Comparative Analysis on Effect of Accounting Data and Macroeconomic Variables in Predicting Stock Returns

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ABSTRACT

The purpose of this research is to analyze the effects of macroeconomic variables on forecasting the stock return. For this purpose, data on 121 firms accepted on the Tehran Stock Exchange during the years 2012 to 2021 have been analyzed using regression model of data with different frequencies (MIDAS), and the relationship between forecasting future performance of stock returns and macroeconomic variables are investigated. The results show that the variables of firm size, intangibles assets, Tobin's Q, financial leverage, and market to book value ratio have a significant effect in explaining the returns of firms' stock. The findings show the special attention of investors and creditors to accounting and economic criteria in explaining stock returns, and the continuation of such trend can lead to an increase in the efficiency of the capital market.

Keywords:

Stock Returns, Accounting Data, Macroeconomic Variables, Midas

1. Introduction

Predicting the future is one of the most important challenges for humans and they have tried to prepare themselves to face the conditions that will arise in the future. The necessity and attention to the future issues and their prediction, which have long been discussed in the financial markets, and with the increasing expansion and complexity of these markets they have gained significant importance, in a way that the managers of investment firms in such markets are seeking to use the latest scientific tools to analyze the financial markets. Among the financial markets, the capital market is affected not only by the national economy, but also by the global economy (Abbar, 2011).

In the stock market, forecasting stock returns is very important in financial empirical studies and it is considered as an economic concept in investment strategies and decisions. In addition, it is one of the fundamental concepts of market efficiency, which will estimate the unknown values of future. Although the forecasting of stock return may represent the results of the forecast, it does not contain any information about the degree of inherent uncertainty or associated volatility. For this reason, it may be said that comparing the forecast is only considered as a limited value related to the evaluation of forecast capabilities. As Chatfield (1993) and Christoffersen (1998) stated, interval forecasts are more valuable for decision makers, because it allows them to evaluate the forecasting ability fully and meaningfully (Pan and Politis, 2016). As the interest of stock buyers and sellers depends on the market trend and the market trend is associated with the international economy, internal factors and other factors, therefore, the prediction of stock returns is very complicated task or it is unpredictable.

Stock returns can be better analyzed through changes in stock prices. Changes in stock returns can easily be used to draw conclusions about stock prices. However, forecasting stock returns has been interested many researchers for many years, because stock returns are affected by many variables and predicting it is not an easy task (Westraland and Narayan, 2012).

In recent years, many effective factors have been proposed that helped in predicting stock returns. In this way, the researchers and practitioners in the fields of decision-making and forecasting have been seeking to identify the variables that affect the outcome of decision and forecasting. Therefore, if it is possible to predict stock returns using some variables and develop the models for it, the more reliable conditions will be created in the capital market, allowing the development of investment and the optimal allocation of the invested funds in the financial markets.

As many comprehensive research has been conducted so far on the use of macro structural models to predict stock returns by considering the role of economic variables, identifying and introducing the variables used in the models can help the decision making on investment and policy making. Therefore, forecasting stock returns is considered as one of the most important investment decisions in the stock market, which has been made through various models in the investment industry. One reason for using these models is the development of financial economics (Rahnami Roodpashti, 2014). Considering that the investors should be prepared to deal with adverse fluctuations in the expected returns, then, long-term forecasting of financial returns plays a critical role in portfolio allocation (Cales et al., 2013).

This research aims to develop a model for forecasting stock returns based on accounting data and macroeconomic. In order to achieve this goal, the mixed data sampling at different frequencies (MIDAS) as well as seasonal and monthly time series data between 2012 and 2021 are used.

Research background

Yousefi Tazarjan et al. (2021) studied stock price forecasting in the Stock Exchange using a hybrid model based on recurrent neural network, adaptive neuro-fuzzy inference system**,** and fuzzy expert system. Their study proposes an adaptive neural-fuzzy approach to predict the stock price for next day in Isfahan Mobarakeh Steel Company stock data. Four technical indicators are used as input to the system, including moving average, exponential moving average, relative strength index, and moving average of convergence-divergence. The output of this system predicts the price of Isfahan Mobarake Steel Company stock for next day.

Ebrahimian et al. (2021) studied the prediction of the daily trend of stock prices using sentiment text mining of social network users and data mining of technical indicators. In their research, for the first time, a model with 72.08% accuracy was developed to predict the direction of the stock movement and predicted the short-term trend of stock. by analyzing the sentiments of users' comments and combining it with 20 technical indicators, using three data mining algorithms of decision tree, Naïve Bayes and support vector machine. The results suggested that the support vector machine had a better performance than the other algorithms. Moreover, it found that the next day trading volume and the number of comments had a significant correlation, and the results of the Granger causality test showed that the aggregation of daily sentiments of users could be used to predict the stock price.

Zeinali and Yazdanian (2021) studied the stock return prediction based on kernel distribution and mixture of normal distributions. The results showed that both mixture of normal distributions and kernel approximation could provide favorable predictions for 5-day stock returns through quartiles 90% of return distribution. Comparison of the accuracy in these two methods showed that the kernel approximation as a non-parametric method of return prediction had a higher accuracy compared to the mixture of normal distributions.

Tabatabai Nasab and Shah Moradi (2021) studied the effect of economic uncertainty on the dynamic relationship between profit quality and return in the listed firms on the Tehran Stock Exchange, using the approach of exchange market pressure. The results indicate a positive dynamic relationship between profit quality and stock returns. In addition, currency crises have a negative and significant relationship with returns, and at the time of crisis, the effect of profit quality on stock returns decreases.

