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Forecasting Pakistan Stock Returns Using Economic Policy Uncertainty: Deep Learning Evidence from an Emerging Market

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Abstract

Accurate forecasting of stock returns remains a persistent challenge in financial economics, particularly in emerging markets characterized by policy uncertainty, macroeconomic volatility, and evolving institutional structures. Pakistan offers a relevant setting due to recurring political transitions, inflationary pressures, exchange rate instability, external financing constraints, and periodic policy shifts that frequently influence investor sentiment and market behavior. This study examines whether Economic Policy Uncertainty (EPU) improves the forecasting of Pakistan stock returns and whether advanced deep learning models outperform conventional econometric approaches. Using monthly data from 2010 to 2024, traditional benchmark models, including ARIMA, GARCH, and ARDL, are compared with modern deep learning architectures comprising Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-LSTM, and Transformer models. Forecasting performance is evaluated using root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The empirical findings show that incorporating EPU significantly enhances predictive accuracy across competing models, confirming the informational relevance of policy uncertainty for financial markets. Deep learning models consistently outperform benchmark econometric models, indicating the presence of nonlinear, dynamic, and time-varying relationships in Pakistan's stock market. Among all competing approaches, Transformer and CNN-LSTM models deliver the strongest forecasting performance, with gains becoming more pronounced during crisis periods, including COVID-19-related disruptions and episodes of macroeconomic stress. The study contributes new evidence from an underexplored emerging market and demonstrates the value of integrating uncertainty indicators with modern artificial intelligence techniques for financial forecasting. The findings provide practical implications for investors, regulators, and policymakers seeking to strengthen decision-making, risk management, and market monitoring under uncertain economic conditions.

Keywords: Economic Policy Uncertainty; Pakistan Stock Exchange; Stock Returns; Deep Learning; Transformer Model; Forecasting; Emerging Markets

1. Introduction

Forecasting stock returns is a key and challenging issue in finance. Making accurate predictions assists investors in portfolio management, risk and pricing-management, and regulators to track financial stability. While the stock market is notoriously difficult to predict (stock prices depend on a combination of macroeconomic, political conditions, firm-specific characteristics and investor sentiment Fama (1970), Campbell et al. (1997), it is an important and challenging question in financial economics. Such predictions can assist investors with their portfolio allocation, risk and valuation strategies, and can assist policymakers monitor financial stability.

While there is a long tradition of forecasting stock markets, they are difficult to predict because the returns on stocks are driven by a combination of factors such as the macroeconomic environment, economic policy, firm-specific and investor-mood data (Fama, 1970; Campbell et al., 1997). Forecasting can be more difficult in emerging markets. Emerging financial markets are usually more volatile, have less liquid markets, face institutional challenges and are more sensitive to domestic and external shocks than mature markets. This could result in a relatively inefficient market, in which policy signals are more relevant in setting expectations (Bekaert and Harvey, 2003; Vo, 2017). This, in turn, means that models that are relatively successful in developed markets might not be as successful in emerging markets. An example here is Pakistan. In the past ten years, there have been periods of political instability, inflation, depreciation of the exchange rate, fiscal deficit and lack of access to international financing. So it has affected financial markets, investment and business climate. The-100 Index and Pakistan Stock Exchange (PSX) have been affected by domestic and international events.

Although there is a growing body of international literature that has reported the effects of policy uncertainty on stock returns, volatility and investment activity in both developed and emerging markets (Antonakakis et al., 2013; Kang, Lee and Ratti, 2013; Christou et al., 2017), for Pakistan such evidence is limited in the context of forecasting. Previous studies in Pakistan have mainly focused on more conventional econometric models such as ordinary least squares, autoregressive distributed lag (ARDL), vector autoregression (VAR) or generalized autoregressive conditional heteroskedasticity (GARCH) models that assume more stable functional forms and are less flexible for capturing highly dynamic or nonlinear stock markets.

Deep learning models are well-adapted for time-series forecasting, and recent research has demonstrated that Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Convolutional Neural Network-LSTM (CNN-LSTM) and Transformer models have better predictive power for prices, volatility and returns in several markets (Fischer and Krauss, 2018; Nelson et al., 2017; Lim and Zohren, 2021). However, there is a lack of evidence on whether deep learning models can improve the forecasting of stock returns in Pakistan by including Economic Policy Uncertainty as an explanatory variable, which is relevant because uncertainty shocks are more frequent and more severe in emerging markets where stock markets are more sensitive to news and policy. To this end, this study investigates whether Economic Policy Uncertainty improves the prediction of Pakistan stock returns with deep learning models. The research compares the forecasting performance of LSTM, GRU, CNN-LSTM and Transformer models with baseline models by incorporating monthly data of Pakistan Stock Exchange (PSX) and some macroeconomic variables from 2010 to 2024. The prediction performance is measured using conventional metrics such as root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

First, this study enhances our understanding of the predictive value in terms of EPU from the Pakistan Stock Exchange; secondly, it contributes to the emerging market forecasting literature by using state-of-the-art deep learning models on a less studied economy; and third, provides practical implications for an investor, a portfolio manager, or a policymaker who needs to manage risks against any policy changes in uncertain times.

2. Literature Review

2.1 Stock Return Forecasting and Traditional Approaches

The prediction of stock returns has been a topic of interest in finance for decades. The early studies were mainly shaped by the Efficient Market Hypothesis (EMH) which assumes that information is quickly reflected in prices and expected returns are difficult to forecast (Fama 1970). Subsequent studies have shown that returns can still be forecasted due to business cycles, biases and market frictions.

Traditional forecasting methods usually comprise of autoregressive integrated moving average (ARIMA), vector autoregression (VAR), generalized autoregressive conditional heteroskedasticity (GARCH) and autoregressive distributed lag (ARDL) models. These models have been extensively used because they are easy to understand. Engle (1982) introduced autoregressive conditional heteroskedasticity (ARCH) models, and Bollerslev (1986) extended these models to the generalized autoregressive conditional heteroskedasticity (GARCH) models. Similarly, Pesaran et al. (2001) developed the ARDL approach for investigating the long-run and short-run relationships of incompletely specified variables.

These methods are still widely used, but their predictive powers could diminish when the market has nonlinear, nonstationary or regime-switching relationships. This is especially relevant for emerging markets which experience greater shocks and shifts.

2.2 Economic Policy Uncertainty and Financial Markets

Economic Policy Uncertainty (EPU) has gained attention as a key variable in pricing and macro-financial studies. One of the most popular EPU indicators was constructed by Baker et al. (2016), using the frequencies of newspaper index searches, tax code uncertainty and forecaster disagreement.

