Journal of Money and Economy
Vol. 18, No. 2, Spring 2023
pp. 175-204
DOI: 10.61186/jme.18.2.175

Original Research Article

Identifying and Prioritizing Systematic Risk Indicators on the Rate of Return in Investment Companies

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Received: 28 Jan 2021 Approved: 18 Feb 2024

Existing models do not adequately capture how changes in the external environment (systematic risk) affect corporate returns. This study addresses this gap by identifying explanatory variables and an experimental model design. The sample includes 16 investment companies over two periods, 2006-1 and 2020-4. We inputted 69 systematic risk variables into the model and identified the 1-12 non-fragile variables affecting investment company weighted averages using a Bayesian model averaging approach. The findings show that the non-official hard currency exchange rate is the most robust variable influencing the Tehran Stock Exchange. Thus, stocks with the highest correlation to the foreign exchange rate should be selected when forming a portfolio. Moreover, fiscal policy variables directly impact investment company weighted average returns. Consequently, portfolios of quasi/semi-government-owned companies will see higher return fluctuations.

Keywords: Returns, Systematic Risk, Optimal Portfolio, Investment Companies, Bayesian Average
JEL Classification*:* G11, G32, C6

1 Introduction

The work of Keim and Stambaugh (1986), conditional asset pricing models that incorporate instrumental variables have been developed to predict future stock returns. These conditional models, which contain time-varying alphas or betas, provide new insights into explaining stock return patterns. Lettau and Ludvigson (2001) utilize macroeconomic variables as instrumental variables and demonstrate that conditional models exhibit greater return predictability compared to unconditional models. Moreover, Avramov and Chordia (2006)

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employ an optimal portfolio strategy derived from mean-variance theory and show that accounting for time-variation in alphas leads to superior portfolio performance, indicating that return predictability is linked to changes in alpha over time. An outstanding question is whether this return predictability stems from additional risk factors related to the time-varying alpha in conditional models or from time-variation in betas. While the variance of stock returns has been extensively analyzed, and an increasing number of studies have examined the relation between return variance and expected returns, few studies have approached this from the perspective of idiosyncratic risk.

People who invest based on economic logic expect higher returns on riskier investments than on safe ones. They anticipate investing in corporate stocks will be more profitable than buying fixed-income assets. Similarly, they expect to earn relatively higher returns by buying shares of volatile, high-yield companies rather than relatively safe companies. Undoubtedly, the stock market constitutes a vital part of a country's economy, as the largest amount of capital globally is exchanged through stock markets. Moreover, the national economy is strongly affected by the stock market. Some of the variables impacting the stock market are the financial data of economic enterprises extracted from the accounting systems of these firms. The extent of the impact of this data is complex and somewhat unclear. In fact, the wide range of explanatory variables affecting portfolio performance has raised a fundamental question among researchers: what variables should be included in empirical models of portfolio return regression? This issue is known as "model uncertainty." Failure to address model uncertainty can lead to bias and inefficiency in parameter estimates, inappropriate predictions, and incorrect statistical inference. It should, therefore, be considered in experimental studies.

"Averaging of all models" or "Bayesian model averaging" are among the methods to address the model uncertainty problem. The innovation of this paper is thus the use of Bayesian econometrics with Bayesian model averaging to overcome uncertainty in selecting variables affecting portfolio performance and rating each stock exchange share.

The remaining structure of the article is as follows: In the second part, the general theoretical framework of the research is introduced. In the third part, the research method is discussed. In the fourth section, the variables of the model are presented. The fifth part includes the estimation of the model and the analysis of the results. Finally, the conclusion is presented in the sixth section.

[DOI: 10.61186/jme.18.2.175]

2 Theoretical Foundations and Review of Research Background

The Arbitrage Pricing Theory (APT) prices equity by considering a set of systematic risk factors assumed to influence returns, following a generative multifactor model and an arbitrage argument. Empirical studies, primarily of developed markets. It have proposed various approaches to identify types of systematic risk factors for multifactor models. Classifies risk factors based on observability, dividing them into market, macroeconomic, fundamental, sector, technical, and statistical factors. Overall, empirical evidence is contradictory, both supporting and rejecting the APT, especially when using statistical factors.

The market factor approach essentially interprets the Capital Asset Pricing Model (CAPM) with one observable common factor. Both macroeconomic and fundamental models have been extensively discussed, with many papers examining predefined variable sets, procedures, and methodologies for different countries. Findings have generally been favorable for both, although no consensus exists on the factor's nature.

The macroeconomic approach seeks to identify a priori observable macroeconomic time series that proxy systematic risk factors, macroeconomic variables comprise four categories: inflation, industrial production, investor confidence, and interest rates. Conversely, the fundamental approach approximates factors using predefined financial and accounting variables reflecting exposure to unobservables like size, leverage, cash flow, price-earnings ratio (P/E), and book-to-market ratio. As with macroeconomic models, there is no agreement on the factor's nature.

The key difference is that macroeconomic models take risk premiums as given, estimating exposures, while fundamental models do the inverse. The other security-specific approaches use technical and sector variables as proxies, although little investigation has occurred. The statistical approach uncovers suitable factors through latent variable techniques like Principal Component Analysis (PCA) and Factor Analysis (FA), jointly estimating risk premiums and exposures.

Roll et al. (1980) and Hasbrouck and Saar (2001) obtained favorable results, revealing between three and five priced factors in the American stock market. Beenstock and Vergottis (1989) and Carbonell et al. (2003) for the Spanish Stock Exchange (SSE).

There is no clear supremacy of one approach over the others. Among the previous theoretical and empirical comparative studies, Maringer (2004) summarizes the advantages, disadvantages, and recommended uses of macroeconomic, fundamental, and statistical models. Teker and Varela (1998)

[DOI: 10.61186/jme.18.2.175]

show that the statistical model outperforms the macroeconomic one for the US market. Cauchie et al. (2004) demonstrate that statistical factors better represent the determinants of the Swiss market stock returns than the macroeconomic ones. Consequently, three well-known risk analysis and portfolio management firms, MSCI-BARRA3, FTSE-BIRR4, and SUNGARD-APT5, have opted mostly for the fundamental, macroeconomic, and statistical approaches, respectively, for constructing their worldwide multifactor risk models, portfolio analytics, and risk-reporting commercial products.

More recent studies have attempted to combine the different approaches. Fundamental models could be used as an approach to extract the effect of the macroeconomic factors by dividing the model's common fundamental factors into two sub-parts: one explained by macroeconomic factors and the other by non-macroeconomic factors.

