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ETF Markets' Prediction & Assets Management Platform Using Probabilistic Autoregressive Recurrent Networks

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Abstract: The significance of macroeconomic policy changes on ETF markets and financial markets cannot be disregarded. This study endeavors to predict the future trend of these markets by incorporating a group of selected economic indicators sourced from various ETF markets and utilizing probabilistic autoregressive recurrent networks (DeepAR). The choice of economic indicators was made based on the advice of a domain expert and the results of correlation estimation. These indicators were then divided into two categories: "US" indicators, which depict the impact of US policies such as the federal reserve fund rate and quantitative easing on the global markets, and "region-specific" indicators. The findings of the study indicate that the inclusion of "US" indicators enhances the prediction accuracy and that the DeepAR model outperforms the LSTM and GRU models. Furthermore, a web platform has been developed to apply the DeepAR models, which enables the user to predict the trend of an ETF ticker for the next 15 time-steps using the most recent data. The platform also possesses the capability to automatically generate fresh datasets from corresponding RESTful API sources in case the current data becomes outdated.

Keywords: Macroeconomic policy, ETF markets, Financial markets, DeepAR, Economic indicators, Machine learning

Introduction

An ETF, or exchange-traded fund, is a type of investment security that functions similarly to a mutual fund. It usually follows a specific index, industry, commodity, or set of assets(JAMES CHEN, 2022). For the standard retail or institutional investor, the process of buying and selling ETF shares is straightforward. The guidelines and procedures for trading ETFs are similar to those of the stock market. The shares are traded on the secondary market, just like stocks or closed-end funds, and not directly bought from the fund or resold to it. As they are traded like stocks, ETFs can be bought or sold at any point during the trading hours(Gastineau, 2001).

An ETF comprises several underlying assets, as opposed to a stock which holds only one. Due to the presence of multiple assets in an ETF, it is often favored for the purpose of diversification(JAMES CHEN, 2022). Conversely, changes in macroeconomic policies and announcements play a significant role in impacting the daily trading volumes of ETFs(Daniel Nadler & Anatoly Schmidt, 2015).

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In particular, macroeconomic policies of the United States, such as changes in the federal funds rate and market volatility, not only affect the ETF markets within the country but also have a ripple effect on other markets globally. For instance, fluctuations in the US market can lead to changes in other markets such as India, Russia, Mexico, and Turkey, and similar spillover effects are observed with European market volatility impacting markets in Mexico and South Korea (Yavas & Rezayat, 2016). This research aims to explore the influence of incorporating a distinct macroeconomic indicator on a selected group of ETF markets.

Related Work

In the realm of stock and ETF market prediction, multiple approaches have been explored, utilizing a variety of techniques(Z. Chen et al., 2021). One study (Liew & Mayster, 2018) assessed the performance of three commonly used machine learning algorithms (DNNs, RFs, and SVM) in predicting ETF returns. The authors introduced a gain measure to evaluate the efficacy of each algorithm and horizon, while segmenting the input feature variables into different information sets. Their results indicate that the most important predictive features vary depending on the ETF being predicted.

Another approach (Matsunaga et al., 2019) utilized a graph neural network structure, connecting companies through various relations such as supplier-customer, shareholder, and industry affiliations. This technique leverages the network structure to incorporate the interconnectivity of the market for more accurate stock price predictions, rather than relying solely on historical stock prices or hand-crafted features. The authors used a rolling window analysis method on 225 markets in Japan over roughly 20 years and found that the combination of knowledge graph data and graph neural networks holds strong potential for creating a more generalizable and practical stock market prediction mechanism compared to a baseline LSTM model.

A study (Nelson et al., 2017) utilized a large number of technical indicators to feed an LSTM neural network, along with data from different stocks from the Brazilian stock exchange. The authors employed a rolling window approach, generating a new neural network at the end of each trading day and using the most recent model to make predictions on the following day. The results were promising, with up to 55.9% accuracy in predicting if a particular stock price would increase in the near future.

