:
$$k_{(i)}^{max} = n - i + 1 \dots (8)$$

And thus:
$$\Lambda_i = n - i + 2 \dots (9)$$

This estimator demonstrated a correct and coherent comprehension of Λ_i. It has proved by many studies to perform better than any other estimator previously proposed. Indeed, it has been applied in our study.

In their research, SONG et al. [20] applied three entropy metrics to each person's movement pattern:
- Random entropy: demonstrates how predictable a user's location is if each place is visited with an equal probability.
- The temporal uncorrelated entropy: defining the variety of visitation patterns.
- The actual entropy: depends on the order in which the nodes were visited and the amount of time spent at each location, in addition to the frequency of visitation, thereby capturing the whole spatiotemporal order present in a person's mobility pattern.

The results of calculating the upper bound of predictability for both of the random entropy and the temporal uncorrelated entropies indicated that the temporal order of the visiting pattern contains a major portion of predictability and therefore they are inefficient as a tool for prediction. Therefore, we are estimating in our study the actual entropy utilizing a Lempel Ziv estimator with stronger statistical features to estimate the entropy rate [37].

Stocks with incomplete data are excluded, the log ratios between successive daily closing prices are the data points, which are transformed using the conventional method for analysing price movements:

$$r(t) = \ln\left({P_t}/{P_{t-1}}\right) \dots (10)$$

And: P_t and P_{t-1} are the prices at the instants t and $t-1$ respectively.

For the benefit of the estimators and to remove any extraneous factors from the model that might have an impact on the outcomes and conclusions drawn from the data. Those data points have been discretized into 4 different states. Previous studies have discretized their data to 4, 8 or even 16 states, in order to keep things simple and make it simpler to interpret the discrete states economically, we use 4 since it is mainly irrelevant to the outcomes. The discretization procedure is really straightforward. We have n observations of log returns which are real numbers. We sort them in ascending order and divide into 4 equal parts, each with $n/4$ observations (i.e. quartiles). So that first quartile is the $n/4$ observations with lowest values:

$$a < X_i < b$$

Where a is the lowest observation and b is the 25th percentile observation when ordered). Hence, we end up with 4 buckets and we assign values to each them. As we use discrete mathematics, it doesn't really matter what value we assign to each bucket/quantile, can be 1,2,3,4 or a, b, c, d. For the simple example, starting with time series X:
$$X = \{-0.9, 0.1, 0.3, -0.4, -0.1, -0.2, 0.7, 0.6\}$$

We assign a, b, c, d and got:
$$a = \{-0.9, -0.4\}$$

$b = \{-0.2, -0.1\}$

$c = \{0.1, 0.3\}$

$d = \{0.6, 0{,}7\}$

The discrete time series would be:

$X' = \{a, c, c, a, b, b, d, d\}$

Then we calculate the entropy of the discrete time series.

3. Data and empirical results:

3.1. Data description:

The Wind Financial Terminal platform has been used to download the data. In this work, we estimate the entropy of the following stock market exchange's daily closing price time series:

- NASDAQ 100 index, S&P 500 index.
- SSE index, SZSE 500 composite index.

Datasets for the S&P 500 (89 and 389) and Nasdaq 100 cover the period from January 5, 2010, to May 28, 2019, while those for the SSE Index and SZSE 500 composite index cover the period from January 4, 2000, to May 28, 2019. (315 and 245 stocks).

3.2. Empirical results:

For the purpose of comparison in order to get more confidence on S^{est} efficiency, we quantified the entropy rate of Y, a variable with full randomness, which finds its value in the $\{1,2,3,4\}$. Theoretical entropy is defined as follows using SHANON's entropy of such a single random variable:

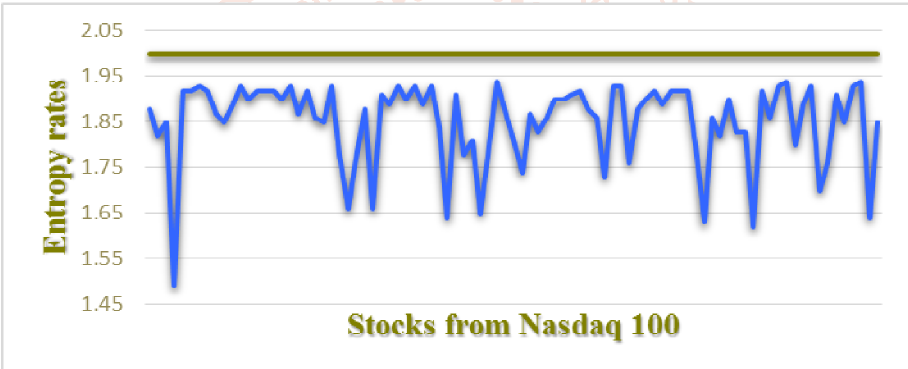
$$H(X) = -\sum_i p(x_i) log_2 p(x_i) \dots (11)$$