Adham et al. (2021) compared the explanatory power of linear and non-linear models in order to predict the expected returns of stocks. The results suggest that among the linear models, the coefficients of market variables, size and value in Carhart Model are higher than the coefficients of other models. The results of the estimation of non-linear models indicate that threshold self-explanatory models have higher coefficients than logistic smooth transition models. Moreover, using the homogeneity test of comparing means have shown that the least standard error of means is resulted from the threshold non-linear self-explanatory model based on trading volume, indicating that this model is more accurate in explaining stock returns. The results of the Carhart Model test indicate that the variable coefficient of the market factor is 2.1 and it is statistically significant. In other words, for one unit change in the market factor, the excess return of stocks will change by 2.1 in the direct direction. Therefore, the higher the mean of market return relative to the risk-free return as a measure of market factor, the higher the excess return of the stock. The results of the estimation of non-linear models also show that threshold self-explanatory models have higher coefficients than logistic smooth transition models. Thus, in the threshold self explanatory model, the lag of stock return and the lag of transactions turnover ratio have a higher threshold.

MirArab Baigi (2020) studied the theory of popularity in the financial market of Iran and its relationship with the volatility of stock returns and stock returns in the Tehran Stock Exchange. The results of the research show that the popularity of stocks has a positive and significant relationship with stock returns, stock volatility and beta coefficient of firms. In other words, stock popularity can increase stock returns, stock volatility, and beta coefficient.

Zhang and Zhao (2021) investigated 'forecasting stock returns of Chinese oil companies: Can investor attention help?' and their empirical results indicate that investor attention helps in forecasting stock returns and its ability to predict the US and Hong Kong markets is stronger than its ability to predict the Chinese A-share market. For the US and Hong Kong markets, the investor's attention-oriented forecasting models improve the accuracy by 35% compared to the benchmark model. However, for the A-share market, the new forecasting models are only better when it is one month ahead. In addition, this paper confirms that investor attention has economic value and can help mean-variance investors to obtain returns with more certainty equivalent return.

Abdullah (2020) evaluated the impact of economic uncertainty in the United States on the returns and stock market prices of oil-rich firms in the Persian Gulf region. This study examined the oil-rich countries, including Saudi Arabia, Qatar, UAE, Kuwait, Bahrain, and Oman, and used the Granger causality test to evaluate the effects of uncertainty. The findings show that stock prices are affected by economic uncertainty in the US, but how this uncertainty affect each country is not the same. The analysis of vector auto-regression model also shows the negative impact of economic uncertainty shock on stock prices.

Bagirov and Mateus (2019) investigated the relationship between oil prices, stock market and financial performance of European oil and gas companies. they used the VAR (1), GARCH (1,1) model during the period from 2005 to 2014, and showed that in most cases, the reaction of stock markets to changes in crude oil prices is different in each sector.

Innovation and significance of the study

One essential issue that has always attracted the attention of investors and financial analysts is the selection and evaluation criteria of investors when choosing firms' stocks. It seems that from the point of view of investors, the amount of increase in wealth is important either through the increase in the price and value of the company or through the cash profit. Therefore, stock returns are likely the important criterion in the financial decisions of many investors.

On the other hand, a review of literature suggests that the factors related to six groups, including financial statements (Yao et al., 2011), disclosure quality (Mouseli & Hosseini, 2009), corporate governance mechanisms (Lee and Lin, 2010); audit quality (Bugeja, 2011); stock market characteristics (Lischewski, & Voronkova, 2012); and macroeconomic factors (Izedonmi & Abdullahi, 2011) affect the stock returns and investors' decisions. It is so important that the Securities and Exchange Organization has started to issue guidelines such as the executive guidelines for information disclosure of the firms registered with the organization (2007), guidelines for certified auditing institutions in the Securities and Exchange Organization (2013), internal control guidelines (2013) and corporate governance guideline (in the pre-approval stage) in order to protect the rights of investors and to organize and develop a transparent and fair securities market (information system for issuers of the Securities and Exchange Organization).

The main question of this research is whether it is possible to predict the stock returns effectively using accounting data and combining them with economic information based on data analysis methods (Midas regression and GMM)?

Research methodology

Forecasting methods are divided into two main groups, qualitative methods and quantitative methods, based on the degree of dependence on mathematical and statistical methods. In quantitative methods that are completely mathematical, data related to the past are analyzed with the aim of predicting the future value of the desired variable. In general, quantitative forecasting methods can be divided into regression and non-regression categories. The regression methods include the Midas process, which is a widely used regression. In this research, this method is used to address the question that whether accounting data and macroeconomic factors has an effect on the prediction of stock returns or not. Therefore, with regard to the different stages of the research, the current research methodology is an analytical-inferential method.

The statistical population of this research consists of all the accepted firms on the Tehran Stock Exchange. The research period spans from 2012 to 2021. In this research, a sample of 121 firms was selected based on the following criteria:

a) As the research period is from 2012 to 2021, the firm must have been accepted on the Stock Exchange before 2012 and its name has not been removed from the list of accepted firms until the end of 2020;

b) In order to increase the power of comparison and data assimilation related to the selected companies, the financial year of the firms must end at the end of March every year;

c) Due to the lack of clarity in the boundaries between operational activities and financing in financial firms (investment, and financial intermediary firms, banks, financial institutions and insurance firms, etc.), these firms have been excluded from the research.

Mixed data method with different frequencies (MIDAS)

In the traditional method of time series modeling to predict economic variables, all the variables of the model necessarily have the same frequency. For example, if the dependent variable is seasonal, the explanatory variables must be seasonal too.

As such, when there are annual, seasonal and monthly variables in a regression model, it is not possible to estimate the coefficients of this regression unless the seasonal or monthly data are converted to annual data, and then the regression coefficients will be estimated. However, a technique has been invented recently that allows inclusion of variables with different frequencies in a regression and estimation of their coefficients. Such model has two major advantages. First, putting both high-frequency and low-frequency variables in a regression makes it possible to predict the dependent variable more accurately for the near future. Second, when new information is obtained about high frequency variables, it is possible to revise the previous prediction provided for the low frequency dependent variable of the model. Klein and Sojo (1989) first established development of models that can use a combination of data with different frequencies in a regression in development of structural macro-econometric models.