Another LSTM-based method for stock returns prediction (K. Chen et al., 2015) was applied to the China stock market, transforming historical data into 30-day sequences with 10 learning features and 3-day earning rate labeling. Based on the earning rate, the sequences were categorized into seven ranges, with the aim of ensuring a comparable number of training sequences in each category. The study found that normalization improved accuracy and suggested that different stock sets may impact prediction accuracy, warranting separate predictions for different stock types.

A comparison between ARIMA, LSTM, and GRU for time series forecasting (Yamak et al., 2019) was conducted using one-day interval Bitcoin exchange rate data in American dollars from November 28th, 2014 to June 5th, 2019. The authors applied normalization, log transformation, and dealt with stationarity and seasonality in the dataset. The results showed that the ARIMA model had the best accuracy and time, though this outcome may be due to several factors such as the chosen parameters and the amount of data, which was relatively small for this study. The results also revealed that GRU performed better than LSTM, although RNN is typically more effective on larger datasets.

Dataset

The dataset in question pertains to 18 different ETF tickers, as listed in Table 1. These tickers are differentiated into different regions, including but not limited to "US", "EU", and "China". A comprehensive analysis of the dataset reveals that there are three distinct sets of features, each of which is assigned to the tickers based on their respective regions. These sets of features are:

Base Features: This category of features is present across all regions and encompasses common ticker attributes, such as "Open", "Close", "High", "Low", "Volume", and "Adjusted Price". The data for these features is obtained from the "Yahoo Finance" API.

US Features: This category encompasses a set of selected USA macroeconomic and monetary indicators, including but not limited to the Federal Reserve Fund Rate, Consumer Price Index, and Federal Reserve Total Assets.

These indicators have been selected on the basis of recommendations from domain experts and are included in all regions. This approach is based on the assumption that the US economy and its policies have a significant impact on all regions. The primary source of data for these features is the "Federal Reserve Economic Data" API.

Region-Specific Features: As the name implies, this category of features comprises region-specific macroeconomic and monetary indicators that have a potentially significant impact on the respective regions. To maintain consistency, the data for this category of features is obtained from the same source as that for the US Features, that is, the "Federal Reserve Economic Data" API.

A complete summary of the different features and the corresponding regions is provided in Appendix 1 terms "Base", "US", and "RS" represent the Base Features, US Features, and Region-Specific Features, respectively.

Given that the timeseries starting date for each feature varies between different features within the same ticker, it was deemed appropriate to utilize the most recent starting date among these features in order to avoid any data gaps within the features of a single ticker. Additionally, a standard scaling technique has been applied to each ticker individually, in order to maintain the data shape for that particular ticker.

Table 1. Summary of ETF tickers and associated features in the platform.

No.	Code	Name	Region
1	BND	Vanguard Total Bond Market Index Fund	US
2	CEMB	iShares J.P. Morgan EM Corporate Bond	Emerging Markets
3	EMXC	iShares MSCI Emerging Markets ex China	Emerging Markets ex. China
4	EWG	iShares MSCI Germany	Germany
5	EWH	iShares MSCI Hong Kong	Hong Kong
6	EWQ	iShares MSCI France	France
7	EWU	iShares MSCI United Kingdom	UK
8	FXI	Shares China Large-Cap	China
9	GLD	SPDR Gold Shares	US
10	GOVT	iShares U.S. Treasury Bond	US
11	IGOV	iShares International Treasury Bond	US
12	IVOO	Vanguard S&P Mid-Cap 400 Index Fund	US
13	JNK	SPDR Bloomberg High Yield Bond	US
14	VGK	Vanguard European Stock Index Fund	EU
15	VIOO	Vanguard S&P Small-Cap 600 Index Fund	US
16	SPY	SPDR S&P 500 ETF Trust	US
17	VOO	S&P 500 ETF	US
18	VWOB	Vanguard Emerging Markets Government Bond Index Fund	Emerging Markets

Methodology

During the implementation phase, three distinct models were evaluated with respect to the various tickers: Long Short-Term Memory (LSTM) networks, Gated Recurrent Unit (GRU) networks, and Probabilistic Autoregressive Recurrent Networks (DeepAR).