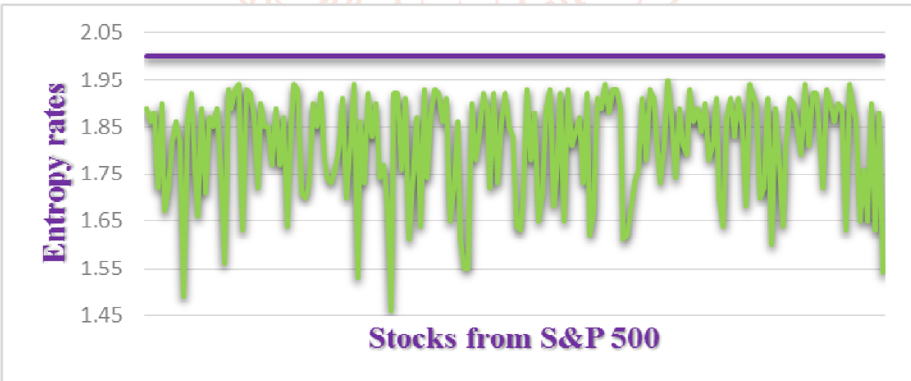
Hence:

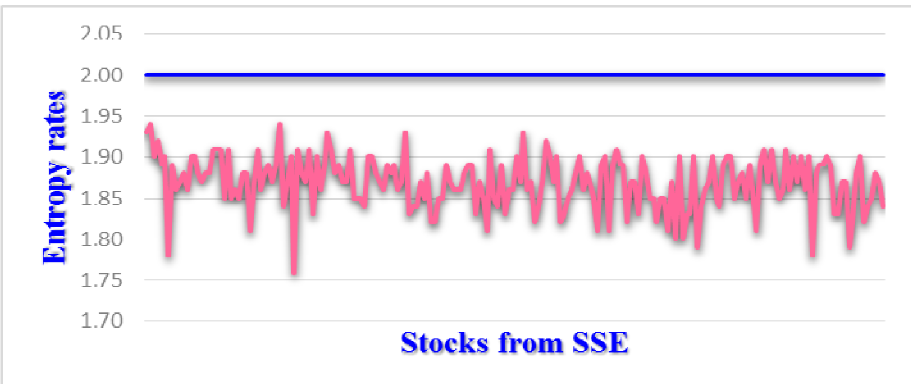
$$H(Y) = -(p(1)log_2p(1) + p(2)log_2p(2) + p(3)log_2p($$

$$= -\left(\frac{1}{4}log_2\frac{1}{4}\right) = -\left(\frac{1}{4}log_2(4^{-1})\right) = -\left(\frac{1}{4}log2^{-2}\right) = 2$$

After transforming the data in the standard way, we discretize them into 4 groups. The same number of data points are present in each group. We calculate the entropy rate for each stock before determining the upper bound of predictability.







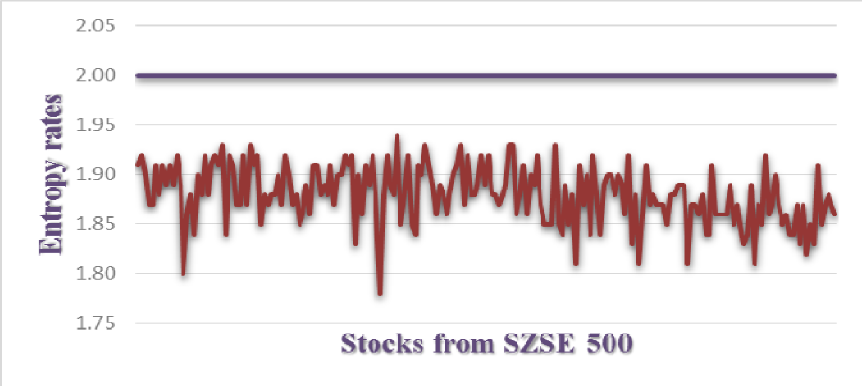


Figure 1: Entropy rates for daily returns from: Nasdaq 100, S&P 500, SSE and SZSE 500.