The empirical investigation of multivariate asset-pricing models in emerging stock markets has been relatively scarce, with most studies based on a macroeconomic perspective finding two or three priced factors. Results have been mixed concerning pricing factors across markets. Regarding the present study, only two reviews have used the statistical definition of the APT - Dhankar and Kumar (2006) on the Indian Stock Exchange - revealing two and five priced factors, respectively.

Little research has examined the application of the APT for the Mexican Stock Exchange. Conversely, Additionally, López-Herrera et al. (2011) use a multifactor beta model to explain macroeconomic factor relationships with asset pricing in Mexico, the US, and Canada, analyzing market integration.

Studies focused on Latin America have utilized APT under different approaches. Finally, Da silva et al. (2008) use APT to infer Brazilian bank failure probability.

In a research, examines the predictability of efficiency and structure modeling and reports that out-of-sample US dividend predictability is weaker due to structural failures and coefficient changes over time. Based on the study's findings, the investor can increase profitability by up to 1.2% compared to forecasts based on ordinary least squares by utilizing dynamic averaging models, which consider instability, variable-time coefficients, and model uncertainty. Regarding time-variable parameters and non-static models, Bossaerts & Hillion (1999), Pastor and Stambaugh (2003), Pesaran and Timmermann (2002), have examined the relationship between modifications in predictor variables and stock returns following structural failures in recent years. In aresearch ,focus on random fluctuations, and Dangl

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and Halling (2012) focus on time-varying coefficients within the framework of the state climate model to embark on projecting the S&P 500 index.

In this research, investigated the effects of macroeconomic factors and corporate events on the systematic risk index according to the jump beta approach. Jump beta and continuous beta were considered the two indicators for systematic risk of firms to investigate the effect of macroeconomic factors and corporate events on systematic risk indicators. The findings revealed that the impact of macroeconomic factors on continuous beta changes was greater than the impact on jump beta. While inflation does not significantly affect continuous jumping beta changes, increasing the growth rate increases both types of beta, and increasing the exchange rate decreases both types. This reduction in jump beta is approximately four times that of continuous beta. A review of corporate events indicated that there was a significant decrease in the jump beta 2 or 3 weeks before the approval of the capital increase and a significant increase in the continuous beta one week before the capital increase. Furthermore, positive adjustment news reached the market sooner than negative adjustment news. Announcing earnings as a positive adjustment causes a slight increase in the continuous beta in the third or fourth week before the event, and a negative adjustment causes a significant decrease in the continuous beta around the time of occurrence. However, the announcement of earnings does not significantly affect the beta jump.

Hosseini and Bayat (2016) examined government dependence on the systematic risk of companies by collecting data on 76 companies listed on the Tehran Stock Exchange (TSE) for the years 2005-2014. The research hypothesis was tested utilizing regression coefficient analysis. The findings indicate a direct and significant relationship between government dependence and systematic risk. In other words, it can be stated that companies with government dependence are more likely to be exposed to political risk, among the factors affecting systematic risk. Maghsoud, et al. (2016) investigated the effects of macroeconomic uncertainty on TSE returns via the stochastic fluctuation model with a time change approach. They utilized TVP-SV and PLS models and compared them with the OLS method in MATLAB and XLSTAT software utilizing real variables (industrial production, real estate sector investment in housing, economic growth, share of government expenditures in GDP, and the growth rate of non-oil exports) and monetary variables (inflation, money supply, exchange rate, oil prices, and domestic gold prices) on TSE share returns. Compliant with the PLS model, it was concluded that economic growth variables and oil prices had a higher impact than other variables on TSE returns. Thereafter, the economic growth and oil

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price variables were inputted into the TVP-SV model. According to the findings, this TVP-SV model has higher efficiency than the OLS model. Based on the findings of the TVP-SV model pursuant to an initial break-in stock return, economic growth during the period had the highest impact on stock returns.

Based on the conclusion of domestic and international research findings, macroeconomic factors significantly affect systematic risk. However, the shortcoming of all previous research is that not many macroeconomic variables are included in analyses of systematic risk returns. Consistent with the methods studied in various studies, a maximum of 8-10 factors affecting the systematic stock market risk are accounted for in the models in each study, and a specific model is always designated to estimate effects. In the present study, not only are a large number of variables included in the model, but it is also possible to estimate various models utilizing the BMA method.

3 Research Methodology

This study employs an analytical approach using the correlation method, as it relies on theoretical foundations and research background from both Iran and internationally. The data analyzed are secondary data extracted from the Central Bank of Iran. The logic execution or argument type is inductive, as the macro and stock index data collection demonstrates the relationship between these variables. Longitudinally, this post-event study analyzes data collected over several years to assess the relationships between variables. While conducted in the present, it utilizes past data to model systematic risk indicators' behavior.

3.1 Research Hypothesis

Accordingly, this paper does not hypothesize but instead poses the following research questions:

1) What are the most significant systematic risk variables affecting the rate of return for investment companies?
2) How do the most important systematic risk variables impact investment companies' rate of return?

The paper structure is as follows: First, theoretical foundations and empirical studies are reviewed. Next, the estimation method fundamentals are explained, followed by the econometric estimation and data analysis. Finally, a summary and policy recommendations are provided.

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3.2 Model Estimation Method

Determining a model M's parameter θ requires the posterior distribution for θ under model M, given by Bayes' theorem:

$$\rho(\Theta|d, M) = \frac{\rho(\mathrm{d}|\theta, \mathrm{M})\rho(\theta|\mathrm{M})}{\rho(\mathrm{d}|\mathrm{M})} \tag{1}$$

Where the explicit conditioning on M indicates that the posterior probability density function (pdf) for θ given data

$$\mathrm{d}, \rho(\theta|d, \mathrm{M})$$

is conditional on assuming a specific model M. This is the usual parameter inference step and often the first level of inference in a problem.