The Long Short-Term Memory (LSTM) network is a specialized type of Recurrent Neural Network (RNN) that was first introduced in 1997 by Hochreiter and Schmidhuber. LSTMs were specifically designed to overcome the problem of long-term dependencies that can occur in traditional RNNs. The ability to retain information over extended periods of time is a defining characteristic of LSTMs (Christopher Olah, 2015; Hochreiter & Schmidhuber, 1997).

The LSTM cell contains additional gates, specifically the input, forget, and output gates, which are utilized to determine which signals will be transmitted to the subsequent node. The current connection between the previous hidden layer and the current hidden layer is represented by the weight matrix W. Meanwhile, the weight matrix U connects the inputs to the hidden layer. The candidate hidden state, denoted as $\tilde{C}$, is computed based on the current input and the previous hidden state. The internal memory of the unit, referred to as C, is a combination of the previous memory, multiplied by the forget gate, and the newly calculated hidden state, multiplied by the input gate. The behavior of all gates in the LSTM cell is described by the equations depicted in Figure 1(Varsamopoulos et al., 2018). The activation of the forget gate enables the LSTM to determine, at each time step, which information should not be forgotten and to accordingly modify the model's parameters. Consequently, this addresses the vanishing gradients problem(Nir Arbel, 2018).

GRU was introduced in 2014 by Cho et al. as a streamlined alternative to the Long Short-Term Memory (LSTM) cell. Despite achieving comparable performance to LSTMs, GRUs are computationally more efficient and often faster to compute(Cho et al., 2014).

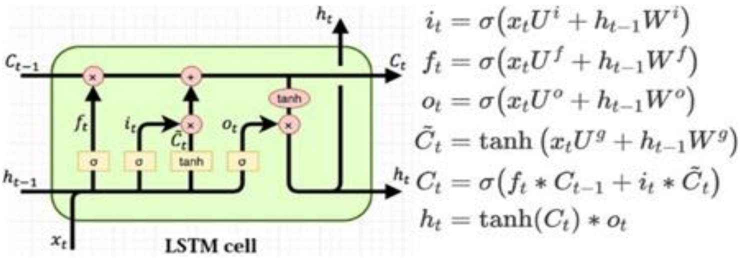

Figure 1**.** Diagram of the Structure and Mathematical Representation of an LSTM Cell

The GRU architecture consists of two gates, the reset gate and the update gate, which are used to control the flow of information from the previous hidden state to the current hidden state. The reset gate determines the extent to which the previous state should be remembered, while the update gate controls the proportion of the new state that is derived from the old state. These two gates are implemented as fully connected layers with a sigmoid activation function and their inputs are the current time step and the previous hidden state (Zhang Aston et al., 2022). Figure 2 provides a visual representation of the inputs and outputs of the reset and update gates in a GRU cell.

Finally, the DeepAR model differs from the previous two models LSTM and GRU, as they are deterministic models, while DeepAR is a probabilistic model. The latter may be more appropriate in the context of financial data, given its inherently uncertain nature. DeepAR proposes an RNN architecture for probabilistic forecasting, incorporating Gaussian likelihood for real-valued data and negative-binomial likelihood for positive count data, with special considerations for time series with widely varying magnitudes (Salinas et al., 2017).