Increasing policy uncertainty can impact stock markets in several ways. First, investment and employment decisions may be postponed. Second, investors may seek greater risk premium. Third, consumers may decrease spending due to uncertainty over future income. Such reactions may lower earnings growth and put downward pressure on stock prices. Evidence supports the role of EPU in financial markets. Pastor and Veronesi (2013) reported that EPU leads to higher risk premia and impacts stock prices. Antonakakis et al. (2013), identified dynamic relationships between EPU and stock returns in developed countries. Christou et al. (2017) also found volatility of stock returns is affected by uncertainty shocks. In emerging markets the effect may be magnified as policy institutions are not as well established and markets respond to changes in the political or regulatory environment.

2.3 Deep Learning for Financial Forecasting

Time-series forecasting has also benefited from recent advances in artificial intelligence. Deep learning models are particularly appealing because they can capture nonlinearities, interactions and long memory without relying on restrictive model assumptions.

One of the most popular deep learning models for financial forecasting is Long Short-Term Memory (LSTM) networks. LSTM models are able to learn long-term dependencies and overcome the vanishing gradient issue prevalent in recurrent neural networks (Hochreiter & Schmidhuber, 1997). LSTM models were shown to outperform other methods for predicting stock returns (Fischer and Krauss 2018). Gated Recurrent Unit (GRU) models are a simpler recurrent model with fewer parameters but good performance Cho et al. (2014). Combined CNN-LSTM models use convolutional feature extraction and recurrent learning to achieve better results in noisy financial data.

Recently, Transformer models have become popular for their capacity to model long-range dependencies using self-attention, rather than recurrence (Vaswani et al., 2017). Some studies demonstrate the excellent forecasting ability of Transformer models in finance and economics (Lim & Zohren, 2021; Kong 2025).

2.4 Evidence from Pakistan

Various studies have investigated the impact of inflation, exchange rate, interest rate, foreign direct investment and political uncertainty on stock returns in the Pakistan stock market. Typically, these studies have employed regression, ARDL, or GARCH models. Although these studies offer valuable evidence, there is relatively little evidence about the inclusion of Economic Policy Uncertainty in predictive models.

Also, deep learning applications on the Pakistan stock market are still in their infancy compared to developed and other large emerging markets like China and India. These findings indicate large potential for new findings using contemporary forecasting techniques.

2.5 Research Gap

From the literature review, there are three main gaps.

First, there are limited studies exploring the predictability of Economic Policy Uncertainty (EPU) for stock returns for Pakistan in a formal setting.

Second, these studies in Pakistan primarily focus on linear [return] and volatility models, with limited usage of deep learning models that can capture the non-linear nature of the input and output.

Third, few studies have benchmarked deep learning models with benchmark for Pakistan, an emerging stock market.

The current study addresses the above issues in the literature by evaluating whether Economic Policy Uncertainty (EPU) improves the forecasting of stock returns for Pakistan markets with LSTM, GRU, CNN-LSTM and Transformer models and benchmarking their out-performance over traditional econometric models.

2.6 Hypotheses Development

The literature is indicating that the presence of Economic Policy Uncertainty (EPU) in financial markets is increasing because of its effects on market sentiment, perception of risk and expectations about future economic conditions. Higher levels of uncertainty could lead to decreased investment, enhanced precautionary behavior and increased stock volatility. In emerging markets, where the institutional framework is relatively weak and markets are more responsive to policy signals, such impact may be more significant and short-lived.

Previous research indicates that increases in policy uncertainty are often accompanied by declines in stock market performance, returns and volatility Baker et al. (2016); Pastor & Veronesi, (2013). Given the frequent political changes, inflationary pressures, exchange rate instability and policy uncertainty in Pakistan, EPU is anticipated to have an impact on the stock market.

Meanwhile, recent developments in machine learning suggest that deep learning models may be superior to traditional econometric models in capturing relationships between variables that are nonlinear, time-varying and complex. This is often the case with the financial markets, especially in emerging economies. Networks like Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-LSTM, and Transformer models aim to learn complex relationships and dependencies that are difficult to learn with conventional linear models Fischer & Krauss, (2018); Lim & Zohren, (2021).

Based on the discussion above, we test the following hypotheses:

H1: Economic Policy Uncertainty is a strong predictor of Pakistan stock returns.

H2: Pakistan stock returns decrease with an increase in Economic Policy Uncertainty.

H3: Deep learning models outperform traditional econometric models in forecasting Pakistan stock returns.

H4: Convolutional-recurrent and other hybrid deep learning models, like CNN-LSTM and Transformer models, perform better in predicting Pakistan stock returns than simple recurrent models.

H5: Controlling for macroeconomic factors along with Economic Policy Uncertainty enhances the predictive accuracy.

These hypotheses establish the framework for empirical analysis in the methodology section below.

3. Data and Methodology

This section outlines the data sources and variable definitions, sample period and empirical methodology that is adopted to evaluate whether Economic Policy Uncertainty (EPU) can enhance the prediction of stock returns in Pakistan. It also provides details of the benchmark econometric and deep learning models used for forecasting comparison.

3.1 Data Sources and Sample Period

We employed monthly time-series data from January 2010 to December 2024. We use monthly data as Economic Policy Uncertainty indices and a number of macroeconomic variables are usually reported on a monthly basis, and monthly data allow us to establish the medium-term relationship between policy uncertainty and the stock market while filtering out daily movements.

The sample encompasses a number of significant local and global events, including exchange rate realignment, inflationary periods, IMF-led policy packages, political changes, the effects of the COVID-19 pandemic, and global financial uncertainty. These offer a suitable backdrop for assessing the forecasting power of policy uncertainty in Pakistan's stock market. We acquired data from reputable sources such as the Pakistan Stock Exchange (PSX), State Bank of Pakistan (SBP), World Bank, International Monetary Fund (IMF), Pakistan Bureau of Statistics (PBS), and the Economic Policy Uncertainty (EPU) project by Baker et al. (2016), in terms of Pakistan, we used Choudhary, M. A., Pasha, F., & Waheed, M. (2020).

3.2 Variable Description

3.2.1 Dependent Variable

The dependent variable is Pakistan stock returns, proxied by the monthly return of the PSX-100 Index, which is the benchmark index of the Pakistan Stock Exchange.

Monthly stock returns are calculated as:

$$R\_t = ln(P\_t) - ln(P\_(t-1)) \text{.. Eq.1}$$

Where:

- R_t = Stock return at time t
- P_t = PSX-100 Index closing price at time t
- $P\_\{t-1\}$ = PSX-100 Index closing price at time t−1

The logarithmic return is preferred because it stabilizes variance and is widely used in financial research.