A method recently devised by Ghysels, Santa-Clara, and Valkanov (2004) and further extended by Ghysels, Cinco, and Valkanov is known as the "mixed data method with different frequencies" or MIDAS.

Before introducing the mixed data method with different frequency or MIDAS, we will first describe the notation of the variables that have different frequencies.

For this purpose, suppose that there are two stable time series with different frequencies, i.e. $\{Y_t\}_t$and $\{X\tau\}\tau$, where Y_t is the dependent variable and X_τ is the explanatory variable (high-frequency), t is the time unit used for the low-frequency variable, or in other words, the frequency unit of the low-frequency variable.

To make connection between two variables with t and τ frequencies, the coefficient S is supposed. This coefficient is a fraction of the time interval between t and t-1; in such a way that $m = \frac{\backslash}{s}$ determines how many times the variables of the high-frequency time series, X_τ, have been observed in this interval. Then, $t = \tau.m$, and as a result, X_τ is m times higher than the frequency of $\{Y_t\}_t$ per time unit t.

When Y_t is a function of the explanatory variable X, it is specified as follows (Bayat and Nofarasti, 2014):

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$$y_t = C_0 + \beta x_t^{(m)} + u_t$$

The weighting function, $w(j;\theta)$, which is the core of MIDAS, represents a polynomial for applying specific weights to extended intervals of X_τ.

Ghysels (2014) introduced the Midas weighting functions in the order of functions such as Almon weight function, exponential Almon weight function, and beta weighting function, and the general form of the weighting functions is defined as follows:

)2 (

$$w(j;\theta) = \frac{\varphi(j;\theta)}{\sum_{j=1}^{j\max} \varphi(j;\theta)}$$

Depending on the type of function $\varphi(j;\theta)$ as well as the maximum number of intervals (j max), the weighting function can be different from frequency to frequency and from variable to variable. This function is formed based on j and θ parameters which are the counter of intervals and a vector containing one to several θ respectively.

One of the weighting functions used in Midas is Almon function, in which the coefficient β and weights of w are estimated as a common parameter, $\beta.w_t(j;\theta)$. According to Almon equation, this weighting function is as follows:

(3)

$$\beta.w_t(j;\theta) = \sum_{j=0}^{j\max} \sum_{\rho=0}^{p} \theta_\rho . j^\rho$$

This weighting function generates different coefficients based on the different values of θ and ρ parameters, which are the orders of Almon polynomial. In Figure (1), the weights generated by Almon weight function are presented with different values of θ parameters.

In addition to the Almon weight function, Ghysels (2009) has introduced different weighting functions for

Midas, such as the exponential Almon weight function and beta weight function. The exponential Almon weight function, which has high flexibility, is written as follows:

(4)

$$w(j;\theta)=\frac{\exp\left(\theta_1 . j+\theta_2 . j^2\right)}{\sum_{j=1}^{j\max}\exp\left(\theta_1 . j+\theta_2 . j^2\right)}$$

This weighting function can generate ascending, descending or inverted U shapes for the weights. Each of these various shapes can be generated and placed in the model by selecting appropriate and different parameters. In this function, if $\theta_1=\theta_2=0$, the form of the exponential Almon weight function turns into a simple average function and applies fixed, equal weights to all intervals.

Another function that can be used for weighting is written as follows; it is called beta interval function, because it is derived from beta probability distribution function.

(5)

$$w\left(j/m,\theta_1;\theta_2\right)=\frac{F\left(j/m,\theta_1;\theta_2\right)}{\sum_{j=1}^{j\max}F\left(j/m,\theta_1;\theta_2\right)}$$

Where:

$F\left(j/m,\theta_1;\theta_2\right)=\frac{x^{a-1}(1-x)^{b-1}\Gamma(a+b)}{\Gamma(a)\Gamma(b)}$, $\Gamma(b)$، $\Gamma(a)$ and $\Gamma(a+b)$ are Gamma functions, and $\Gamma(a)=\int_0^\infty e^{-x}.x^{a-1}$, if $\theta_1=\theta_2=1$. This function will turn into a simple time average, producing equal weight for all intervals.

In parametric form, the Midas model may be considered as a linear model, but it is converted to a non-linear function by applying the weights related to wide intervals and imposing a parametric constraint function on the model. Then, according to Ghysels et al. (2004), it is necessary to use the NLS nonlinear estimation method to estimate the coefficients of the Midas model, minimizing the sum of squares of the disturbance term as follows: (Bayat and Nofarasti, 2014).

(6)

$$\hat{\theta}=\arg\min_{\theta\in R}\left(y_t-\beta\sum_{j=0}^{j\max}w(j;\theta).L^{j/m}x_t\right)^2$$

In this equation, a numerical algorithm is used to find the θ for minimization of the term inside the parentheses. By applying a cycle, this algorithm, finds an appropriate parameter for vector θ and seeks to minimize the relation $\left(y_t-\beta\sum_{j=0}^{j\,max}w(j;\theta).L^{j/m}x_t\right)^2$.

