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Research Paper

Predicting Stock Returns Based on the Approach of Bayesian Averaging Models; Quantum Finance and Continuous Wavelet Analysis[1]

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INTRODUCTION

Here's a revised version of the text, focusing on clarity, conciseness, and improved flow:

REVISED TEXT:

"Linear models, due to their limitations in capturing the complex conditional distribution of data, their inability to reflect dynamic behavior, and restrictive assumptions that diverge from reality, often fail to accurately predict returns in modern financial markets. This research aims to identify the most suitable model for forecasting stock returns within the Tehran capital market across various time horizons.

Numerous methods have been developed for predicting stock returns and identifying behavioral patterns, including machine learning approaches such as support vector machines, tree-based decision methods, gradient boosting machines, distributed

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random Bayesian inference, autoencoders, reinforcement learning, time-varying parameter models, and quantum financial models. However, a universally dominant approach for designing an optimal stock return model remains elusive. A key challenge is determining the most effective model for predictive accuracy.

Another significant issue is the temporal instability of stock return prediction models. Models often struggle to provide accurate predictions across short, medium, and long-term horizons. Research indicates that the coefficients of variables influencing stock returns vary significantly across these time frames. This aligns with Le Chatelier's principle in economics, which suggests that elasticity tends to be greater in the long term, resulting in notable differences in coefficients and elasticity over time. Therefore, identifying the optimal model for each time horizon is a critical objective of this study.

The efficacy of predictive models is influenced by factors such as the specific market, time period, country, input variables, and the defined dependent variable. However, nonlinear models generally demonstrate superior accuracy compared to linear models. Nonlinear models offer the flexibility to adapt to evolving market conditions, as their estimated coefficients are not static. This adaptability makes nonlinear approaches more effective in capturing the intricate and dynamic nature of financial data.

MATERIALS AND METHODS

The central hypothesis of this research is that the predictive accuracy of stock return models varies over time. This study aims to develop a novel framework for modeling stock return distributions, making it a practical research effort. The theoretical foundations and research background were established through a literature review. This research employs a causal-comparative design, utilizing the total stock market index return.

The data analyzed spans the period from September 23, 2018, to September 23, 2022, using daily stock market data. To predict and model stock returns, the study investigates a range of estimation models, including classical or structural regressions, non-structural regressions, time-varying parameter Bayesian regressions, discrete and continuous wavelet transform models, metaheuristic approaches, simple and deep artificial neural networks, stochastic differential models, and financial quantum models.

RESULTS AND DISCUSSION

This study employs two standard metrics, Mean Squared Forecast Error (MSFE) and Mean Absolute Forecast Error (MAFE), to determine the optimal model for various time horizons.

Table 1. Forecast Performance Criteria Across Different Forecast Horizons

		1-day		16-day		32-day	
forecast interval model type1-day		MAFE	MSFE	MAFE	MSFE	MAFE	MSFE
Time-varying Bayesian-parameter models	$TVP-AR(1)-X\quad DMA(\alpha=\lambda=0.99)$	0/071	0/009	0/087	0/011	0/125	0/016
	$TVP-AR(1)-X\quad DMA(\alpha=\lambda=0.95)$	0/062	0/007	0/076	0/009	0/109	0/012
	$TVP-AR(1)-X\quad DMA(\alpha=\lambda=0.90)$	0/057	0/006	0/070	0/007	0/100	0/011
	$TVP-AR(1)-X\quad DMS(\alpha=\lambda=0.99)$	0/076	0/014	0/093	0/017	0/134	0/025
	$TVP-AR(1)-X\quad DMS(\alpha=\lambda=0.95)$	0/067	0/008	0/082	0/010	0/118	0/014
	$TVP-AR(1)-X\quad DMS(\alpha=\lambda=0.90)$	0/053	0/006	0/065	0/007	0/093	0/011
	$TVP-AR(1)-X\quad DMA(\alpha=0.99,\lambda=1)$	0/073	0/010	0/090	0/012	0/129	0/018
	$TVP-AR(1)-X\quad DMA(\alpha=0.95,\lambda=1)$	0/067	0/008	0/082	0/010	0/118	0/014
	$TVP-AR(1)-X\quad BMA(\alpha=\lambda=1)$	0/014	0/002	0/017	0/002	0/095	0/064
	WLS	0/020	0/022	0/025	0/027	0/075	0/059
Non-structural models	$BVAR-Minnesota$	0/078	0/011	0/096	0/014	0/137	0/019
	VAR	0/083	0/012	0/102	0/015	0/146	0/021
	ARMA	0/050	0/017	0/062	0/021	0/088	0/030
	MSVAR (Prosperity regime)	0/033	0/029	0/041	0/036	0/058	0/051
	MSVAR(Recession regime)	0/014	0/003	0/047	0/024	0/025	0/005
	MSVAR(normal regime)	0/051	0/009	0/063	0/011	0/090	0/016
structural models	OLS	0/157	0/106	0/193	0/130	0/277	0/187
	GLS	0/146	0/090	0/180	0/111	0/257	0/159
Wavelet models	discrete	0/047	0/008	0/058	0/010	0/083	0/014
	Continuous	0/033	0/006	0/041	0/007	0/058	0/011
Metaheuristic approaches	Ant Colony Optimization	0/073	0/010	0/090	0/012	0/129	0/018
	Particle Swarm Optimization.	0/087	0/009	0/107	0/011	0/153	0/016
	Artificial Bee Colony Algorithm.	0/074	0/002	0/091	0/002	0/130	0/004
	Imperialist Competitive Algorithm.	0/100	0/321	0/123	0/395	0/176	0/565
Neural network approaches	Perceptron	0/078	0/011	0/096	0/014	0/137	0/019
	Recurrent Neural Network.	0/083	0/012	0/102	0/015	0/146	0/021
	Feed Forward	0/070	0/016	0/086	0/020	0/123	0/028

		1-day		16-day		32-day	
forecast interval model type1-day		MAFE	MSFE	MAFE	MSFE	MAFE	MSFE
	Convolutional Neural Network.	0/063	0/028	0/077	0/034	0/111	0/049
	Deep Learning and Neural Network.	0/071	0/009	0/087	0/011	0/125	0/016
Random differential	Geometric Brownian Motion.	0/062	0/007	0/026	0/019	0/109	0/012
	Heston	0/057	0/006	0/031	0/027	0/100	0/011
Financial quantum	Quantum Harmonic Oscillator.	0/076	0/011	0/024	0/019	0/134	0/019

Table 1 demonstrates that the accuracy of stock return prediction models varies across different time periods. This highlights the need for time-frame-specific forecasting.

CONCLUSION

The findings reveal that Bayesian model averaging was most accurate for short-term predictions, Quantum Harmonic Oscillator models excelled in the medium term, and wavelet models were superior for long-term stock return forecasting. These results underscore the varying accuracy of the reviewed models across different time horizons, reinforcing the necessity of time-frame-specific predictions.

Based on these results, the use of nonlinear models for stock return predictions is recommended. Investors should select models offering the highest accuracy for their specific investment horizon, aligning with their portfolio holding or buying period. These findings are consistent with prior research by Armen et al. (2022), Sarraf et al. (2019), Azevedo et al. (2022), Leo et al. (2022), and Alexiou et al. (2022).

Keywords: Stock Returns, Financial Quantum, Bayesian Averaging, Wavelet.
JEL Classification: G1, G12.