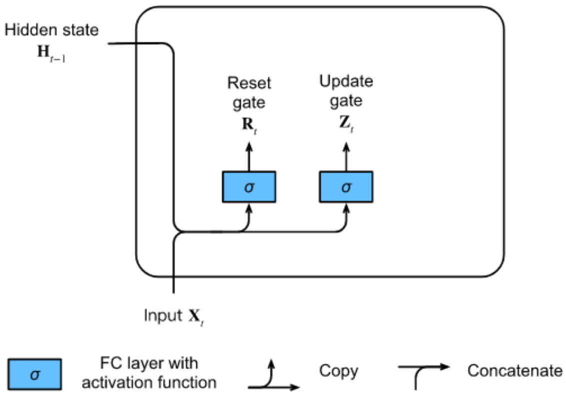

Figure 2. Structure and computation of the reset and update gates in a gated recurrent unit (GRU) model.

During the training process of DeepAR, as depicted in Figure 3, the network inputs at each time step t, include the covariates $x_{i,t}$, the target value at the previous time step $z_{i,t-1}$, and the previous network output $h_{i,t-1}$.

The network output:

$$h_{i,t} = h(h_{i,t-1}, z_{i,t-1}, \quad x_{i,t}, \Theta)$$

is then utilized to calculate the parameters $\theta_{i,t} = \theta(h_{i,t}, \Theta)$ of the likelihood $\ell(z|\theta)$, which is used for training the model parameters. As for prediction, the history of the time series $z_{i,t}$ is fed in for $t < t_0$, then in the prediction range for $t \geq t_0$ a sample $\hat{z}_{i,t} \sim \ell(\cdot\,|\theta_{i,t})$ is drawn and fed back for the next point until the end

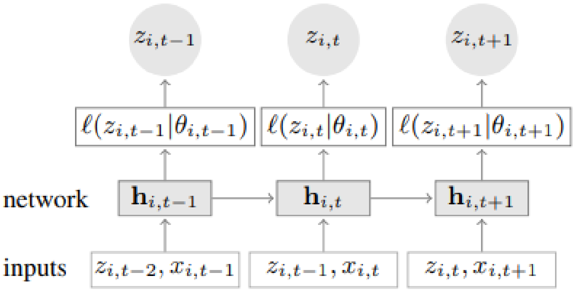

Figure 3. Mathematical operations in DeepAR during training.

of the prediction range $t = t_0 + T$generating one sample trace. Repeating this prediction process yields many traces representing the joint predicted distribution (Salinas et al., 2017).

System Architecture

The platform functions predominantly through the utilization of Django, a highly regarded Python framework that offers robust authentication and authorization features. With access to the platform limited to registered users only, the framework ensures that all data is effectively stored and secured within a PostgreSQL database. The platform also incorporates an additional set of tables that are designed to allocate each Ticker with a specific set of features and to locate it within a designated country and region. It should be noted that these features can be assigned to multiple regions.

Users are provided with the ability to effortlessly update Ticker data and conduct predictions. Upon updating the Ticker data, a RESTful API call is automatically triggered to both the Yahoo and FRED APIs, thus facilitating the real-time compilation of the updated dataset. To guarantee the platform operates with optimal efficiency and reliability, a reverse proxy approach has been implemented through the utilization of the NGINX server. This approach ensures that user requests are first effectively handled by the NGINX server, and then passed efficiently to Django through Gunicorn as necessary, as demonstrated in **Hata! Başvuru kaynağı bulunamadı.**.