As shown in Fig.1, the entropy rates of the daily returns from both American stock markets (Nasdaq 100 and S&P 500) and Chinese stock markets (SSE and SZSE 500) have always been less than the theoretical entropy rates which is equal to 2. The numerical results found in this study are in the following table:

Entropy rates	Nasdaq 100	S&P 500	SSE	SZSE
Max	1,94	1,95	1,93	1,94
Min	1,49	1,46	1,73	1,78

Table 1: Max and Min of the entropy rates

These findings means that returns are not random, but also not easily predictable.

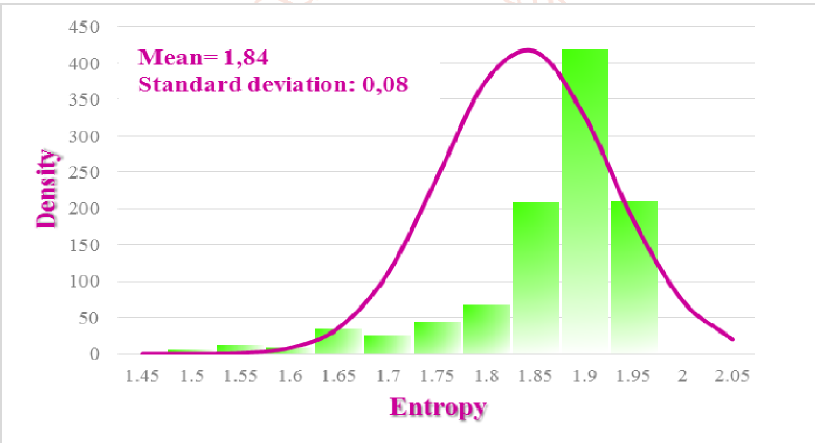


Figure 2: Distribution of the entropy rates of all the stocks

Figure 2 shows the distribution of all the stocks combined, and a normal distribution is drawn with the same mean and standard deviation. The entropy of the original time series is high since theoretical upper bound is equal to 2. As seen from both figures 1, 2 and Table 1, despite the tremendous entropy, it is clear that the time series is not random.

Matching the logarithm bases in both equations 2 and 4 by taking them to base 2 allowed as to avoid an overestimation for both predictability and its upper bound as shown in graphs 3 and 4.

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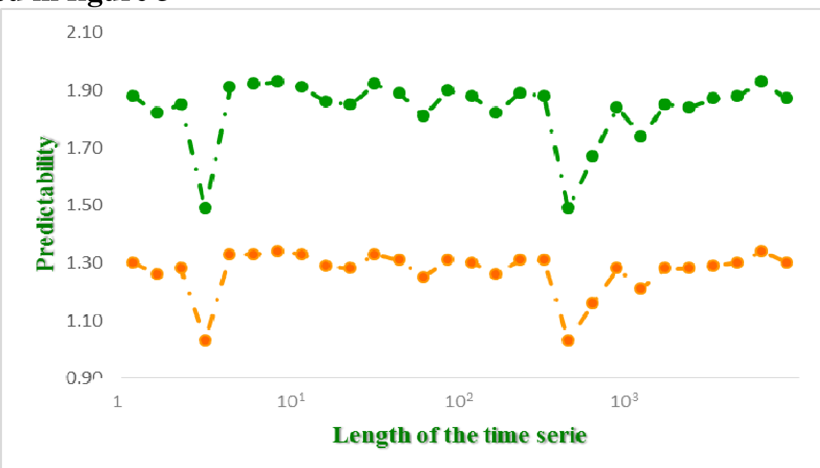