Forecasting by Midas model: One advantage of Midas model is the ability to predict the current state of the dependent variable by a term containing newly published data. As $\beta_k=\beta.w(j;\theta)$, y_t is estimated as:

(9)

$$y_t=C_0+\sum_{i=1}^{\rho}\alpha_i y_{t-i}+\sum_{k=1}^{n}\sum_{j=0}^{m-1}\beta_k x^{(s)}_{t-k-j/m}+u_t$$

And then, the following relation is used to make predictions:

$$y_t=C_0+\sum_{i=0}^{\rho-1}\alpha_i y_{t-i}+\sum_{k=1}^{n-1}\sum_{j=0}^{m-1}\beta_k x^{(s)}_{t-k-j/m}+\sum_{s=m-d+1}^{m}\gamma_s x_{t+1-\frac{s-1}{m}}+u_{t+1},\ S\rangle 0 \quad (10)$$

Where, d represents the most frequent periods for which new data are published. In the above equation, the third term refers to the past and the fourth term refers to the future. By using these equations, it is possible to predict the future values of the desired variables and to use the data published in high frequency to revise our predictions.

Forecasting evaluation criteria: in order to compare the forecasting power and choose the best forecasting method, different criteria are used, including mean squared error (MSE), root mean squared error (RMSE), mean absolute value of error (MAE) and mean percentage of absolute value of error (MAPE).

These criteria are represented in the following equations (Suri, 2012):

(11)

$$MSE = \frac{\sum_{t=T+1}^{T+m} \left(Y_t^f - Y_t\right)^2}{m}$$

(12)

$$RMSE = \sqrt{\frac{\sum_{t=T+1}^{T+m} \left(Y_t^f - Y_t\right)^2}{m}}$$

(13)

$$MAE = \frac{\sum_{t=T+1}^{T+m} \left|Y_t^f - Y_t\right|}{m}$$

(14)

$$MAPE = \frac{100 \sum_{t=T+1}^{T+m} \left|\frac{Y_t^f - Y_t}{Y_t}\right|}{m}$$

In these equations, m is the length of forecast period, (Y_t) is actual values and (Y_t^f) is the predicted values which measure the amount of predicting error. These four criteria have been used to measure the power of prediction in this study.

The Generalized Method of Moments (GMM)

Among the appropriate econometric methods to solve or reduce the problem of endogeneity of institutional indicators and the correlation between institutional variables and other explanatory variables, there is model estimation method using generalized moments of dynamic panel data. The econometric method that has been widely used in economic studies is using two-stage least squares econometric method. The requirement of using this method is to find a suitable instrumental variable to solve the problem of endogenousity of institutional variables, but this method has limitations, such as difficulty of finding a suitable instrumental variable and the limited nature of these types of variables. Also, this method cannot solve the problem of correlation between explanatory variables and reduce or eliminate collinearity in the model.

Using the generalized moments method of the dynamic data panel has the advantages of considering individual heterogeneity and other information, and removing the bias in cross-sectional regressions, which results in more accurate estimates, with higher efficiency and lower linearity in the generalized moments. The method of generalized moments of the dynamic data panel is used when the number of cross-sectional variables (N) is greater than the number of time and years (T) (N>T), which is also the case in this study, that is, the number of countries is greater than the number of times (Bond, 2002; Baltagi, 2008).

Research hypotheses

H1: forecasting models based on accounting data have the necessary power to explain stock return fluctuations.

H2: forecasting models based on macroeconomic variables have the necessary power to explain stock return fluctuations.

H3: the combined forecasting model based on accounting data and macroeconomic variables have more power to explain stock return fluctuations compared to any of two separate models.

Research variables

The total price index of the Tehran Stock Exchange is a representative of the performance of the Iranian stock market. The variables of this research are classified into two groups of accounting and economic data. Five variables are related to macroeconomic factors, including: exchange rate, oil fluctuations, economic growth, Covid-19 and inflation rate; and seven accounting variables include: stock return, market value to book value, intangible asset, price-to-earnings ratio, economic added value, Tobin’s Q ratio and firm size, which are calculated and defined in the table below.

Baker, Bloom, Davis, and Kost (2019) used a mechanized approach to quantify the role of COVID-19 and other infectious diseases in US stock market volatility. In the first step, they calculated monthly fractions of articles from 11 major US newspapers, including (a) terms related to the economy, (b) terms related to stock markets, and (c) terms related to market volatility. They rescaled the monthly series to match the mean VIX since 1985. A newspaper-based Equity Market Volatility (EMV) tracker plotted alongside the VIX itself with an entry showing recent data with a weekly frequency. They showed that the EMV tracker performs well in reflecting the time series behavior of implied stock market volatility and tracks real stock market volatility well. In the second step, they identified a subset of EMV articles that contain one or more terms related to Covid-19 or other infectious diseases. They specifically flagged EMV articles that mentioned one of the terms of epidemic, pandemic, virus, flu, disease, corona virus, MERS, SARS, Ebola, H5N1, or H1N1. By multiplying the fraction of EMV articles that contain one of these terms by the EMV tracker, they obtained the infectious disease EMV tracker.

Table 1. Research variables

Type of variable	Description	Symbol	Measurement	Reference
Variables based on indicators derived from accounting data				
Dependent	Stock return	SP	ratio of opening and closing price difference to opening price	Leo Rajan Pereira2019
Independent	market to book value	NV/BV	Market value minus book value minus total liabilities	Stewart 1991
Independent	Firm size	SIZE	the log of the firm's market value, as the product of number of shares issued by the firm times the stock price at the end of financial year	studied samples
Independent	price to earnings ratio	P/E	ratio of the average stock price during the financial period to the earnings per share	seo.ir
Independent	Intangible assets	INT	ratio of the book value of intangible asset at the end of the period to the book value of total assets at the end of the period	Leo Rajan Pereira2019
Dependent	Tobin's Q	TOBINS Q	market value to the book value of equity	Lewellen and Badrinath, 1997
Independent	Economic added value	EVA	Economic profitability or net operating profit minus the cost of capital	Brigham and Erhart, 2010
Variables based on economic data				
Independent	Exchange rate	ER	amount of the national currency that must be paid to get the currency of another country	Central bank
Independent	Inflation rate	INF	change in a price index Consumer Price Index	Central bank
Independent	Economic growth	GDP	total value of final products (in Rial) produced by economic units residing in the country in a certain period of time (annual or seasonal)	Statistics Center
Independent	Oil fluctuations	POIL	the ratio of today and yesterday price difference to yesterday price	OPEC website
Independent	Covid-19	COVID		Ssrn.com

Research findings

The findings in table 2 present the descriptive statistics of the research data.