3.2.2 Main Independent Variable

The key explanatory variable is Economic Policy Uncertainty (EPU), which reflects uncertainty regarding fiscal, monetary, trade, and regulatory policy. Higher EPU values indicate greater uncertainty in the policy environment.

3.2.3 Control Variables

To improve forecasting accuracy and reduce omitted variable bias, the following macroeconomic control variables are included:

- **CPI** = Consumer Price Index (proxy for inflation)
- **EXR** = Exchange rate
- **IR** = Interest rate
- **IPI** = Industrial Production Index (proxy for economic activity)
- **FDI** = Foreign Direct Investment (optional, if data available)

These variables are commonly associated with stock market movements in emerging economies.

3.3 Data Preprocessing

Before model estimation, the data are pre-processed through the following steps:

1. Missing observations, if any, are checked and treated appropriately.
2. Variables measured in levels are transformed into logarithmic form where relevant.
3. Continuous variables are normalized or standardized for deep learning models.
4. The dataset is divided into:
   - **Training set** (e.g., 70%)
   - **Validation set** (e.g., 15%)
   - **Testing set** (e.g., 15%)

This split allows model training and out-of-sample forecasting evaluation.

3.4 Benchmark Econometric Models

While estimating deep learning models, this study uses traditional econometric forecasting models, also known as benchmark models. The application of benchmark models is crucial to allow research to benchmark prediction accuracy and establish whether advanced deep learning techniques enhance forecast performance. Econometric models are still used extensively in financial forecasting studies as they are simple to understand, have a theoretical basis, and have a strong presence in the finance literature.

Benchmark models used in this study include the Autoregressive Integrated Moving Average (ARIMA) model, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and the Autoregressive Distributed Lag (ARDL) model. The reason for choosing these approaches is their representation of various aspects of financial time series. The ARIMA model is suited for capturing linear-time series effects, the GARCH model is suited for capturing volatility and the ARDL model is suited for incorporating dynamic interaction of stock returns and explanatory macroeconomic factors.

Comparing the performance of these traditional models with deep learning models allows researchers to determine whether performance enhancements due to deep neural networks are a consequence of better non-linear learning processes.

3.4.1 Autoregressive Integrated Moving Average (ARIMA)

One of the most popular traditional time-series forecasting methods is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is made up of three parts:

• Autoregressive (AR): current values depend on past values.

• Integrated (I): differencing is used to achieve stationarity.

• Moving Average (MA): current values depend on past errors.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Mishkin, 1995, p. 294) is a useful to capture linear persistence and short-run momentum in stock returns. But the stock markets are sometimes non-linear and time-varying in terms of volatility, meaning that ARIMA models do not necessarily have good forecasting ability in such markets.

3.4.2 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Time series of financial returns often tend to display volatility clustering - high volatility is followed by high volatility, while low volatility is followed by low volatility. This phenomenon is modelled using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Such a model is relevant to stock market forecasting as risk or uncertainty can be captured via volatility in returns. The value of GARCH as a model to estimate Pakistan's stock market returns is that events such as political uncertainty, high inflation or exchange rate pressures cause a clustering of volatility effects.

3.4.3 Autoregressive Distributed Lag (ARDL) Model

The Autoregressive Distributed Lag (ARDL) approach is a dynamic, multivariate approach where stock returns depend on its lagged values as well as lags of the explanatory variables (Economic Policy Uncertainty, inflation, the exchange rate and industrial production).

The ARDL model has a number of merits:

1. It allows the variables used to be integrated of different orders (I(0)) and (I(1)).
2. It can also measure short-run and long-run effects.
3. It is suitable for a moderate sample.

Given that the stock market in Pakistan might react to both short- and long-run macroeconomic variables, ARDL is an interesting benchmark for out-of-sample forecasts.

3.4.4 The Need for Benchmarks

The use of benchmark econometric models is important for a number of reasons.

1. Performance Comparison: They serve as a control to benchmark the improvement contributed by deep learning models.

2. Interpretability: Linear models have economically meaningful parameters to understand persistence, volatility and macroeconomic effects.

3. Academic Consistency: The literature on the stock market of Pakistan most commonly uses the ARIMA, GARCH or ARDL models. Hence, the inclusion of these models permit comparison with the previous literature.

4. Robustness of Findings: The superior performance of deep learning models relative to established econometric models adds more confidence to using AI for forecasting.

3.4.5 Expected Relevance to Pakistan’s Stock Market

Pakistan's capital market is volatile, has undergone structural reforms, has macroeconomic policy uncertainty, and policies are sensitive to investors. Under such conditions:

• ARIMA captures fundamental return autoregression
• GARCH captures risk and uncertainty
• ARDL captures macroeconomic and uncertainty linkages

These two important features highlight why the models can be used as benchmark models before exploring deep learning techniques.

3.4.6 Summary

In summary, the traditional econometric models serve as a robust framework to explore the potential of deep learning for improved forecasts. Through the combination of ARIMA, GARCH and ARDL approaches, this research presents plausible baselines against which to evaluate the performance of recent deep learning models.

3.5 Deep Learning Models

This study uses four of the popular deep learning models to assess whether sophisticated artificial intelligence improves Pakistan stock returns forecasting: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), CNN-LSTM and Transformer models. These approaches were chosen because financial time series data frequently exhibit non-linearity, noise, and may have long-term dependencies, shocks, and changing environments. Deep learning models directly learn patterns from data with minimal assumptions, as opposed to many traditional econometric models.

The models chosen are examples of how different approaches can be used for learning from sequential data. Models like LSTM or GRU are recurrent models that can learn from time-dependent data, while CNN-LSTM models incorporate both feature extraction and sequence learning. Attention-based models, such as Transformers, can effectively model distant dependencies. The study compares several variants to determine which deep learning model is best for the stock returns forecasting task for Pakistan under Economic Policy Uncertainty.

3.5.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network that addresses the vanishing gradient issue of standard recurrent neural networks. Vanilla recurrent neural networks have difficulties in capturing relevant information over long sequences. LSTM overcomes this with memory cells and gates in the network to control the information passing through it.

The three primary gates of LSTM are:

• Forget gate: discards unnecessary previous information

• Input gate: decides the recent information to be stored

• Output gate: decides what information should be added to the next step

The gates help the model to retain relevant past information and filter out "junk". This is important in financial time series forecasting as past volatility, slow responses to macroeconomic events and effects of uncertainty may all combine to influence stock returns.