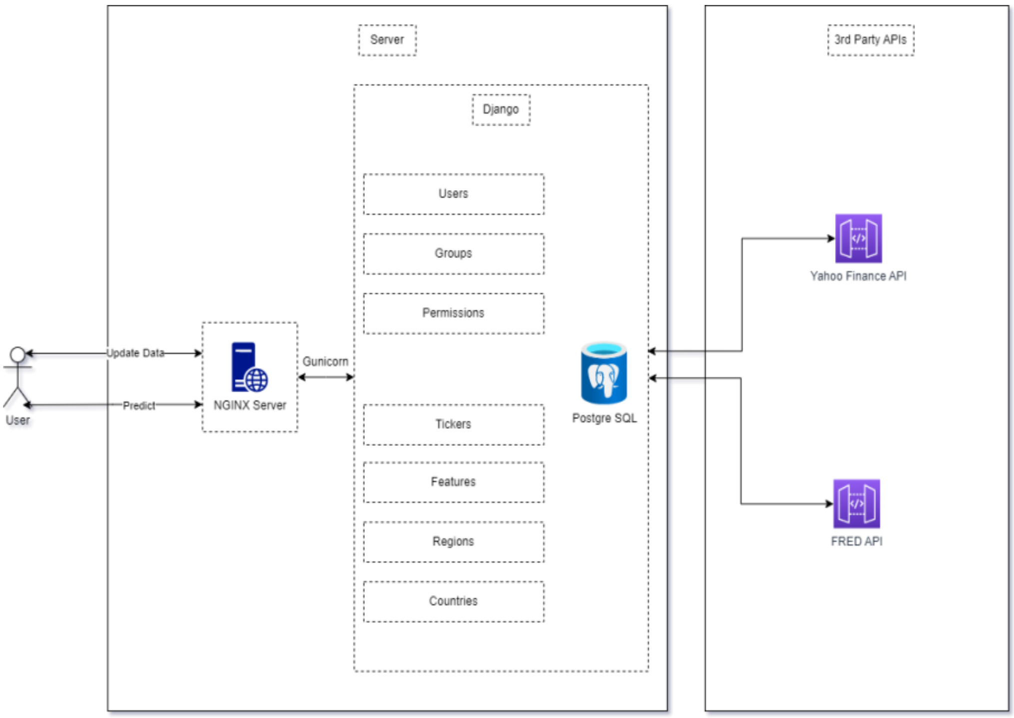

Figure 4. The architecture of the platform

Experiment

Prior to conducting experiments on the three models, several data preprocessing steps were undertaken. These included data standardization through the utilization of Standard Scaler and Min-Max Scalar and the calculation of a correlation matrix to identify and eliminate correlated features. Additionally, calculated features were added to the dataset, such as "3-Day Moving Average", "10-Day Moving Average", "Buy-Sell on Close", "Buy-Sell on Open", "Day of the Year", and "Month of the Year", with the aim of capturing additional trends in the data. Once the dataset was prepared, 20% was reserved for testing purposes and 80% was utilized for training. During the training phase, the sliding window technique was employed, with the model utilizing 30 time-steps for training and predicting the next 15 time-steps, as depicted in Figure 5.

The structure of the models utilized in this study comprised of a fully connected Recurrent Neural Network (RNN) structure with seven hidden layers and a ReLU activation function. During the training phase, the Adam optimization algorithm was utilized with a learning rate of 0.001 and a total of 700 epochs.