Table 2 presents the research variables, indicating the frequency for each variable separately. The macroeconomic variables such as covid-19, economic growth, inflation rate and exchange rate were measured on monthly basis. Accounting data, including firm size, Tobin's Q, price-to-earnings ratio, intangible assets, market-to-book value, financial leverage, and economic added value were measured on annually basis. The mean return of exchange rate is equal to 0.117, indicating the percentage of fluctuations caused by the exchange rate, the increase of which will increase the risk of market. The highest and lowest values for the research sample were related to the years 2017 and 2018, respectively. The mean for oil price fluctuations is -0.020. This value indicates the percentage increase in the cost price of products produced by industrialized countries, and as a result, it causes an increase in the value of imported goods in developing countries such as Iran, because the country's budget is dependent on oil. The highest amount of fluctuation was in 2016 and the lowest amount of fluctuation was in 2013. The mean of stock return shows that 16% of the sample firms had a suitable return, the highest value was for Kalbar Dairy

Company in 2012 and the lowest value was for Mehvarsazan Company in 2015. The mean of the corona virus is a macro-economic variable, which had an mean of 269.90 for the studied sample. The mean of economic growth shows that 26% of the studied samples were affected by real variables of economic activity such as GDP. The highest value was in 2016 and the lowest value was in 2013. The mean of inflation rate and exchange rate estimated as 1.755 and 11.344, respectively. Regarding the accounting data, the highest value for the size of the firm was related to Isfahan Mobarake Steel Company in 2019 and NoushMazandaran Company in 2018. The mean of Tobin's Q variable is 2.496, indicating the value and profitability of the studied companies, which the highest value was obtained for Alumra company in 2013 and the lowest was obtained value for Chadormelo company in 2011. The highest and lowest value of price to earnings ratio in 2016 was obtained for Mehrkam Pars and Sina Chemical companies, respectively. The mean of intangible asset suggests the existence of non-physical and non-tangible assets of the studied firms. The highest value for market to book value variable was obtained for Khark Petrochemical Company in 2013 and the lowest value was obtained for Pars Khodro Company in 2018. The mean of financial leverage shows that 56% of the sample firms are in the category of risky companies. The highest amount of financial leverage was related to Combine Manufacturing Company in 2012 and the lowest amount was related to Iran Fiber Company in 2018. The mean of economic added value as one of the profitability variables is at a low level, which was the highest and lowest value in 2013 for Nasir Machine and Razi Pharmaceutical Glass companies, respectively.

Table 2. Descriptive statistics

skewness	SD	Min	Max	Median	Mean	Symbols	Variables
0/159	2/013	-35/350	26/244	0/000	0/117	PREXCHANGE	Exchange rate return
0/413	2/671	-26/347	27/140	0/000	-0.020	POIL	Oil price fluctuations
-0.311	2/770	-173/734	120/729	0/000	0/163	PSTOCK	Stock return rate
3/277	229/17	3/060	1393/080	11/410	90/269	COVID	Corona virus
-0/521	3/519	-10/594	7/572	0/614	0/264	GDPR	Economic growth
1/525	1/467	-0/346	7/050	1/426	1/755	INF	Inflation rate
-0/188	1/012	9/363	12/986	11/360	11/344	ER	Exchange rate
0/934	1/572	10/352	20/768	14/405	14/615	SIZE	Firm size
6/881	2/866	0/446	46/971	1/629	2/496	QTOBIN	Tobin's Q
15/415	310/189	-602/666	7297/00	8/318	47/620	P_E	Price to earnings ratio
6/608	195944/4	0/000	1986785	2863/0	47781/6	NTA	Intangible assets
11/199	10/952	-48/250	227/682	2/594	4/812	MTB	Market value to book value
0/362	0/216	0/012	2/077	0/564	0/560	LEV	Leverage
-0/706	0/222	-1/191	1/070	-0/003	-0/026	EVA	Economic added value

Source: Research findings

Stationary test of research variables

One of the major problems that may occur in the regression of mixed data is dummy regression, in which there is no significant relationship between variables despite the existence of high R2. In order to ensure the relationships in the regression are significant, and there is no dummy variable, stationary test and unit root test were performed on the research variables. In the unit root test, the null hypothesis indicates the existence of a unit root, and if the probability is less than 0.05, the null hypothesis will not be accepted with a probability of 95%.Table 3 presents the results of stationary tests of the variable.

The results of stationary test illustrate that most of the variables in all four methods of Levin, Lin and Chu, Im, Pesaran and Shin, generalized Fisher-Dickie Fuller, and Fisher, Phillips-Perron, are fixed and some variables are fixed at least in one method. Therefore, the results indicate that the research variables are stationary and the null hypothesis saying that variables have a unit root is not accepted. As result, the relationships in the regression are non-artificial and significant.