The second level of inference is the Bayesian model comparison, which aims to determine the relative probability of models. The posterior probability of a model$M_i$given the data, $\rho(M_i|d)$ is related to the Bayesian evidence or model likelihood $\rho(\mathrm{d}|(M_i)$by:

$$\rho(M_i|d) = \frac{\rho(\mathrm{d}|(M_i)\rho((M_i)}{\rho(\mathrm{d})} \tag{2}$$

Where $\rho(M_i)$is the prior for the model $M_{i,}\rho(d) = \sum_i \rho(\mathrm{d}|(M_i)\rho(M_i)$, which is a normalization constant (where the sum runs over all available models) and

$$\rho(\mathrm{d}|(M_i) = \int d\theta\rho(d|\theta, M_i)\rho(\theta|M_i)$$

$$\rho(\mathrm{d}|(M_i) = \int d\theta\rho(d|\theta, M_i)\rho(\theta|M_i) \tag{3}$$

is the Bayesian evidence, which appears as a normalization factor in Equation (1). Given two competing models (M_i, M_j), the change in their relative probability from the prior (before seeing the data) to the posterior (after the data is accounted for via the likelihood) is given by the Bayes factor β_{ij}:

$$\beta_{ij} = \frac{\rho(d|M_i)}{\rho(d|M_j)} \tag{4}$$

Where large (small) values of βij denote a preference for $M_i, (M_i)$,
The 'Jeffreys scale' gives an empirical scale for translating lnBij into strengths of belief, with thresholds |lnβ_{ij}|=1.0,2.5, 5.0 separating levels of inconclusive, weak, moderate, and strong evidence, respectively . Recently, the framework of model comparison has been extended to include the possibility of 'unknown model' discovery (Starkman, et al. 2008; March et al. 2011).

The third level of inference is Bayesian model averaging (BMA), which aims to determine constraints on common parameters among the models of interest (M_i, with i= (1,…, N) accounting for the uncertainty in selecting the correct model. This is the most general inference that can be obtained on the parameter values, as long as the list of models is reasonably complete. The model-averaged posterior distribution for a parameter θ is:

$$\rho(\theta|d) = \sum_i^N \rho(\theta|d, M_i)\rho(M_i|\mathrm{d}) \tag{6}$$

$$= \rho(M_i|\mathrm{d}) \sum_{i=1}^{N} \beta_{ij}\rho(\theta|d, M_i)$$

$$\rho(M_i|d) = \frac{1}{1+\sum_{i=2}^{N} \beta_{ij}} \tag{7}$$

Where the models' posterior probabilities, $\rho(M_i|d)$are replaced by the Bayes factors in the second equality with respect to a reference model, here M_i. Next, it is assumed that the prior probabilities for the N models are all equal, i.e., $\rho(M_i) = 1/N$, (i= 1,…, N). With this assumption, the posterior for $\mathcal{M}_1$ is given by:

$$\rho(M_i|d) = \frac{1}{1+\sum_{i=2}^{N} \beta_{ij}} \tag{7}$$

BMA has been applied to the dark energy equation of state in Liddle et al. (2006), the scalar spectral index in Parkinson & Liddle (2010).

Computation of the Bayes Factors

Given two or more models, computing the Bayes factors entering Equation (5) requires evaluating the multidimensional integral in Equation (3). Here, we are interested in the case where the models are nested, i.e., one model is obtained from a more complicated one for a specific choice of some parameters in M1. The extra parameters are the curvature Ω_k and/or the dark energy equation of state parameters $w_0 or\ w_a$, depending on the model. For example, a curved universe reverts to a flat one for $\Omega_k = 0$, or an evolving dark energy equation of state reverts to a cosmological constant model for $w_0 = 1$, $w_0 = a$. In this case, the Bayes factor between models Mi and Mj can be written as:

(8)

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$$\beta_{ij} = \frac{\rho(\vartheta|d, M_i)}{\rho(\vartheta|M_j)}$$

Where we have split the more complicated model's parameters a $\theta = (\psi, \vartheta)$, with φ being the extra parameters of model M_j, which reduces to the simpler model M_j for $\vartheta = \vartheta^*$is expression is known as the Savage–Dickey density ratio (SDDR, see Verdinelli & Wasserman (1995) and references therein). For cosmological applications, see Trotta (2007). The numerator is simply the marginal posterior for φ, evaluated at $\vartheta = \vartheta^*$ (which can be easily obtained with standard Markov Chain Monte Carlo techniques), while the denominator is the prior density for the extra parameters ϑ under the more complicated model, evaluated at the same point.

Once the Bayes factor for nested models, which differ by one parameter at a time, has been obtained using Equation (8), the Bayes factor between other models, which have two or more nested parameters between them, can be easily derived. If modelM_j has one more parameter than model M_k , which in turn has one more parameter than M_j , the Bayes factor between models i and j is:

$$\beta_{ij} = \beta_{ik} \times \beta_{kj} \tag{9}$$

Where the Bayes factor β_{ik} and β_{kj} can be obtained via the SDDR, a similar technique has been adopted .

The difference between this approach and traditional regression models is as follows (Figure 1).

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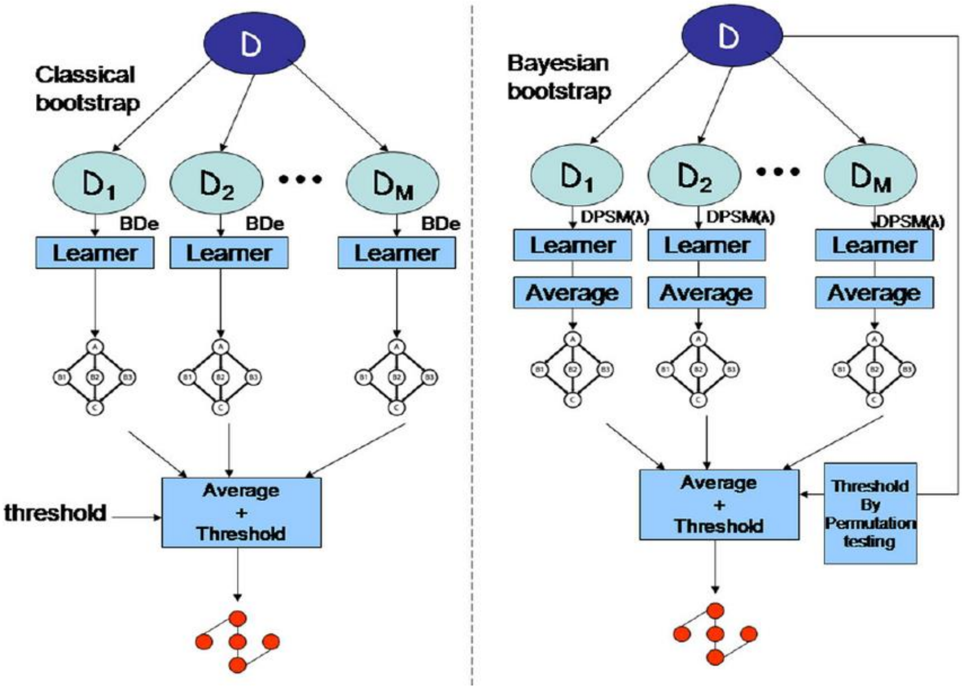

Figure 1. Process differences between BMA models and traditional models
Source: Gibbons et al.(2008)

As shown, only one sampling run is done in the classical method, while this process is repeated in the Bayesian method until the optimal threshold level is reached, detecting the important variables due to the iterative sampling. As a result, the model specification error is eliminated with this method. The chart below shows the coding process for this BMA model algorithm (Figure 2).