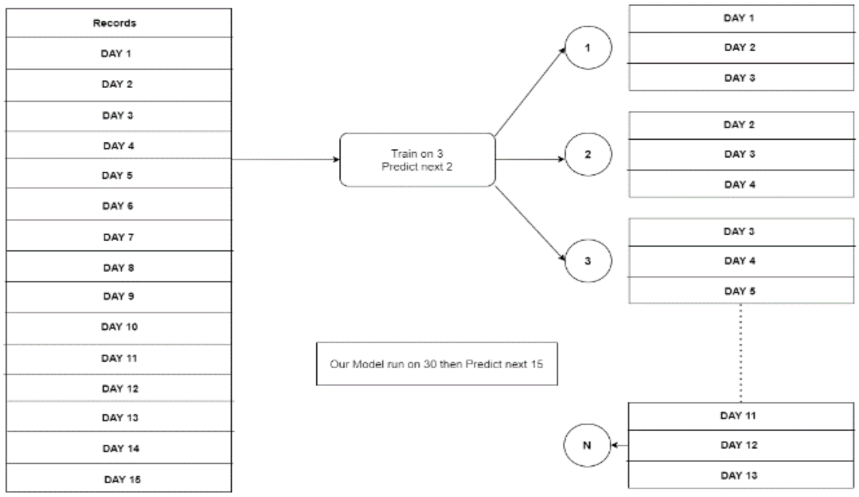

Figure 5. Sliding window training methodology for time-series predictions

Results

To ensure that the models could effectively predict future values without any data contamination, the predictions produced by the models were compared with a separate test dataset. The LSTM and GRU models are deterministic in nature, and as a result, they generated a single prediction for the predetermined time span. This is visually depicted in **Hata! Başvuru kaynağı bulunamadı.**, where the predicted values are represented in orange, and the actual values are shown in blue. Conversely, the DeepAR model is probabilistic, and therefore, it generated predictions with a 50% and 90% confidence interval, which are represented by light green and dark green in Figure 4, are compared against the actual values depicted in blue.

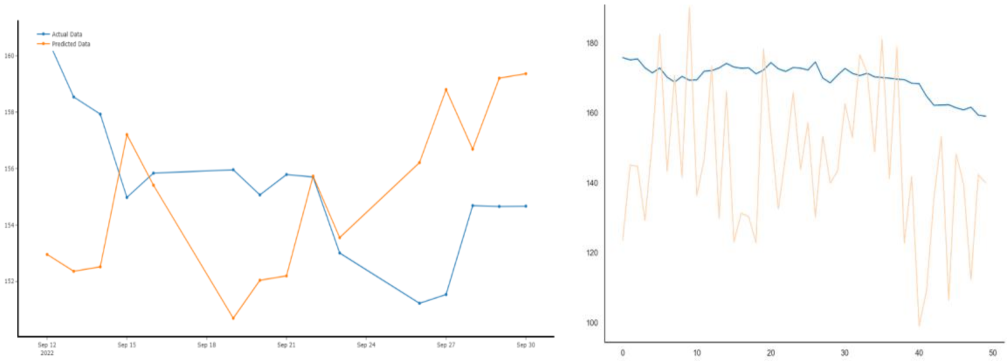

Figure 6. Comparative performance of LSTM (Left) and GRU (Right) models for ETF price prediction on GLD ticker.

In the present study, the Mean Absolute Percentage Error (MAPE) was utilized to assess the accuracy of the time-series models in comparison to actual values. MAPE is defined as the average absolute percent error of each time period, calculated as the ratio of the absolute difference between actual and predicted values and the actual values(scikit-learn.org, n.d.). The mathematical expression for MAPE can be represented as follows:

$$\text{MAPE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} \frac{|y_i - \hat{y}_i|}{max(\epsilon, |y_i|)}$$

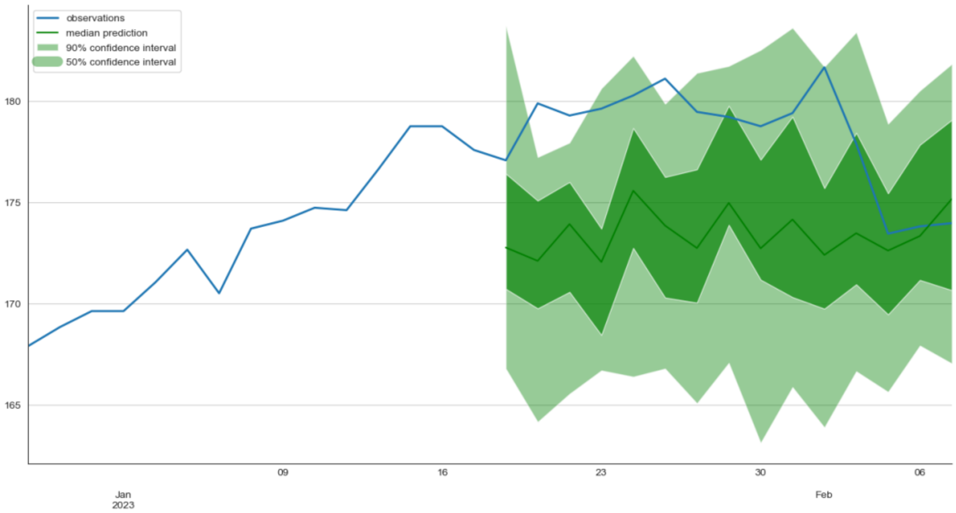

Figure 4. Assessment of DeepAR model for ETF price prediction on GLD ticker.