Table 3. The results of the stationary test

PP - Fisher Chi-square		**ADF - Fisher Chi-square**		**Im, Pesaran and Shin W-stat**		**Levin, Lin & Chu t***		**test / Variable**	
Probability	Statistic	Probability	Statistic	Probability	Statistic	Probability	Statistic		
0/000	2263/12	0/000	9108/40	0/000	-474/153	0/000	-582/308	PSTOCK	Stock return rate
0/000	2228/90	0/000	3228/90	0/000	-615/06	0/000	-732/92	PREXCHANGE	Exchange return rate
0/000	2228/90	0/000	26700/7	0/000	-293/560	0/000	-260/343	POIL	Oil fluctuations
0/000	640/483	0/000	760/139	0/000	-18/135	0/000	-22/133	COVID	Covid-19
0/000	660/24	0/000	1588/20	0/000	-32/690	0/000	-37/726	GDPR	Economic growth
0/000	21314/36	0/000	228/90	0/000	-44/16	0/000	-38/515	INF	Inflation rate
0/028	287/94	0/000	373/77	-	-	0/000	-13/577	ER	Exchange rate
0/000	325/834	0/000	322/04	0/018	-2/089	0/000	-9/091	SIZE	Firm size
0/000	553/218	0/000	468/162	0/000	-3/766	0/000	-9/74	QTOBIN	Tobin’s Q
0/000	461/30	0/000	447/70	0/000	-4/815	0/000	-10/601	P_E	Price to earnings ratio
0/008	288/737	0/000	327/39	0/000	-154/81	0/000	-731/71	NTA	Intangible assets
0/000	674/25	0/000	549/69	0/000	-6/19	0/000	-12/496	MTB	Market to book value
0/004	303/5	0/000	382/14	0/000	-4/605	0/000	-13/158	LEV	Leverage
0/000	625/41	0/000	586/96	-	-	0/000	-8/018	EVA	Economic added value

Source: Research findings

H1 test results

The results obtained from testing the first hypothesis, i.e. forecasting model based on the accounting data explains the stock returns, is presented in Table 4.

It can be seen that the values of the 95% confidence level in Table (3) indicate that most of the accounting data have an information load in explaining stock returns in the securities market. Durbin-Watson's statistic value is estimated equal to 2.098 and as it is between 1.5 and 2.5, so the lack of correlation in the remaining components of the above regression model is confirmed. The coefficient of determination shows that 51% of the resulting changes in stock returns can be explained by the significant accounting data of this model. Moreover, the informative criteria of Akiake, Schwartz and Hannan-Quinn in the accounting data-based forecasting model show that the restrictions imposed on the coefficients of the specified Midas model are statistically significant and adequate. According to Kuzin et al. (2011), the Midas regression approach is a direct forecasting tool, because it directly connects the dependent variable to the lagged and current independent variables and creates different forecasting models for each time horizon. Midas regression has the ability to place a variable with a low frequency against variables with higher frequencies in a regression without performing any of the multiplication operations. Therefore, in this research, in order to explain stock returns, variables with different frequencies were used in Midas regression. Accounting datasets that help explain the stock returns of firms include firm size, intangible assets, price-to-earnings ratio, Tobin’s Q, economic added value, financial leverage, and market-to-book value. These data were calculated on an annual basis and checked on stock returns with a three-year interval. The results of Table (4) show that at first, the dependent variable, i.e. the stock return rate with one lagging period, was fitted with the prediction of the stock return. According to the coefficient estimated for this variable and the significance level below 0.05, it can be said that this variable has a positive and significant relationship with the prediction of stock returns. Then, annual accounting data were included in the model to check whether forecasting accounting data could explain stock return or not. In addition, due to the low probability level of the t-statistic of firm size variable with an interval of three periods (0.000) from the acceptable error level (0.05), the results of the test show that the firm size, as an accounting data, has a significant relationship with the prediction of stock returns. Firm size with three lagging intervals as the predictor explains the accounting predictor of stock returns.

Table 4. Coefficients of the forecasting model based on accounting data

$$\text{Log}\,\frac{P_1}{p_0} = \beta_0 + \beta_1 \text{Size}_{i.t} + \beta_2 \text{NTA}_{i.t} + \beta_3 \text{P/E}_{i.t} + \beta_4 \text{QTobin}_{i.t} + \beta_5 \text{EVA}_{i.t} + \beta_6 \text{LEV}_{i.t} + \beta_7 \text{MTB}_{i.t} + \varepsilon_{i.t}$$

Direction	significance	t-statistics	Coefficient	Symbol	Variable
	0/691	-0/396	-0/029	C	
Positive and meaningful	0/000	58/216	0/115	PSTOCK (-1)	Stuck return rate
Annual accounting data with three interval period					
Significant	0/000	8/270	0/139	SIZE (-1)	Firm size
			0/005	SIZE (-2)	
			-0/128	SIZE (-3)	
Significant	0/009	-2/610	-0/166	NTA (-1)	Intangible assets
			-0/037	NTA (-2)	
			0/091	NTA (-3)	
No relationship	0/608	0/511	0/00001	P_E (-1)	Price to earnings ratio
			0/00004	P_E (-2)	
			0/00001	P_E (-3)	
Significant	0/000	9/500	0/018	QTOBIN (-1)	Tobins' Q
			-0/018	QTOBIN (-2)	
			0/056	QTOBIN (-3)	
No relationship	0/196	-1/292	-0/009	EVA (-1)	Economic added value
			0/0008	EVA (-2)	
			0/002	EVA (-3)	
Significant	0/017	-2/375	-0/093	LEV (-1)	Leverage
			-0/009	LEV (-2)	
			0/073	LEV (-3)	
Significant	0/000	4/418	0/002	MTB (-1)	Market to book value
			0/0005	MTB (-2)	
			-0/0001	MTB (-3)	
0/518		R-squared			
0/512		Adjusted R-squared			
2/098		Durbin-Watson			
4/951		Akaike info criterion			
4/952		Schwarz criterion			
4/952		Hannan-Quinn criterion			