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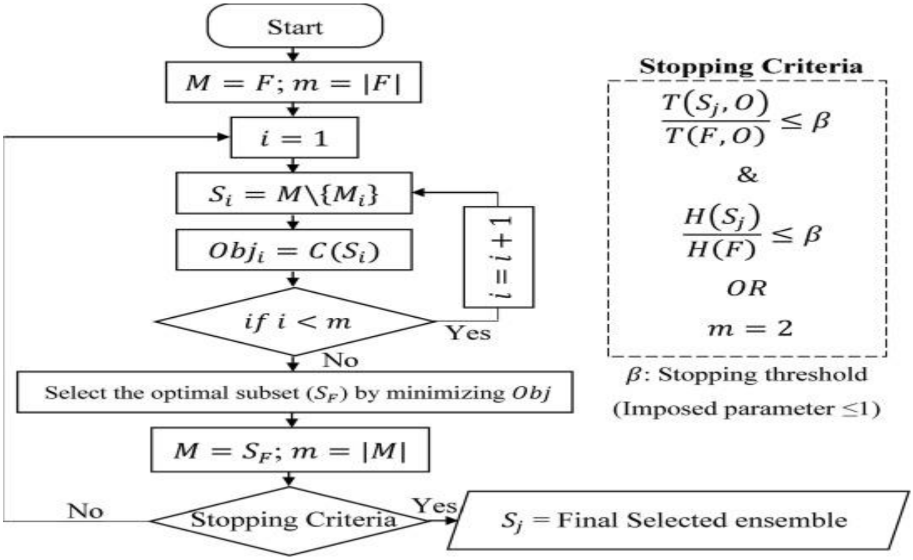

Figure 2. The BMA model algorithm
Source: Darbandsari and Coulibaly(2019)

As observed above, model estimation continues until the probability of a variable's presence in the optimal model exceeds the threshold level. Thus, only variables meeting the threshold level are present in the final model. The optimal model is obtained using the process shown below (Figure 3).

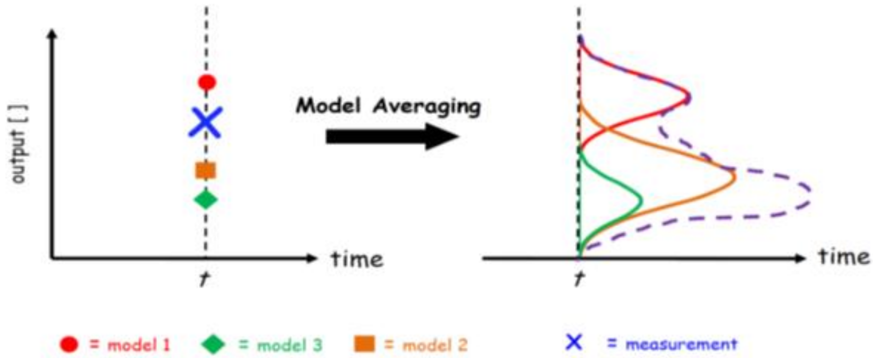

Figure 3. The meaning process in optimal models by the BMA method
Source: Monteith et al.(2011)

The Bayesian Model Averaging method combines the posterior distributions from the three optimal models to create an averaged distribution. This has greater accuracy and efficiency than any individual model.

4 Research Variables

After normalizing the data, the regression models should be estimated in this section. The data normalization aims to unify them and remove heterogeneity concerns (between research data for projecting the model). Another concern in model projection is the high number of variables affecting stock returns in the present study. In this research, 69 indicators are taken into account to determine factors affecting stock returns. The most important indicators affecting stock returns should be identified utilizing the BMA method to resolve this issue. In addition to its many advantages, the business model also has its limitations. The first restraint is related to the previous function utilized in this method, which is almost always considered normal and can lead to unlimited risk. In addition, the normal distribution sequence is narrow. The second limitation of this method is pertinent to prior function variance (g-prior), which is only to facilitate calculations and does not have a strong theoretical justification. Finally, the third drawback of the BMA method is the length of the calculations, which require simulation and approximation methods or algorithms. Therefore, it greatly reduces the volume of calculations via this estimator. It also allows the prior distribution to be applied according to a clearer concept of uncertainty about the role of

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auxiliary variables (Masanjala &,Papageorgiou, 2008). Ultimately, however, the same efficiency of both methods is evident in estimating model coefficients and the same results based on dual approaches. Consequently, the BMA method was designated to project the model in the present study (Mehrara & Ghobad-Zaadeh, 2016).

The research's statistical sample consists of 16 investment companies in the periods 2006-1 and 2020-4.

In estimating a suitable pattern, variable selection uncertainty is always among the main concerns. For instance, there are numerous variables, each of which (and their effects on stock returns) has been studied in various previous studies. As a result, there are multiple models that examine factors that determine stock returns as stipulated in previous studies. However, which model is the most accurate is ambiguous. Bayesian econometrics overcomes this uncertainty by utilizing the Bayesian Model Averaging (BMA) approach, simultaneously inputting all variables that could potentially impact the dependent variable, thereby assessing the importance of each variable in explaining the outcome. Considering this advantage and the possibility of using advanced software programs, researchers have been motivated to focus more on Bayesian econometrics. The effects of 62 potential variables (Table 1) related to stock returns have been analyzed using the BMA method. In light of the aforementioned information, certain questions arise: First, how are investment companies' return models affected by the inputted variables? Second, do different variable levels influence the findings on investment companies' returns? Third, is it possible to have variables in the model without a strong theoretical basis?