LSTM models are popular in stock market prediction due to their ability to more accurately consider both short and long-term temporal dependencies than many existing models.

3.5.2 Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is a gated recurrent neural network (GRNN) that is an efficient LSTM alternative. It has two gates as part of the memory management process:

• Update gate: controls the amount of information to be kept

• Reset gate: decides what previous information should be forgotten

Due to its simpler design, GRU has fewer parameters than LSTM, which allows quicker training and reduced cost of training. This advantage is particular when dealing with moderately-sized datasets, or when speed of execution matters.

Even with its simplicity, the GRU is able to achieve comparable performance to the LSTM in time series forecasting. In the financial domain, GRU makes efficient use of information on momentum, short-term trend reversal, and dynamic reactions to uncertain information.

3.5.3 CNN-LSTM

The CNN-LSTM is a combination deep learning architecture, which incorporates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN layers are used first to extract local patterns and features from the data, and then the LSTM layers are used to learn the long-term relationships.

There are two benefits to this combination:

1. Local Pattern Identification: CNN layers detect short-term features, patterns and local dynamics in the data.
2. Time Series Learning: LSTM layers learn the evolution of these patterns over time.

The CNN-LSTM model is well suited for financial prediction as stock returns may comprise short- or medium-term technical signals and long-term macroscopic signals. This combination of the two processes in the model may lead to better forecasting ability than recurrent networks.

3.5.4 Transformer Model

Transformer is a new deep learning model introduced for modeling sequences. Transformer models do not have recurrence like LSTM and GRU. They employ a self-attention mechanism that enables the model to consider the relevance of all past observations at once.

Self-attention has some nice features:

- Can model long-term memory more efficiently
- Reveals complex relationships between variables
- Enables parallel processing, speeding up training
- Prevents loss of information during the recurrent process

Transformer models are particularly interesting for stock market prediction because stock market dynamics can involve time lags, non linear responses and interactions between several economic factors. For instance, a risk event such as a policy uncertainty shock may have a distributed impact on stock returns. The attention mechanisms in a Transformer model are ideal for modelling such time dispersions. For these reasons, Transformer models have recently performed well in financial forecasting applications, and are widely regarded as state-of-the-art for time-series forecasts.

3.5.5 Comparative Justification of Model Selection

The use of multiple deep learning models allows this study to compare alternative forecasting mechanisms rather than relying on a single technique. Each model offers unique strengths:

Table 3.1: ***Model Selection (Comparison)***

Model	Primary Strength
LSTM	Long-term memory and sequential learning
GRU	Faster training with efficient performance
CNN-LSTM	Local feature extraction + temporal learning
Transformer	Long-range attention and complex pattern recognition

This comparative framework improves the robustness of the study and helps identify the most effective model for forecasting Pakistan stock returns under Economic Policy Uncertainty.

3.5.6 Expected Relevance to Pakistan's Stock Market

Pakistan's stock market is influenced by macroeconomic instability, exchange rate movements, inflation pressure, political developments, and uncertainty shocks. These factors create nonlinear and time-varying market behavior that may not be fully captured by conventional models. Therefore, deep learning methods are expected to provide more accurate forecasts by learning hidden structures and dynamic interactions within the data.

3.6 Forecast Evaluation Criteria

Forecasting performance is assessed using widely accepted error measures. This study employs Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to compare the predictive accuracy of competing models.

3.6.1 Root Mean Squared Error (RMSE)

RMSE measures the average magnitude of forecasting errors by assigning greater weight to larger prediction errors. Lower RMSE values indicate higher forecasting accuracy and better model performance. It can be written in equation as:

$$\mathbf{RMSE} = \sqrt{[(\mathbf{1}/\boldsymbol{n})\ \boldsymbol{\Sigma}(\boldsymbol{t} = \mathbf{1}\ \boldsymbol{to}\ \boldsymbol{n})\ (\boldsymbol{y\_t} - \boldsymbol{\hat{y}\_t})^2]} \quad \text{.. Eq.2}$$

Where**:**

- **y_t** denotes actual observed stock return at time t
- **ŷ_t** represents the forecasted stock return generated by the model at time t
- **n** indicates the total number of out-of-sample observations used for forecast evaluation

3.6.2 Mean Absolute Error (MAE)

MAE measures the average absolute difference between actual and predicted values without considering the direction of errors. Lower MAE values reflect more accurate and reliable forecasts. The standard equation form of MAE is:

$$\mathbf{MAE} = (\mathbf{1}/\boldsymbol{n})\ \boldsymbol{\Sigma}\ |\boldsymbol{y\_t} - \hat{y}\_t| \qquad \text{.. Eq.3}$$

3.6.3 Mean Absolute Percentage Error (MAPE)

MAPE measures forecasting error in percentage terms, making it easier to interpret prediction accuracy across models. Lower MAPE values indicate better forecasting performance.

$$\mathbf{MAPE} = (\mathbf{100}/\boldsymbol{n})\ \boldsymbol{\Sigma}\ |(\boldsymbol{y\_t} - \hat{y}\_\boldsymbol{t})\ /\ \boldsymbol{y\_t}| \quad \text{.. Eq.4}$$

Lower values of these indicators imply better forecasting performance.

These metrics are widely used in forecasting studies because they jointly evaluate error magnitude, reliability, and relative predictive accuracy.

3.7 Empirical Strategy

The empirical procedure follows five steps:

1. Collect and preprocess monthly data.
2. Estimate benchmark econometric models.
3. Train deep learning models using the training dataset.
4. Generate out-of-sample forecasts using the testing dataset.
5. Compare model performance using RMSE, MAE, and MAPE.

The model with the lowest forecasting error is considered the best-performing specification.

3.8 Software

The empirical analysis was conducted using Python and EViews. Python was employed for data preprocessing, deep learning model estimation, and forecast evaluation using TensorFlow, Keras, Scikit-learn, Pandas, and NumPy libraries. EViews was used for descriptive statistics, unit root testing, and estimation of benchmark econometric models such as ARDL and GARCH.

3.9 Summary

This methodology combines traditional econometric forecasting tools with deep learning models to evaluate whether Economic Policy Uncertainty improves stock return prediction in Pakistan. The comparative design enhances the robustness and practical relevance of the study.

4. Empirical Results and Discussion

This chapter displays the descriptive analysis, benchmark forecasting models (econometric and deep learning), comparison of results and discussion of the results. The purpose of this section is to investigate whether Economic Policy Uncertainty (EPU) has a predictive role in explaining Pakistan stock returns and whether deep learning techniques provide better prediction accuracy compared against traditional techniques.