Figure 3 : The entropy rates with different logarithm bases

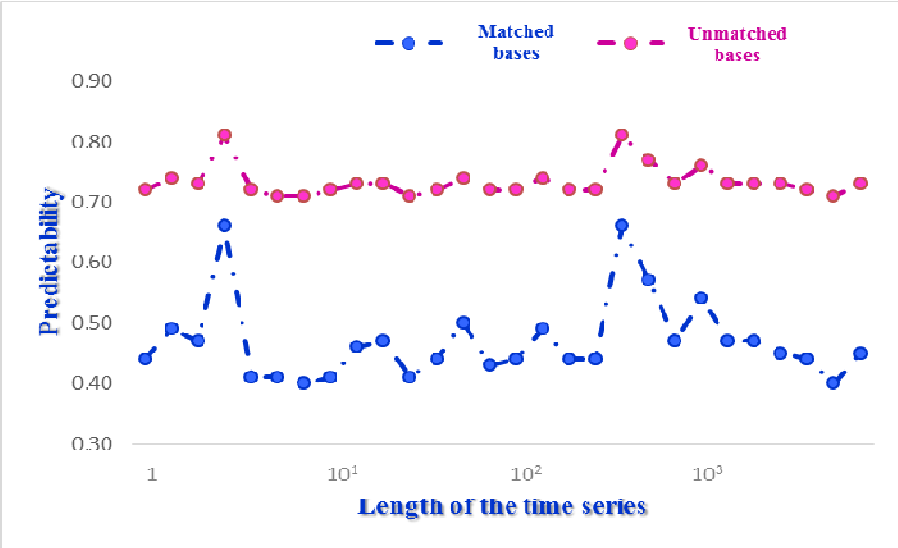

Figure 3: The predictability Π_{max} with matched and unmatched logarithm bases

The green graph in Fig.3 represents the time series predictability measured using log_2 while the orange one using log_{10}. The entropy rates are always higher when the logarithm base is taken to 2 which means it shows a lower predictability. Hence, base 10 logarithm reveal an overestimation of the entropy rates. Same conclusion can be getting from Fig.4 since it shows that Π_{max} have always been higher in the case of using log_{10}. By using log_2 we avoided the overestimation leading to incorrect results.

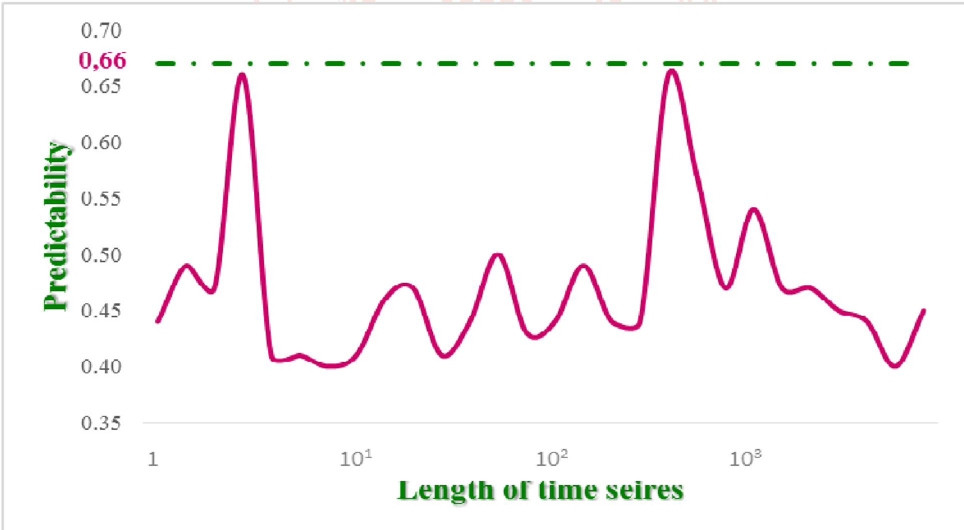

Figure 4: Changes of upper bound predictability Π_{max}

As shows Fig.5, the maximum value attained by the Π_{max} is 0,66, which means that at least 44% of time the stocks prices changed in a manner that seems random. In other terms, 66% of the time, the returns future changes can be predicted. This confirms that an overestimation of 81% obtained using unmatched logarithm bases has been avoided. Despite the apparent randomness of price changes, this bounded distribution indicates that a historical record of the daily returns' movement conceals an unexpectedly high degree of potential predictability. The results reveal a predictability of the returns, which are financial time series, but also showed that they are very difficult to be predicted accurately. The stock markets' volatility and instability, which make it difficult to predict events with precision, are caused by a variety of factors.

Conclusion:

It is crucial and of great importance to predict the return of the stock market accurately since a successful prediction of stock prices may provide alluring benefits. Usually, it plays a role in a financial trader's decision to purchase or sell an instrument. Due to the excessive number of variables that have the potential to influence stock prices, these tasks are extremely difficult and complicated. The degree of stock return predictability is a crucial and fascinating subject in economics and financial practice. Consequently, this paper aims to measure how predictable are stock market returns. By adopting an analytical framework that has been extensively used different type of data, this paper explores the limits of predictability in return's dynamic. An overestimation of this limit has been avoided, and the findings of this study present a 66% potential predictability in returns changes instead of 81% which is higher than expected because of the difficulty of the return's predictions. Further investigations ought to be performed to affirm whether this outcome is hearty and shows up on other stock market also.

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