The first answer is based on the fact that BMA models only provide the most probable theoretical support and findings from other studies. There is no requirement for the findings to match the theoretical support. In order to answer the second question, research data is normalized because the scales of the variables differ - some are percentage-based (e.g., inflation) while others are level-based (e.g., oil revenues). The third answer aligns with the existential philosophy behind BMA models. Econometrics experts using these models have always faced uncertainty in selecting the right variables and models (type, number, and composition of variables). Many variables influence investment returns theoretically, but not all can be included in conventional econometric models. Therefore, researchers have utilized variable combinations based on theory and personal preferences (Mehrara & Ghobad-Zaadeh, 2016. The Bayesian Averaging Model approach was developed in Bayesian econometrics to address this problem. In addition to overcoming

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uncertainty in selecting effective variables, this approach also handles uncertainty in selecting the optimal model (Koop & Korobilis, 2010). This article uses the BMA method to overcome uncertainties in model and variable selection, comprehensively evaluate factors affecting investment returns, and rank each factor's influence. Consequently, since this method aims to specify the optimal regression model, any potential variable affecting the dependent variable can exist, whether there is theoretical support or it is based solely on the researcher's perspective (Wasserman, 2000).

Table 1
Introducing the Variables of this Research

Variable Type	Return Variable	Theoretic Return Expectation	Reference
Dependent	Oil Revenues (Billion Rials)	Effect: +	Vaaghefi et al., 2015
Independent Systematic Risk Indicators	The Ratio of Government Spending to Government Deficits	Effect: -	Shahbazi et al., 2015
	Government Expenditure (Billion Rials)	Effect: +	Shahbazi et al., 2015
	Budget Deficit (-) or Surplus (+) (Billion Rials)	Effect: -	Shahbazi et al., 2015
	Gold Coin Price (Tamaam Bahaar; Old Sesign) (Thousand Rials)	Effect: -	Barati et al , 2013
	Deviation of Unofficial from Official Foreign Currency Exchange Rates (Rials)	Effect: +	Mehrabian and Chegni, 2014
	Official Foreign Currency Exchange Rate (Rials)	Effect: +	Mehrabian and Chegni, 2014
	Unofficial Foreign Currency Exchange Rate (Rials)	Effect: +	Mehrabian and Chegni, 2014
	Total Consumer Index (Without Units) at Fixed Prices of 2011	Effect: +	Abbasi-Nejad et al., 2017
	Inflation Rate (%)	Effect: +	Abbasi-Nejad et al., 2017
	Industrial Sector Value Added (%)	Effect: +	Bahaar-Moghadam and Salari, 2012
	Industrial Sector Value Added at Fixed Prices of 2004 (Billion Rials)	Effect: +	Bahaar-Moghadam and Salari, 2012
	Gross Domestic Product at Base Prices of 2004 (Billion Rials)	Effect: +	Bahaar-Moghadam and Salari, 2012
	Formation of Gross Fixed Capital at Current Price (Billion Rials)	Effect: +	Bahaar-Moghadam and Salari, 2012
	Export of Goods and Services at Current Prices (Billion Rials)	Effect: +	Hosseini & Bayaat, 2016
	Import of Goods and Services at Current Prices (Billion Rials)	Effect: -	Hosseini & Bayaat, 2016
	Existing Account Balance With Current Prices (Billion Rials)	Effect: +	Hosseini & Bayaat et al., 2016

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	Net Foreign Assets of of CBI (Billion Rials)	Effect: +	Fadaeiinejad and Farahani, 2017
	Foreign Assets of CBI (Billion Rials)	Effect: +	Fadaeinejad and Farahani, 2017
	Foreign Debts of CBI (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Foreign Debt to Foreign Assets Ratio of CBI	Effect: -	Fadainejad and Farahani, 2017
	Debt Owed of Banks to CBI (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Monetary Base by Resources (Billion Rials)	Effect: +	Vakili et al., 2022
	Banknotes, Etc. Held by Banks andNon-Bank Credit Institutions (Billion Rials)	Effect: +	Vakili et al., 2022
	Net Foreign Assets of the Banking System (Billion Rials)	Effect: +	Fadaeinejad and Farahani, 2017
	Foreign Assets of the Banking System (Billion Rials)	Effect: +	Fadaeinejad and Farahani, 2017
	Foreign Assets of CBI (Billion Rials)	Effect: +	Fadaeiinejad and Farahani 2017
	Foreign Assets of Banks (Billion Rials)	Effect: +	Fadaeinejad and Farahani, 2017
	Foreign Currency Debts of the Banking System (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Foreign Currency Liabilities of CBI (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Foreign Currency Liabilities of Banks (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Government Debt Owed to the CBI (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Government Debt Owed to Banks and Non-Bank Credit Institutions	Effect: -	Fadaeinejad and Farahani, 2017
	Private Sector Debt to the Banking System (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Money (Billion Rials)	Effect: +	Vakili et al., 2022
	Banknotes, etc., in Circulation (Billion Rials)	Effect: +	Vakili et al., 2022
	Observable Deposits (Billion Rials)	Effect: +	Vakili et al., 2022
	Quasi Money	Effect: +	Vakili et al., 2022
	Liquidity Based on Its Constituent Factors (Billion Rials)	Effect: +	Vakili et al., 2022
	Crude Oil Exports (Thousand Barrels/Day)	Effect: +	Bayaat et al., 2016
	Ascending Coefficient of Money (money/monetary base)	Effect: +	Vakili et al., 2022
	Ascending Coefficient of Money (Liquidity/monetary base)	Effect: +	Vakili et al., 2022
	Export to GDP Ratio	Effect: +	Bayaat et al., 2016
	Current Account Deficit to GDP Ratio	Effect: +	Bayaat et al., 2016
	Import to GDP Ratio	Effect: -	Bayaat et al., 2016

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	Government Expenditure Ratio to GDP	Effect: +	Shahbazi et al., 2015
	Budget Deficit to GDP Ratio	Effect: -	Shahbazi et al., 2013
	Real GDP Growth Rate (%)	Effect: +	Bahaar-Moghadam & Kavarooyi, 2012
	Land/Property Price Index in Tehran (Without Units)	Effect: -	Toraabi & Hooman, 2011
	Index of Housing/Property Rentals in Tehran (Without Units)	Effect: -	Toraabi & Hooman, 2011
	Gross Domestic Product at Current Prices (Billion Rials)	Effect: +	Bahaar-Moghadam & Kavarooyi, 2012
	Liquidity Growth Rate (%)	Effect: +	Rezaeii et al., 2019
	Liquidity to Foreign Assets Ratio of the CBI	Effect: +	Fadaeinejad and Farahani, 2017
	Liquidity to Net Assets Ratio of the Banking System	Effect: +	Fadaeinejad and Farahani, 2017
	Ratio of Loans Provided by Banks to the Private Sector Divided by GDP	Effect: +	Fadaeinejad and Farahani, 2017
	Government to GDP Debt Ratio	Effect: -	Shahbazi et al., 2013
	Growth Rate of Credits/Loans Provided to the Private Sector (%)	Effect: -	Fadaeinejad and Farahani, 2017
	Total Debt Owed to the Banking System (Billion Rials)	Effect: -	Fadaeinejad and Farahani, 2017
	Inflation Rate Squared	Effect: +	Abbasinejad et al., 2017
	US GDP Growth Rate (%)	Effect: -	Proposal By Researcher
	US Inflation Rate (%)	Effect: +	Proposal By Researcher
	Oil Price (US$)	Effect: +	Vaaghefi et al., 2015
	KOF Index	Effect: +	GolKhandaan, 2016
	Business Climate Index	Effect: +	Researcher's Viewpoint
	Good Governance Index	Effect: +	Researcher's Viewpoint
	Institutional Climate Index	Effect: +	Researcher's Viewpoint
	Misery Index	Effect: -	Researcher's Viewpoint
	Economic Resilience Index	Effect: +	Kazemi et al., 2020
	Sanctions Index	Effect: -	Researcher's Viewpoint