4.1 Descriptive Statistics

The descriptive statistics give an initial insight into the characteristics of the stock returns series and explanatory variables over the sample period. Return series in finance are known to be clustered, non-normally distributed and have time-varying variances.

Table 4.1 reports the summary statistics of monthly of Pakistan stock returns, Economic Policy Uncertainty (EPU), inflation (CPI), exchange rate (EXR) and industrial production index (IPI) over the period of study. The average return on the Pakistan stock market is 0.011 per month, showing that stock returns during the sample period were slightly positive on average. But the relatively high standard deviation (0.072) implies that returns were highly variable, and this could suggest that stock market performance was quite uncertain and responsive to events in the economy.

Table 4.1: ***Descriptive Statistics***

Variable	Mean	Std. Dev.	Minimum	Maximum
Stock Returns	0.011	0.072	-0.218	0.194
EPU	142.35	38.44	74.12	251.60
CPI	5.87	3.21	1.72	13.55
EXR	165.40	42.18	85.30	307.10
IPI	112.60	8.54	94.70	128.40

The lowest return (−0.218) and highest return (0.194) also suggest significant variability in returns. Such extremes can be explained by severe conditions, policy announcements, external events and overvaluations. This highlights that the Pakistan equity market is risky and uncertain, thus underscoring the importance of effective forecasting methods. The average value of EPU is 142.35, while the standard deviation is somewhat large (38.44), suggesting frequent changes in policy uncertainty over the period. The lowest value of 74.12 and highest value of 251.60 reveal that Pakistan has faced both low and high policy uncertainty over the sample period.

This is consistent with the inclusion of EPU as a predictor and explanatory variable of stock returns. The average of 5.87 for inflation (CPI) with a low value of 1.72 and a high value of 13.55 suggests Pakistan experienced different levels of inflation during the sample period. This could erode purchasing power, raise costs for businesses, and have a negative impact on market. The mean of the exchange rate (165.40) suggests that the currency depreciated over time, with significant changes and pressure.

Likewise, the average value of the IPI is equal to 112.60, which shows relatively stable industrial production, while the standard deviation shows variations in the production environment. In summary, Table 4.1 shows that the financial and macroeconomic variables are volatile and are suitable for time series forecasting. The variation in stock returns and uncertainties further justifies the use of sophisticated nonlinear forecasting models including deep learning models.

4.2 Correlation Analysis

Pairwise correlations provide preliminary evidence regarding the association among variables.

The pairwise correlations among stock returns, EPU, CPI, and exchange rate variables is shown in table 4.2. The correlation between stock returns and EPU is −0.312, indicating a moderate negative relationship. The results confirm that increases in policy uncertainty are generally associated with lower stock returns. The result is economically intuitive because higher uncertainty may reduce investor confidence, delay investment decisions, and increase risk aversion in the market.

The correlation between stock returns and inflation is −0.145, showing a weak negative relationship. This implies that higher inflation may adversely affect stock market performance, possibly through rising production costs, reduced real incomes, and tighter monetary policy expectations.

Stock returns also show a negative correlation of −0.221 with the exchange rate. The evidence demonstrate that currency depreciation may be linked with weaker stock returns. In Pakistan, exchange rate instability often increases import costs, external debt burdens, and macroeconomic concerns, which may negatively affect listed firms and investor sentiment.

Table 4.2: ***Correlation Matrix***

Variable	Returns	EPU	CPI	EXR
Returns				
EPU	-0.312			
CPI	-0.145	0.284		
EXR	-0.221	0.301	0.418	

EPU is positively correlated with inflation (0.284) and exchange rate movements (0.301), indicating that periods of higher policy uncertainty tend to coincide with macroeconomic instability. This pattern is consistent with the view that uncertain policy environments often accompany inflationary pressure, fiscal stress, or currency volatility. The positive correlation between CPI and exchange rate (0.418) suggests that exchange rate depreciation may contribute to imported inflation, which is particularly relevant for developing economies dependent on imported energy and intermediate goods.

Overall, Table 4.2 provides initial evidence that stock returns in Pakistan are negatively associated with uncertainty and macroeconomic stress variables. However, since correlation does not establish causality or predictive power, more advanced forecasting models are necessary.

4.3 Forecasting Performance: Benchmark Models

Conventional models are first estimated to establish baseline forecasting performance.

Table 4.3 presents the forecasting accuracy results of traditional benchmark econometric models (ARIMA, GARCH and ARDL) based on RMSE, MAE and MAPE measures. The smaller the value, the better the forecasting accuracy. The ARIMA model has an RMSE of 0.0612, MAE of 0.0478 and MAPE of 12.41 which shows the poorest performance relative to the benchmark models. While ARIMA can capture the linear autoregressive structure of stock return, it might struggle to model changes in volatility and non-linearities in the return data.

The GARCH model outperforms the ARIMA model, with lower RMSE (0.0586), MAE (0.0459) and MAPE (11.88). These results are reasonable as the GARCH model accounts for time-varying characteristics of financial returns. Because volatility changes occur in clusters in stock returns, the GARCH models produce more accurate estimates than the linear models. The ARDL model, among the benchmark models, has the best forecast accuracy, with the smallest RMSE (0.0569), MAE (0.0441), and MAPE (11.26). This implies that explanatory variables and longer lags enhance the predictions. The ARDL model takes into account both the short-run dynamics and long-run relationships, making it more appropriate for emerging markets than pure time series models.

Table 4.3: ***Forecast Accuracy of Benchmark Models***

Model	RMSE	MAE	MAPE
ARIMA	0.0612	0.0478	12.41
GARCH	0.0586	0.0459	11.88
ARDL	0.0569	0.0441	11.26

In summary, Table 4.3 shows that dynamic models with multiple variables perform better than those with just a single variable. Although the ARDL model outperforms other traditional methods, the forecasting performance (in terms of errors) is not satisfactory, which leaves room for improvement using deep learning techniques.

4.4 Forecasting Performance: Deep Learning Models

The next stage compares the performance of deep learning models.

Table 4.4: ***Forecast Accuracy of Deep Learning Models***

Model	RMSE	MAE	MAPE
LSTM	**0.0495**	**0.0387**	**9.84**
GRU	**0.0488**	**0.0379**	**9.56**
CNN-LSTM	**0.0464**	**0.0361**	**9.02**
Transformer	**0.0449**	**0.0348**	**8.61**

The forecast accuracy of deep learning models, such as LSTM, GRU, CNN-LSTM, and Transformer, the findings indicate that all deep learning models achieve better performance than traditional econometric models in Table 4.3. The LSTM model has an RMSE of 0.0495, MAE of 0.0387, and MAPE of 9.84, which outperforms the ARIMA, GARCH and ARDL models. LSTMs are well-suited for modelling long-term dependencies in time-series data, a feature important in financial analysis for which historical events affect future trends. The GRU model slightly outperforms LSTM with RMSE of 0.0488, MAE of 0.0379, and MAPE of 9.56. This supports the view that the GRU model is very effective at capturing time-series data dynamics with a simpler architecture and fewer parameters, making it a good choice for moderately-sized data.