Additionally, the Root Mean Square Error (RMSE) was employed to evaluate the quality of the predictions. RMSE provides information on the deviation of the predictions from the true values, as determined through the Euclidean distance(C3 AI, 2022). The calculation of RMSE involves finding the square root of the mean square error, as described by the following equation(scikit-learn.org, 2022):

$$\text{MSE}(y, \hat{y}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}-1} (y_i - \hat{y}_i)^2$$

Table 2 presents a comparison of the performance of the models: Long Short-Term LSTM, GRU, and DeepAR. The performance is measured by the above two metrics, MAPE and RMSE.

Table 2. Comparison of performance metrics for long short-term LSTM, GRU, and DeepAR models in ETF markets prediction.

Code	MAPE			RMSE		
	LSTM	GRU	DeepAR	LSTM	GRU	DeepAR
BND	0.063	0.054	0.044	6.43	5.10	3.45
CEMB	0.065	0.082	0.026	7.77	10.39	3.01
EMXC	0.046	0.092	0.034	8.19	12.17	4.78
EWG	0.075	0.099	0.069	5.86	9.63	5.09
EWH	0.055	0.066	0.011	9.51	11.24	6.12
EWQ	0.070	0.053	0.051	6.06	5.04	4.97
EWU	0.069	0.077	0.071	6.74	7.06	6.89
FXI	0.044	0.073	0.013	7.10	8.32	3.21
GLD	0.031	0.074	0.024	8.96	13.11	7.38
GOVT	0.088	0.087	0.036	9.14	8.97	5.64
IGOV	0.039	0.045	0.034	7.75	9.20	7.12
IVOO	0.084	0.087	0.075	4.87	5.83	4.29
JNK	0.056	0.064	0.058	5.02	6.41	5.81
VGK	0.057	0.100	0.030	8.23	12.58	6.04
VIOO	0.069	0.091	0.068	5.03	8.71	4.90
SPY	0.089	0.100	0.024	7.30	13.66	5.16
VOO	0.079	0.059	0.049	4.47	4.10	3.95
VWOB	0.040	0.099	0.039	8.87	11.84	7.65

The results indicate that, in general, the incorporation of macroeconomic features in time-series models leads to low MAPE values. The data demonstrates that DeepAR outperforms LSTM and GRU models, as it yields smaller MAPE values in almost all markets. For instance, in the BND market, DeepAR had a MAPE value of 0.044, while LSTM and GRU models recorded MAPE values of 0.063 and 0.054, respectively. In addition, the RMSE value of DeepAR in the BND market was 3.45, while LSTM and GRU models recorded RMSE values of 6.43 and 5.10, respectively.

Despite the superior performance of DeepAR compared to the other models, there is still room for improvement. In some markets, such as VWOB, the range of predicted values can be enhanced even further. To summarize, this comparison highlights the importance of including macroeconomic factors in time-series models and shows that the DeepAR model outperforms the LSTM and GRU models in terms of forecasting accuracy.