Source: Findings of Various Studies
CBI=Central Bank of Iran

5 Research Findings

Due to the novelty of Bayesian Averaging Models in accounting, the purpose of the calculations is explained simply before addressing the statistical description. The objective here is to regress all possible combinations of the 69 variables affecting investment firm returns. For example, if there are three

[DOI: 10.61186/jme.18.2.175]

explanatory variables x1, x2, and x3 related to the dependent variable Y, there would be the following six possible regressions:

Y=x1
Y=x2
Y=x3
Y=x1, x2
Y=x1, x3
Y=x2, x3
Y=x1, x2, x3

With this approach, all possible states of the explanatory variables are initially regressed on Y. There are several key points about this method. First, a variable may not be present in all possible models (e.g., x1 only exists in four of the cases above). Second, a variable like x1 does not necessarily affect Y significantly in all models where it appears. Accordingly, the ratio of significant models to total models containing a variable indicates if that variable belongs to the optimal model. Third, calculating all possible states becomes infeasible with increasing variables. Consequently, at a certain number onwards (around 150-200 million regressions), the ratio of a variable's significant existence to total conditions stabilizes toward a figure. Thus, estimating all conditions is unnecessary.

A decision threshold is needed to remove variables. The optimal threshold is set based on the ratio k/n, where k is the number of proposed highest-impact variables, and n is the total number of variables. The choice of k depends on the researcher's perspective. All models in the model space must be calculated to obtain the findings. Given the number of variables studied, the number of possible models (based on the existence or absence of each variable) in the model space equals 269. This corresponds to over 590,000 billion regression models. In other words, the model space contains 269 models, consistent with assuming model uncertainty. Without applying personal views or preferences in model selection, all models should be analyzed, and all model data should be utilized to obtain the findings.

In the Bayesian Average Method, the findings depend on the value of the k meta-parameter (in the above calculations, k was set to 12). This raises the question of whether the research findings would change if the meta-parameter value changed, and if so, what would be the rate of change? In other words, will the choice of expected model size affect the outcome?

Accordingly, the entire sampling process and related calculations were redone, comparing the findings by selecting different $\vec{k}$ values. Importantly, the model space, variables, and data are the same in

[DOI: 10.61186/jme.18.2.175]

these three cases. The only difference is the expected model size. Nonetheless, it is evident that the samples and findings will vary by changing the expected modelsize. This means $\vec{k}$ may be fragile (or non-fragile) across all three quantities. The fragility of some variables may change with modifications to $\vec{k}$.Avariable that was fragile, assuming one $\vec{k}$ value could become non-fragile by increasing the expected model size.

Table 2 aims to identify the correct number for $\vec{k}$ if the researcher mistakenly provides an erroneous initial number of proposed variables. Following the example of Sala-i-Martin et al., the value of k in this study is assumed to fall between 1 and 12 variables. This reflects the expectation that 12 non-fragile variables will ultimately be introduced through the calculation process. However, the final number of robust variables may clearly end up being less or more than 12. Table 2 displays the output findings for k ranging from 1 to 12.

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Table 2

Findings of Non-Fragile Variables in Various Models

Non-Fragile Variables	K
Unofficial market foreign currency exchange rates	K=1
Unofficial market foreign currency exchange rates, oil revenues	K=2
Unofficial market foreign currency exchange rates, oil revenues, business climate index	K=3
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+)	K=4
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate	K=5
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate	K=6
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate	K=7
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate, institutional climate index	K=8
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate, institutional climate index, sanctions index	K=9
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate, institutional climate index, sanctions index, gold coin (Tamaam Bahaar)	K=10
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate, institutional climate index, sanctions index, gold coin (Tamaam Bahaar), real GDP growth rate	K=11
Unofficial market foreign currency exchange rates, oil revenues, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial sector value-added growth rate, liquidity growth rate, institutional climate index, sanctions index, gold coin (Tamaam Bahaar), real GDP growth rate, land/property price index in Tehran	K=12

Source: Research Findings

The model k = 12 estimation findings are summarized below:

Initially, each variable's coefficients and future probability were calculated by obtaining a sample of 5 million regressions from the model space. Then, 5 million more regressions were added to the first sample, and calculations were performed. This process of obtaining coefficients and future probabilities for additional samples of 5 million regressions was continued until convergence was reached in a total sample of 145 million regressions. At that point, there was no need to increase the sample size further to determine non-fragile variables (Table 3). Two conditions must be met to declare a variable as non-fragile: 1) Increasing the future probability of each variable compared to its prior probability, and 2) the future probability level is higher than the defined threshold level ("the initial threshold level = 12 divided by 69 = 0.173").