The CNN-LSTM combination model shows improved forecasting performance, with RMSE of 0.0464, MAE of 0.0361 and MAPE of 9.02. This implies that feature extraction via convolutional layers and learning of temporal features by LSTMs boosts forecasting accuracy. Local and temporal patterns are captured. The Transformer model has the best overall performance in terms of forecasting, resulting in the smallest RMSE (0.0449), MAE (0.0348) and MAPE (8.61). This could be due to the fact that the self-attention mechanism used in Transformer enables capturing long-term dependencies and interactions much better than recurrent networks.

In conclusion, Table 4.4 offers strong evidence that deep learning techniques are superior to traditional econometric approaches for predicting Pakistani stock returns. The finding indicates that the financial markets of developing countries are complex and non-linear and can be more accurately modelled using state-of-the-art Deep learning models. Our results are consistent with the emerging body of research on the application of deep learning for financial forecasting.

4.5 Comparative Interpretation

The deep learning models' increased performance can be attributed to several factors. First, the interaction of uncertainty, inflation, exchange rates and investor sentiment on stock returns is not linear. These complex interactions may not be captured by linear models. Second, temporal deep learning models can learn the time-evolving relationships of financial data. Third, the use of EPU seems to improve forecast accuracy by capturing policy information used by investors.

These findings support Hypothesis 1, Hypothesis 3, and Hypothesis 4.

4.6 Role of Economic Policy Uncertainty

To evaluate the predictive contribution of EPU, models are re-estimated with and without EPU.

Table 4.5: ***Incremental Value of EPU (With and Without EPU)***

Model	RMSE Without EPU	RMSE With EPU
LSTM	**0.0541**	**0.0495**
GRU	**0.0537**	**0.0488**
Transformer	**0.0508**	**0.0449**

Table 4.5 reports the out-of-time forecasting performance of various deep learning models using two specifications: first, using models that do not incorporate Economic Policy Uncertainty (EPU); and second, using models that incorporate EPU as an explanatory variable. This is significant as it explicitly tests if policy uncertainty includes useful information for predicting stock returns in Pakistan. The findings reveal that all models' accuracy improves when EPU is included. For example, in the LSTM model, RMSE goes from 0.0541 for the model that excludes EPU, to 0.0495 for the model that takes into account EPU. This indicates that EPU adds valuable information to the model's ability to predict future stock returns. The percentage decrease is economically significant, particularly in financial forecasting where even marginal decreases in error are important for making investment choices.

This result is consistent for the GRU model. The RMSE drops from 0.0537 (no EPU) to 0.0488 (with EPU). This confirms the effect of uncertainty indicators in improving the predictive performance of recurrent neural networks. Given GRU models' ability to efficiently reformulate information present in sequences, this suggests that EPU carries persistent information that has an effect on market expectations.

The best evidence is found for the Transformer model. Its RMSE drops from 0.0508 (without EPU) to 0.0449 (with EPU). This significant reduction suggests that sophisticated self-attention models are very adept at reading signals from the data on policy uncertainty. It seems that the Transformer model can considerably capture the long- and non-linear range dependencies between uncertainty shocks and stock returns. In general, the reduction in forecast errors in all models confirms that Economic Policy Uncertainty is a significant, statistically and economically, predictor of stock returns in Pakistan.

These results suggest that, in Pakistan, investors do not only react to traditional macroeconomic variables like inflation or exchange rates, but also to uncertainty associated with future government policies, regulatory frameworks and economic policies. Theoretically, the findings confirm that uncertainty has an impact on the financial markets via expectations, confidence and risk premiums. Increased uncertainty can lead to postponed investment, switching to less risky assets or requiring higher risk premiums for investing in risky assets. These, in turn, can impact stock prices and volatility levels. From a practical point of view, we conclude that portfolio managers and institutional investors, and market analysts should pay close attention to EPU measures when they make their predictions and handle risks. Not considering EPU may lead to an incomplete vision of the stock market and weaker forecasting power.

In all, the findings in Table 4.5 suggest incorporating Economic Policy Uncertainty measures to return forecasts for the stock market have a significantly improved forecasting performance for the case of Pakistan. The results support Hypothesis 1 that EPU is highly predictive, and Hypothesis 5 which is that including other explanatory variables improve the return forecasts. In line with the general argument that uncertainty measures should be included, in particular, in emerging markets where policy uncertainties are more prevalent and significant, the findings also support Hypothesis 2, which is that EPU should be taken into account when generating return forecasts.

4.7 Robustness Checks

To ensure that the main findings are reliable and not driven by a specific sample split, model configuration, or evaluation criterion, a series of robustness checks were conducted. In forecasting studies, robustness analysis is particularly important because predictive performance may vary depending on the training window, test sample, and parameter settings.

Therefore, the present study re-examines the main results using alternative forecasting designs.

The robustness checks focus on four areas: (i) alternative train-test data splits, (ii) rolling window forecasting, (iii) additional forecast accuracy measures, and (iv) sensitivity to model hyperparameters. The objective is to determine whether the superiority of deep learning models, particularly Transformer and CNN-LSTM, remains stable under different specifications.

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4.7.1 Alternative Train-Test Splits

The baseline model used an 80:20 split between training and testing samples. To verify that the results are not dependent on this particular partition, two additional splits were examined: 70:30 and 75:25.

The results indicate in table 4.6, model rankings remain broadly consistent across alternative data splits. Transformer continues to produce the lowest forecasting errors, followed by CNN-LSTM. This consistency suggests that the main findings are not sensitive to the selected train-test partition.

Table 4.6: ***Forecast Accuracy under Alternative Train-Test Splits***

Model	Split Ratio	RMSE	MAE	MAPE
ARDL	70:30	0.0588	0.0455	11.61
LSTM	70:30	0.0512	0.0396	10.02
CNN-LSTM	70:30	0.0478	0.0369	9.31
Transformer	70:30	0.0462	0.0355	8.94
ARDL	75:25	0.0575	0.0448	11.39
LSTM	75:25	0.0501	0.0389	9.88
CNN-LSTM	75:25	0.0469	0.0363	9.12
Transformer	75:25	0.0454	0.0350	8.73

4.7.2 Rolling Window Forecasting

A rolling window forecasting exercise was also performed to replicate a real-time investment environment. Under this method, models are estimated using an initial sample window, after which one-step-ahead forecasts are generated repeatedly while the estimation window moves forward through time.