Conclusion

This study aimed to investigate the influence of macroeconomic policy changes on ETF markets and financial markets and predict their future trends. The study utilized a group of selected economic indicators sourced from various ETF markets and utilized probabilistic autoregressive recurrent networks (DeepAR) for prediction. The findings indicate that the inclusion of US indicators enhances the prediction accuracy and that the DeepAR model outperforms the LSTM and GRU models. Furthermore, the study developed a web platform, utilizing the Django framework and a PostgreSQL database, to apply the DeepAR models and predict the trend of an ETF ticker for the next 15 time-steps using the most recent data. The platform also possesses the capability to automatically generate fresh datasets from corresponding RESTful API sources. The results of this study contribute to a deeper understanding of the relationship between macroeconomic policy changes and ETF market trends and offer practical applications for financial forecasting.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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Appendix 1. Summary of macroeconomic indicators and their groups in the dataset

Code	Name	Group
Open	Open Price	Base
Close	Close Price	Base
High	High Price	Base
Low	Low Price	Base
Volume	ETF Volume	Base
Adj Close	Adjusted Close Price	Base
FEDFUNDS	Federal Reserve Fund Rate	US
CPALTT01USM661S	Consumer Price Index	US
DTWEXBGS	Nominal Broad U.S. Dollar Index	US
WALCL	Federal Reserve Total Assets (QE)	US
GDPC1	Real Gross Domestic Product	US
DGS3MO	Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity	US
EMVOVERALLEMV	Overall Equity Market Volatility Tracker	US
RBUSBIS	Real Broad Effective Exchange Rate	US
PAYEMS	Employment Level	US
IRLTLT01USM156N	Long-Term Government Bond Yields: 10-year	US
DGS2	Market Yield on U.S. Treasury Securities at 2-Year Constant Maturity	US
DGS10	Market Yield on Treasury Securities at 10-Year	US
DFII10	Market Yield on Treasury Securities at 10-Year - inflation	US
VIXCLS	CBOE Volatility Index	US

Code	Name	Group
EMVMACROINTEREST	Interest Rates Equity Market Volatility Tracker	US
EMVMACROBUS	Investment Sentiment Equity Market Volatility Tracker	US
NYGDPPCAPKDDEU	Germany Constant GDP per capita	RS
FPCPITOTLZGDEU	Germany Inflation, consumer prices	RS
RBDEBIS	Germany Real Broad Effective Exchange Rate	RS
IRLTLT01DEM156N	Germany Interest Rates: Long-Term Government Bond Yields: 10-Year	RS
LMUNRRTTDEM156S	Germany Registered Unemployment Rate	RS
NYGDPPCAPKDFRA	France Constant GDP per capita	RS
FPCPITOTLZGFRA	France Inflation, consumer prices	RS
RBFRBIS	France Real Broad Effective Exchange Rate	RS
IRLTLT01FRM156N	France Long-Term Government Bond Yields: 10-year	RS
LRHUTTTTFRM156S	France Harmonized Unemployment Rate: Total	RS
NYGDPPCAPKDGBR	UK Constant GDP per capita	RS
FPCPITOTLZGGBR	UK Inflation, consumer prices	RS
RBGBBIS	UK Real Broad Effective Exchange Rate	RS
IRLTLT01GBM156N	UK Long-Term Government Bond Yields: 10-year	RS
LMUNRRTTGBM156S	UK Registered Unemployment Rate	RS
NYGDPPCAPKDCHN	China Constant GDP per capita	RS
FPCPITOTLZGCHN	China Inflation, consumer prices	RS
RBCNBIS	China Real Broad Effective Exchange Rate	RS
SLEMPTOTLSPZSCHN	China Employment to Population Ratio	RS
INTDSRCNM193N	China Interest Rates, Discount Rate	RS
NYGDPPCAPKDHKG	Hong Kong Constant GDP per capita	RS
FPCPITOTLZGHKG	Hong Kong Inflation, consumer prices	RS
RBHKBIS	Hong Kong Real Broad Effective Exchange Rate	RS
TDSAMRIAOGGHK	Hong Kong Amount Outstanding of Total Debt Securities in General Government Sector	RS
SLUEM1524ZSHKG	Hong Kong Youth Unemployment Rate	RS
CLVMEURSCAB1GQEU272020	EU Real Gross Domestic Product	RS
FPCPITOTLZGEUU	EU Inflation, consumer prices	RS
DEXUSEU	U.S. Dollars to Euro Spot Exchange Rate	RS

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