Source: Research findings

Assets of big corporations can act as a factor to predict the stuck return. It results from high volume of operations and high level of profitability in these firms. In addition, due to the low probability level of the t-statistic of the intangible asset variable with an interval of three periods (0.009) from the acceptable error level (0.05), the test results show that the intangible asset has a significant relationship with the prediction of stock returns. Intangible asset with three lagged periods explains the accounting predictor of stock returns, which can be due to its non-physical and non-monetary nature. The results of testing price-to-earnings ratio variable show that the probability level of the t statistic (0.608) is higher than the accepted error level (0.05). As such, the price-to-earnings ratio variable has no significant relationship with stock return prediction. It is also true for the economic added value variable with the t-test probability level of (0.196). The t-test probability level of Tobins'Q, financial leverage and market to book value variables are lower ((0.000), (0.017) and (0.000), respectively) than the accepted error level (0.05), indicating a significant relationship with forecasting stock return. Tobin's Q that is a representative of the firm's value for investors, can explain stock returns as a predictive variable. In addition, market to book ratio, which indicates the firm’s growth opportunities, explains the stock return. Considering the financial leverage, the higher level of financial leverage indicates the firm’s risk, which does not explain stock returns as an accounting data in this research. Therefore, according to the results of the first hypothesis, it can be said that the forecasting model based on accounting data, except for the price-to-earnings ratio and the economic added value, explains the returns of stocks, however with different direction and impact on the return

H2 test results

The results of the second hypothesis, i.e. the forecasting model based on macroeconomic variables explains stock returns, are presented in Table (5).

Table 5. Coefficients of the forecasting model based on macroeconomic data

$$\text{Log}\,\frac{P_1}{p_0} = \beta_0 + \beta_1 \text{PREXCHANGE}_{i.t} + \beta_2 \text{POIL}_{i.t} + \beta_3 \text{COVID}_{i.t} + \beta_4 \text{GDPR}_{i.t} + \beta_5 \text{INF}_{i.t} + \beta_6 \text{ER}_{i.t} + \varepsilon_{i.t}$$

Direction	Significance level	t	Coefficient	Symbol	Variable
	0/515	0/605	0/048	C	
Positive and meaningful	0/000	63/739	0/114	PSTOCK (-1)	Stock return rate
Positive and meaningful	0/000	4/211	0/010	PREXCHANGE	Exchange return rate
Positive and meaningful	0/000	10/251	0/048	POIL	Oil fluctuations
Monthly economic variable with 4 lagged periods					
Positive and meaningful	0/000	11/429	0/0002	COVID (-1)	Covid-19
			0/0001	COVID (-2)	
			-/00001	COVID (-3)	
			-/00001	COVID (-4)	
Positive and meaningful	0/000	4/568	0/004	GDPR (-1)	Economic growth
			0/002	GDPR (-2)	
			-0/0008	GDPR (-3)	
			-0/003	GDPR (-4)	
Positive and meaningful	0/000	۸/۸۶۸	0/030	INF (-1)	Inflation rate
			0/013	INF (-2)	
			-0/002	INF (-3)	
			-0/018	INF (-4)	
Positive and meaningful	0/000	-۹/۴۵۶	-0/079	ER (-1)	Exchange rate
			-0/025	ER (-2)	
			0/027	ER (-3)	
			0/080	ER (-4)	
0/515		R-squared			
0/515		Adjusted R-squared			
2/008		Durbin-Watson			
4/864		Akaike info criterion			
4/865		Schwarz criterion			
4/865		Hannan-Quinn criterion			

Source: Research findings

According to the results of the second hypothesis of the research presented in Table (4), the value of Durbin-Watson test (2.008) indicates the lack of correlation in the remaining components of the regression model. The coefficient of determination in the forecasting model based on macroeconomic variables shows that 51% of the changes in stock returns can be explained by the significant economic variables of this model. In addition, Akiake, Schwartz and Hannan-Quinn tests confirm the adequacy of the coefficients of the developed model coefficients. The results of Table (4) show that at first, the dependent variable, i.e. the stock return rate with one lagging period, was fitted with the prediction of the stock return. According to the coefficient estimated for this variable and the significance level below 0.05, it can be said that this variable has a positive and significant relationship with the prediction of stock returns. Also, in relation to the economic variable of exchange rate, it can be a criterion for determining stock returns. As a major part of the country's annual budget is oil revenues, the least change in oil prices affects the variables of the stock market, which was expected to have a negative relationship between the increase in oil income and the increase in stock market indices. Due to the low probability level of the t statistic of the oil volatility variable with an interval of four periods (0.000) from the acceptable error level (0.05), the test results show that oil price fluctuations as one of the macro-economic variables have a positive and meaningful effect on the prediction of stock returns. In order to develop the model, other variables such as the impact of the Covid-19, economic growth, inflation rate, and exchange rate were included in the prediction model as the variables affecting stock returns.

Due to the low probability level of the t statistic of the Covid-19 variable with an interval of four periods (0.000) from the acceptable error level (0.05), the results show that the Covid-19, as one of the economic variables has a significant relationship with the prediction of stock returns. The Covid-19 epidemic was one of the economic and global factors that affected the economy of all countries. This unexpected variable could reduce the stock returns in the financial markets. In addition, due to the low probability level of the t-statistic of the economic growth variable with an interval of four periods (0.000) from the accepted error level (0.05), it can be said that economic growth has a significant relationship with the prediction of stock returns. One of the measures of real activities is GDP, and the increase in GDP, will increase the stock returns. In other words, an increase in real variables increases future cash flows, leading to higher dividends. Therefore, economic growth can explain stock returns. The low probability level of t statistic of inflation rate and exchange rate variables, as (0.000) and (0.000), respectively, from the accepted error level (0.05) indicates a significant relationship with stock return prediction. An unexpected increase in inflation will reduce the expected return and consequently, the demand for money. Any increase in demand for capital affects expectations for getting unrealistic profits in future. .Also, with the increase in exchange rate fluctuations, the cost of capital increases, leading to increase in expected returns and expected profits of investors. A change in normal (expected) profit leads to a change in unrealistic profit. According to the results of the second hypothesis, it can be concluded that the forecasting model based on macroeconomic variables explain stock returns, but their direction and impact on returns are different.