[DOI: 10.61186/jme.18.2.175]

Table 3

The Initial Stage Process of Sampling and Calculation (Assumption: K=12)

Variables	Sample Includes 5 Million Regressions	Sample Includes 145 Million Regressions		
	Prior Coefficient	Prior Probability	Future Coefficient	Future Probability
Oil Revenue (Billion Rials)	0.01664	0.86658	0.01845	0.97551
The Ratio of Government Spending to Government Budget Deficit	0.10110	0.02293	-0.00634	0.04662
Government Expenditures (Billion Rials)	-0.68565	0.29653	0.04302	0.85351
Budget Deficit (-) or Surplus (+) (Billion Rials)	-0.09018	0.32055	-0.45561	0.57730
Cold Coin (Tamaam Bahaar) (Old Design) (Billion Rials)	0.06089	0.90475	0.03150	0.09169
Deviation of Unofficial Exchange Rate from Official (Rials)	0.00227	0.05787	0.00133	0.12992
Official Rate (Rials)	0.00409	0.84693	0.00348	0.99318
Unofficial Market Exchange Rate (Rials)	0.02381	0.33409	0.02342	0.13621
Total Consumer Index (Without Units) (2011 Fixed Prices)	0.32274	0.54066	0.17818	0.81583
Inflation Rate (%)	0.42165	0.45172	0.12807	0.79862
Industrial Sector Value Added Growth Rate (%)	0.43279	0.22022	0.21126	0.10645
Industrial Sector Value Added Growth Rate (2004 Fixed Prices) (Billion Rials)	0.10110	0.30014	0.00797	0.03406
Gross Domestic Product (2004 Base Prices) (Billion Rials)	0.02981	0.17174	0.03414	0.12632
Formation of Gross Fixed Capital at Current Prices (Billion Rials)	0.08058	0.20919	0.05153	0.04051
Export of Goods and Services at Current Prices (Billion Rials)	-0.11213	0.20155	-0.06909	0.06289
Import of Goods and Services at Current Prices (Billion Rials)	0.00023	0.15394	0.00040	0.05166
Account Balance at Current Prices (Billion Rials)	0.00596	0.22491	0.00658	0.12409
Net Foreign Assets of CBI (Billion Rials)	0.00606	0.10263	0.01279	0.02328
Foreign Assets of CBI (Billion Rials)	-0.03986	0.53607	-0.02186	0.12918
Foreign Debts of CBI (Billion Rials)	-0.69918	1.09071	-0.72541	0.06071
The Ratio of Foreign Debt to Foreign Assets of CBI	-0.01558	0.07424	-0.02500	0.13975
Debts of Banks to CBI (Billion Rials)	0.00023	0.15394	0.00040	0.15466

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Monetary Base by Resources (Billion Rials)	0.05950	0.07424	0.18959	0.15015
Currency (Banknotes, etc.) Held by Banks and Non-Bank Credit Institutions (Billion Rials)	0.49404	0.06223	0.96499	0.12119
Net Foreign Assets of Banking System (Billion Rials)	0.19074	0.09062	0.04468	0.13429
Gross Foreign Assets of Banking System (Billion Rials)	0.00005	0.03930	0.00029	0.09935
Foreign Assets of CBI (Billion Rials)	0.01300	0.12447	0.00552	0.15722
Foreign Assets of Banks (Billion Rials)	-0.01699	0.24020	-0.01443	0.12955
Foreign Currency Debts of Banking System (Billion Rials)	-0.00195	0.10700	-0.03403	0.09935
Foreign Currency Liabilities of Banks (Billion Rials)	-0.06089	0.69875	-0.03150	0.11229
Government Debt Owed to CBI (Billion Rials)	-0.03423	0.06442	-0.01983	0.12447
Government Debt Owed to Banks and Non-Bank Credit Institutions (Billion Rials)	-0.18877	0.42176	-0.05776	0.16820
Debt of Non-Governmental (Private) Sector to the Banking System (Billion Rials)	-0.00240	0.07424	-0.00251	0.09608
Money (Billion Rials)	0.00005	0.03930	0.00028	0.09935
Banknotes, etc., in Circulation (Billion Rials)	0.00596	0.22491	0.00658	0.02109
Observable Deposits (Billion Rials)	0.00606	0.10263	0.01280	0.12572
Quasi Money (Billion Rials)	0.03986	0.53607	0.02186	0.12918
Liquidity Based on its Constituent Factors (Billion Rials)	0.00227	0.05787	0.00133	0.12992
Crude Oil Exports (Thousand Barrels/Day)	0.01558	0.07424	0.02500	0.13975
Ascending Coefficient of Money (Money. Monetary Base)	0.05950	0.07424	0.18959	0.15015
Ascending Coefficient of Money (Liquidity. Monetary Base)	0.72891	0.01648	0.72917	0.00690
The Ratio of Exports to GDP	0.34993	0.40065	0.37043	0.08292
Current Accounts Deficit to GDP Ratio	0.19074	0.09062	0.04120	0.13429
The Ratio of Imports to GDP	-0.20508	0.66709	-0.20655	0.15318
Government Expenditure Ratio to GDP	0.34993	0.07105	0.37043	0.08292
Budget Deficit Ratio to GDP	0.08368	0.26094	0.15352	0.15611
Real GDP Growth Rate (%)	-0.00196	0.41600	-0.03403	0.51135
Land/Property Price Index in Tehran (Without Unit)	0.01300	0.12447	0.00552	0.46622
Rental Housing Index in Tehran (Without Unit)	0.03423	0.06442	0.01983	0.12447
Gross Domestic Product at Current Prices (Billion Rials)	-0.49404	0.06223	-0.96499	0.12119

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Liquidity Growth Rate (%)	0.00240	0.48624	0.00251	0.66258
CBI's Liquidity to Foreign Assets Ratio	0.00020	0.14084	0.00020	0.14521
Banking System's Liquidity to Net Assets Ratio	0.00282	0.08734	0.00228	0.08407
Ratio of Bank Loans to Private Sector Divided by GDP	0.00594	0.10700	0.00522	0.10809
Government Debt to GDP Ratio	0.00205	0.02620	0.00155	0.02620
Growth Rate of Loans Provided to Private Sector (%)	0.08368	0.26094	0.15352	0.11491
Total Debt Owed to the Banking System (Billion Rials)	0.00179	0.03385	0.00143	0.03057
Square of Inflation Rate	0.69918	0.06071	0.72541	0.05968
US GDP Growth Rate (%)	0.12786	0.16595	0.14674	0.16159
US Inflation Rate (%)	0.32426	0.03057	0.24049	0.13139
Oil Prices (US$)	0.13291	0.02948	0.17568	0.11188
Kof index	0.00201	0.02571	0.00152	0.02571
Business Climate Index	0.08210	0.87402	0.15062	0.87451
Good Governance Index	0.00176	0.03321	0.00140	0.02999
Institutional Climate Index	0.68599	0.45213	0.71173	0.62723
Misery Index	-0.12545	0.16282	-0.14397	0.15854
Economic Resilience Index	0.31815	0.02999	0.23595	0.02785
Sanctions Index	-0.13040	0.33792	-0.17237	0.61602

Source: Research Findings
CBI = Central Bank of Iran

In the initial phase, 12 variables were selected (to determine the non-fragile ones) using the aforementioned two conditions. Specifically, 12 variables had higher future probability values than prior probabilities, and these 12 variables had future probability levels exceeding the 0.173 threshold.