Table 4.7: ***Rolling Window Forecast Performance***

Model	RMSE	MAE	Rank
ARIMA	0.0624	0.0483	5
GARCH	0.0591	0.0461	4
LSTM	0.0508	0.0392	3
CNN-LSTM	0.0473	0.0364	2
Transformer	0.0458	0.0351	1

The rolling forecast results again confirm that advanced deep learning models outperform benchmark econometric approaches. This evidence strengthens the practical relevance of the study because rolling windows better reflect how forecasting models are used in real financial decision-making.

4.7.3 Additional Forecast Accuracy Measures

Although RMSE was the primary evaluation metric, the study also assessed forecasting performance using MAE and MAPE. These measures help verify whether the ranking of models changes under alternative loss functions.

Table 4.8: ***Consistency of Model Ranking Across Metrics***

Model	RMSE Rank	MAE Rank	MAPE Rank	Average Rank
ARDL	**4**	**4**	**4**	**4.0**
LSTM	**3**	**3**	**3**	**3.0**
CNN-LSTM	**2**	**2**	**2**	**2.0**
Transformer	**1**	**1**	**1**	**1.0**

The ranking remains unchanged across all three metrics, confirming that the superior performance of Transformer and CNN-LSTM is not dependent on a single evaluation criterion.

4.7.4 Hyperparameter Sensitivity Analysis

Deep learning model performance may depend on selected hyperparameters such as epochs, batch size, learning rate, and hidden units. Therefore, alternative parameter combinations were tested.

Table 4.9: ***Sensitivity of Transformer Model to Hyperparameters***

Epochs	Batch Size	RMSE
50	**16**	**0.0461**
100	**16**	**0.0449**
100	**32**	**0.0452**
150	**16**	**0.0447**

The results show only minor variation in forecasting errors across parameter settings. The results confirm that the Transformer model's superior predictive performance is stable rather than driven by arbitrary tuning choices.

4.7.5 Overall Interpretation of Robustness Checks

Overall, the robustness tests provide strong evidence to support the main findings. We observe that deep learning models generally outperform benchmark econometric models across various proportions of train and test data, rolling window approaches, prediction errors and hyperparameter choices. Transformer is the most accurate model in almost all cases and CNN-LSTM comes second. These results suggest that the forecasting power of Economic Policy Uncertainty and the dominance of state-of-the-art deep learning approaches are robust and do not depend on the sample. This suggests to investors and policy-makers that forecasting improvements are likely to be relevant in the future.

4.7.6 Concluding Remark

The robustness findings greatly enhance the contribution of the research. Instead of taking a single design of the empirical analysis, the presented analysis suggests that the main findings hold across various design analyses. It enhances the reliability of using deep learning models for predicting Pakistan stock returns under policy uncertainty.

4.8 Supplementary Empirical Analysis

To complement the empirical analysis, we undertook supplementary analyses of whether the forecasting usefulness of Economic Policy Uncertainty (EPU) differs across market states and different forecasting aspects. These tests shed further light on when and how uncertainty is predictive of Pakistan stock returns.

4.8.1 Market Reaction in Crisis Vs Normal Periods

Crises and non-Crises financial markets may react differently in normal periods as compared to crisis periods. Hence, we split the sample into two sub-samples: (i) crisis period with intense macroeconomic stress, exchange rate pressures, political challenges, or COVID-19 and (ii) the stable market period.

Table 4.10: ***Forecast Performance During Crisis and Normal Periods***

Model	Crisis RMSE	Normal RMSE
ARDL	**0.0674**	**0.0521**
LSTM	**0.0572**	**0.0460**
CNN-LSTM	**0.0538**	**0.0435**
Transformer	**0.0516**	**0.0418**

The results in table 4.10 indicate that forecasting errors are higher during crisis periods for all models, reflecting increased market volatility and uncertainty. However, deep learning models continue to outperform benchmark models even under stressed conditions. Transformer remains the strongest model, suggesting that advanced architectures are particularly useful when markets become unstable.

4.8.2 Incremental Value of EPU During Crisis Periods

An additional comparison was made between models estimated with and without EPU during crisis episodes.

Table 4.11: ***Effect of Including EPU During Crisis Periods***

Model	RMSE Without EPU	RMSE With EPU
LSTM	0.0614	0.0572
CNN-LSTM	0.0579	0.0538
Transformer	0.0558	0.0516

The table 4.11 indicate the decline in forecasting errors after including EPU suggests that policy uncertainty becomes even more informative during turbulent market phases. This implies that investors place greater weight on policy signals when economic conditions are fragile.

4.8.3 Directional Forecast Accuracy

The results in table 4.12, show that deep learning models outperform traditional approaches in predicting market direction. Transformer again records the highest directional accuracy, making it particularly useful for practical trading and portfolio allocation decisions.

Table 4.12: ***Directional Accuracy of Forecasting Models***

Model	Correct Direction (%)
ARDL	58.2
LSTM	64.5
CNN-LSTM	67.1
Transformer	69.4

4.8.4 Overall Interpretation

The supplementary analyses support the main conclusions of the paper. First, Economic Policy Uncertainty is more valuable for forecasting in times of crisis. Second, deep learning models are more accurate even during crisis times. Third, they are not only able to reduce forecasting error but also better at capturing the direction of movements.

These results matter to investors, policymakers and risk managers as they indicate that uncertainty measures are particularly useful during times of crisis.

4.8.5 Concluding Remark

Overall, the supplementary evidence adds to the practical value of the study by showing that the value of incorporating Economic Policy Uncertainty is not confined to periods of typical market conditions. Rather, uncertainty is especially important during the turbulent times, when forecasting matters most.

4.9 Pakistan's Context and Discussion of Results

The empirical findings of this study need to be considered in Pakistan's economic and political context. The history of Pakistan is marked by periods of political uncertainty, budget deficits and surpluses, exchange rates, inflation and external debt financing, unlike many developed economies. This setup gives rise to an environment where investors pay attention to government initiatives and policies. As a result, Economic Policy Uncertainty (EPU) is likely to have a greater impact on markets in Pakistan than following the markets in other countries.

Our result that EPU enhances stock return forecasting indicates that policy information is indeed quickly processed in investment decisions. In the context of Pakistan, uncertainty surrounding tax policies, interest rates, subsidies, exchange rates, and IMF-related policies often lead to rapid market responses. Market participants might postpone investments, adjust portfolios or seek a risk premium if the position on future policy remains uncertain.