H3 test results

The results of the third hypothesis of the research, i.e., the combined forecasting model based on accounting data and macroeconomic variables explains stock returns, is presented in Table (6).

According to the results of the third hypothesis presented in Table (6), the value of Durbin-Watson test is (2.062), indicating lack of correlation in the remaining components of the regression model. The coefficient of determination of the combined forecasting model based on accounting data and macroeconomic variables shows that 61% of the changes in stock returns can be explained by accounting data and significant economic variables of this model. Also, the adequacy of the developed model coefficients is confirmed by Akiake, Schwartz and Hannan-Quinn tests.

According to the probability of t-statistics of variables predicting stock return rate, predicting exchange rate return and predicting oil fluctuations from the error level (0.05), the results show that these variables have a positive and significant relationship with the dependent variable. Regarding the macroeconomic variables including Covid-19, economic growth, inflation rate and exchange rate with four interval periods, the results show that these variables have significant relationships in the combined model of forecasting macroeconomic variables and accounting data. According to the probability of t-statistics of accounting data, including firm size, Tobin’s Q and market to book value with four interval period from the error level (0.05), the results show a significant relationship between these variables and the prediction of stock returns. In other words, an increase in the variables of firm size, Tobin’s Q and market to book value means an increase in profitability, firm’s value and firm growth opportunities, and these criteria can be effective in predicting stock returns. In addition, there is a significant relationship between intangible assets and stock returns. Also, the results of the third hypothesis showed that no significant relationship was found between the accounting data of price-to-earnings ratio, economic added value and financial leverage with stock returns.

Table 6. Coefficients of the combined forecasting model based on accounting data and macroeconomic variables

Direction	Significance level	t	Coefficient	Symbol	Variable
	0/000	-8/435	-1/056	C	
Positive and meaningful	0/027	61/010	0/129	PSTOCK (-1)	Stock return rate
Positive and meaningful	0/000	8/663	0/024	PREXCHANGE	Exchange return rate
Positive and meaningful	0/000	10/527	0/020	POIL	Oil fluctuations
Monthly economic variables with 4 interval periods					
meaningful	0/000	11/863	0/0003	COVID (-1)	Covid-19
			0/0001	COVID (-2)	
			-0/000004	COVID (-3)	
			-0/0001	COVID (-4)	
meaningful	0/000	6/636	0/007	GDPR (-1)	Economic growth
			0/003	GDPR (-2)	
			-0/001	GDPR (-3)	
			-0/005	GDPR (-4)	
meaningful	0/000	7/969	0/028	INF (-1)	Inflation rate
			0/010	INF (-2)	
			-0/007	INF (-3)	
			-0/025	INF (-4)	
meaningful	0/000	-6/312	-0/062	ER (-1)	Exchange rate
			-0/006	ER (-2)	
			0/049	ER (-3)	
			0/106	ER (-4)	
Annual accounting data with 4 interval periods					
meaningful	0/000	5/398	0/077	SIZE (-1)	Firm size
			0/027	SIZE (-2)	
			-0/021	SIZE (-3)	
			-0/070	SIZE (-4)	
meaningful	0/000	-4/098	-0/202	NTA (-1)	Intangible assets
			-0/086	NTA (-2)	
			0/029	NTA (-3)	
			0/144	NTA (-4)	
No relationship	0/381	-0/875	0/0000001	P_E (-1)	Price to earnings ratio
			0/00002	P_E (-2)	
			0/00004	P_E (-3)	
			0/0006	P_E (-4)	
meaningful	0/000	7/090	0/013	QTOBIN (-1)	Tobin’s Q
			-0/003	QTOBIN (-2)	
			-0/020	QTOBIN (-3)	
			-0/037	QTOBIN (-4)	
No relationship	0/082	-1/739	-0/0009	EVA (-1)	Economic added value
			0/0007	EVA (-2)	
			0/002	EVA (-3)	
			0/004	EVA (-4)	
meaningful	0/186	-1/322	-0/040	LEV (-1)	Leverage
			-0/016	LEV (-2)	
			0/007	LEV (-3)	
			0/030	LEV (-4)	
meaningful	0/003	3/603	0/002	MTB (-1)	Market to book value
			0/0009	MTB (-2)	
			-0/0001	MTB (-3)	
			-0/001	MTB (-4)	
0/625		R-squared			
0/617		Adjusted R-squared			
2/062		Durbin-Watson			
4/827		Akaike info criterion			
4/829		Schwarz criterion			
4/828		Hannan-Quinn criterion			

Source: Research findings

Conclusion

The purpose of this research is to provide a model for predicting stock returns based on accounting data and macroeconomic variables. To do so, relevant information was collected. In this research, in order to explain stock returns, variables with different frequencies were used through Midas regression method.

The results show that the variables of firm size, intangible assets, Tobin's Q, financial leverage, the market to the book value ration have a significant effect in explaining the stock returns. The economic data that helps to explain the returns of stock returns include exchange rate returns, oil fluctuations, Covid-19, economic growth, inflation rate and exchange rate.

According to the results of the first hypothesis of the research, it can be concluded that the forecasting model based on accounting data, except for the ratio of price to earnings and economic added value, explain the return of stocks, but with different direction and impact on the return.

According to the results of the second hypothesis of the research, it can be concluded that the forecasting model based on macroeconomic variables explain stock returns, but with different direction and impact on returns.

Furthermore, the results of the third hypothesis showed that no significant relationship was found between the accounting data of price-to-earnings ratio, economic added value and financial leverage with stock returns, and the prediction model based on macroeconomic variables explains the stock returns.

Overall, the results of testing the research hypotheses are consistent with the results of Pagiro and Matthew (2019) and Yousefi et al. (2021).

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