Since 12 variables were selected while other variables remained, these are called strong, unbreakable/non-fragile variables, while the remaining variables with lower future probabilities of existence than prior probabilities are deemed fragile. According to Table 5, the variables of unofficial foreign currency exchange rate market, oil revenues, business climate index, budget deficits (-) or surpluses (+), inflation rate, value-added growth rate of industrial sector, liquidity growth rate, institutional climate index, sanctions index, gold coin (Tamaam Bahaar), genuine GDP growth rate, and Tehran land/property price index have greater probabilities of future existence than their prior probabilities. Therefore, they are designated as non-fragile variables.

The future coefficients and deviation of future criteria for the variables are stated as follows (3rd and 4th columns). The last column displays the statistical ratio of each variable.

Table 4
Title : The future coefficients and deviation of future criteria for the variables

Variables	Sample Includes 145 Million Regressions	Regressions with 2≤	
Oil Revenue (Billion Rials)	0.0179	0.94134	0.911
Budget Deficit (-) or Surplus (+) (Billion Rials)	-0.4423	0.828647	0.791
Cold Coin (Tamaam Bahaar) (Old Design) (Thousand Rials)	-0.0464	0.560484	0.556
Unofficial Market Foreign Currency Exchange Rate (Rials)	0.0034	0.9912	1.000
Inflation Rate (%)	0.1730	0.792066	0.757
Industrial Sector Value Added Growth Rate (%)	0.1243	0.775358	0.701
Real GDP Growth Rate (%)	-0.0330	0.49646	0.508
Land/Property Price Index in Tehran (Without Unit)	0.0054	0.45264	0.497
Liquidity Growth Rate (%)	0.0024	0.64328	0.654
Business Climate Index	0.1462	0.84904	0.809
Institutional Climate Index	0.6910	0.60896	0.637
Sanctions Index	-0.1673	0.59808	0.581

Source: Research Findings

6 Conclusions and Proposals

The experience of analyzing four decades of TSE activity demonstrates its intense vulnerability and the substantial impact of government policies/strategies and economic conditions on this institution, its activities, and its performance. This leads to a systematic increase in risk and a negative impact on corporate returns. In this study, the Bayesian Average Method was used to estimate and project patterns, as it is more credible, efficient, and suitable for estimation since it does not require accurate distribution information.

In societies with political, social, and cultural stability, the profitability of companies, shareholders, and investors is also stable and somewhat predictable. Decreasing economy-wide "value added" that can ensue from increasing systematic risk in Iran reduces shareholder wealth and willingness to invest in capital markets. Moreover, it cuts down on the benefits of employees, customers, financial decision-makers, and suppliers, adversely affecting the country's investment process and economic growth.

[DOI: 10.61186/jme.18.2.175]

Accordingly, identifying the variables with the highest contribution to systematic risk is of great significance.

This research calculated and assessed the effects of 69 factors shown in prior studies to impact investment company stock returns. The findings revealed 12 variables that had a significant effect. These variables maintained their impact and were non-fragile even with other existing variables. The 12 variables were: unofficial foreign currency market exchange rate, oil revenue, business climate index, budget deficit (-) or surplus (+), inflation rate, industrial value-added growth rate, liquidity growth rate, institutional climate index, sanctions index, gold coins (Tamaam Bahaar), real GDP growth rate, and Tehran land/real estate price index. Comparing the future probabilities of the variables shows that the studied variables have the required non-fragility across all three expected model dimensions. Based on the significant variables in the model, it can be concluded that the Iranian economy's financial stock return index problem is multidimensional. Variables tied to fiscal policy, monetary policy, and exchange rate policy positively and significantly affect this index. Hence, it is advisable to develop policy packages that address inconsistencies (temporal and implementation-wise) in providing policy solutions to reduce systematic risk. The specific environment of the Iranian economy, with a very high effect of non-economic variables (political, etc.), uncertainties, and speculation on the stock market and its fluctuations, should be considered. Therefore, it is recommended to privatize and transfer important currently government-controlled medium and large industry sectors to the much more efficient private sector. Success in privatizing industries and the economy depends on keeping pace with trade liberalization and pricing policies as well as immersing in a competitive environment.

The findings reveal the necessity for a more intense focus on estimating the uncontrollable or systematic risk of financial assets to assess and manage risk. In particular, financial market participants should consider the timeline of the beta index as a potential measure of risk that cannot be controlled by diversifying investment. Instead, investors should utilize risk-hedging strategies to avoid potential risks. The beta index timeline series provides comprehensive data as a measure of investment fund manager performance for capital market participants and a reference for corporate financial managers' decision-making regarding company capital structure.

When deciding on portfolio formation, an investor must consider several factors (such as risk, return, etc.) and compare these factors when selecting stocks from various companies to invest in. Ultimately, stocks that are superior to other available stocks in terms of the desired factors should be

[DOI: 10.61186/jme.18.2.175]

chosen for investment. The findings of the present study are in line with similar studies (such as Nakajima, 2011; Sargent et al., 2006).

The descriptive statistics findings reveal that the research data distribution is not normal. Consequently, a nonlinear relationship can be superior in explaining and elucidating the relationship between systematic risk and investment company stock returns compared to a linear relationship. Therefore, a linear risk-return relationship's capital asset pricing claim is rejected. Consistent with the research findings, multiple variables with various probabilities were effective on stock returns. Consequently, it is recommended to utilize models that are able to differentiate the occurrence probability of each variable at various levels for predicting/forecasting stock returns.

Policymakers and financial market participants are advised not to utilize discretionary policies to ameliorate short-term situations in financial markets since they induce long-term stock market instability despite short-term effectiveness. Consequently, policymaking tools are required to create a policy package (not a single policy) tailored to various situations and contingent on the most significant systematic risk factors. The rationale is that policy packages aim to neutralize the negative effects of implementing one policy by enacting another, minimizing economic, social, and political losses.

Consistent with domestic and international research findings, it is concluded that macroeconomic factors significantly affect systematic risk. The present study findings are in agreement with those of (Diem et al., 2022), (Kang et al., 2021), (Fox et al., 2014), (Nejad-Amiri et al., 2019), (Bayaat et al., 2016), and (Tarighi et al., 2017). The findings stipulate that systematic risk significantly impacts the returns of companies investing in the stock market.

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[DOI: 10.61186/jme.18.2.175]

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