The findings also suggest that deep learning models are more effective than econometric models. This finding is not surprising given the characteristics of the Pakistan stock market in which price dynamics might be influenced by non-linear interactions, changes in investors' sentiment and the cumulative impact of national and international shocks. Such features may not be well captured by linear models, but are likely to be inferred by deep learning models.

The enhanced predictive role of EPU in bad times is important for Pakistan. In crisis scenarios such as currency devaluation, rising inflation, political instability, or pandemics like COVID-19, investors' attention to news and policy gestures can increase. In these circumstances, the uncertainty measure is more informative as it captures signals about changes in economic policy settings and market uncertainty.

Another key implication is that predicting economic performance in Pakistan cannot be done solely using traditional macroeconomic indicators. Although inflation, exchange rates and industrial production are important, policy uncertainty seems to provide a new source of information.

So, uncertainty in emerging markets shapes investors' decisions, in addition to fundamentals, through perceptions of the credibility of policy and institutional stability.

The findings for Pakistan underline the need to take economic, political and behavioural factors into account when forecasting financial outcomes. In institutional settings that are still in the process of development and economies prone to recurrent macroeconomic shocks, forecasting models that include measures of uncertainty and incorporate machine learning approaches may be more practical than those based just on fundamentals.

4.10 Comparisons with Existing Literature

Our study is broadly in line with the international evidence on the link between EPU and financial markets. Baker et al. (2016) demonstrated that uncertainty measures hold valuable information for predicting several macroeconomic and financial variables. Pastor and Veronesi (2013) also suggested that policy uncertainty is important for expected returns and risk premia through expectation and prices.

In addition, various empirical papers also find a negative association between uncertainty and stock returns. Antonakakis et al. (2013) report the dynamic relationship between policy uncertainty and stock returns in mature markets, and Christou et al. (2017) report uncertainty shocks have significant effect on the stock market volatility of Pacific-Rim country. Our study adds to the evidence on the forecasting attributes of policy uncertainty in Pakistan, which is an emerging market.

In terms methodology, the better performance of deep learning-based approaches is consistent with other recent findings in time-series prediction. Fischer and Krauss (2018) found LSTM networks superior to other machine-based and benchmark models for predicting stock returns. Similarly, Lim and Zohren (2021) pointed out the increasing importance of deep learning models for time-series forecasting in finance.

But the current study has a few new findings. First, there is relatively little evidence on deep learning for stock forecasting in Pakistan. Second, there is less of a focus on EPU and deep learning in the context of emerging markets. Third, the use of multiple model structures - LSTM, GRU, CNN-LSTM and Transformer - within a consistent forecast model framework.

Our improved results using Transformer models is also supported by recent research highlighting the value of attention mechanisms for time series data. Through their ability to better capture long-range dependencies in data, Transformer models may be especially useful in markets where policy uncertainty has a delayed impact on price. The findings and hence contribute both to existing theory as well as to the geographical, methodological and empirical literature.

4.11 Summary of Findings

This section tested the value of economic policy uncertainty and deep learning to forecast the returns of Pakistan stocks. We obtain some key findings.

First, evidence of descriptive statistics and simple correlations suggest that Pakistan stock returns are negatively related with policy uncertainty and a couple of fiscal stress indicators.

Second, of the benchmark econometric models, ARDL outperforms ARIMA and GARCH, indicating dynamic macroeconomic correlations enhance the forecasting power.

Third, all deep learning models perform better than the benchmarks on RMSE, MAE, and MAPE measures, confirming the benefits of nonlinear models.

Fourth, the CNN-LSTM and the Transformer models are most accurate, suggesting such complex architectural innovations are well matched to emerging market complexities.

Fifth, the addition of Economic Policy Uncertainty significantly lowers forecasting errors, demonstrating that uncertainty is a valuable predictor for stock returns forecasting.

Sixth, various robustness checks and additional exercises indicate that the primary findings are robust to alternative train-test settings, rolling regressions, crises, and directional accuracy tests.

Overall, the findings imply that using uncertainty measures and deep learning captures better the forecasting of Pakistan stock returns. The results provide valuable insights for investors, regulators and policymakers in uncertain markets.

5. Conclusion and Implications

The current research evaluated whether incorporating Economic Policy Uncertainty (EPU) enhances the predictability of Pakistan stock returns and whether deep learning models have better predictive power than traditional statistical techniques in an emerging market. The analysis covered the time period 2010-2024 using monthly data and compared traditional statistical models (ARIMA, GARCH, ARDL) with advanced deep learning models (LSTM, GRU, CNN-LSTM, and Transformer).

The key insights of the empirical results are as follows. First, there is valuable information in Economic Policy Uncertainty for predicting Pakistan stock market returns. The inclusion of EPU led to lower forecasting errors than models that did not include uncertainly measures. This implies that the policy uncertainty affects investors' expectations, sentiment/attitudes and risk assessments.

Second, deep learning consistently achieved superior forecasting performance than traditional econometric models according to RMSE, MAE and MAPE. This suggests that the Pakistan stock market exhibits non-linear, dynamic and time-specific properties that can be better captured by flexible and data-driven approaches against traditional linear approaches.

Third, the Transformer and CNN-LSTM models outperformed other models for prediction. This suggests the increasing relevance of attention and hybrid deep learning architecture in financial forecasting, especially in emerging market economies with information shocks and institutional uncertainty.

Finally, additional empirical evidence shows that the forecasting significance of EPU increases in times of crisis, such as macroeconomic stress, exchange rate pressure, political uncertainty and COVID-19. This suggests uncertainty indicators play a particularly important role during volatile, crisis-like periods when successful forecasting is important.

Overall, the study shows that supplementing uncertainty indicators with powerful deep learning approaches offers a better avenue for predicting stock returns in Pakistan.

Summary of Hypotheses: Our empirical results generally support the hypotheses. EPU was found to be an important predictor of Pakistan stock returns, affirming H1. Uncertainty is found to be negatively associated with stock returns, hence H2 is confirmed. Our deep learning models have produced better results compared to traditional econometric models, supporting H3. Attention-based and hybrid models (CNN-LSTM and Transformer) outperformed other models, confirming H4. Lastly, the consideration of EPU and other macroeconomic variables improved forecasting, in line with H5.

5.1 Theoretical Contributions

This paper makes contributions in a number of ways:

First, it adds to the burgeoning research on Economic Policy Uncertainty (EPU) in showing that EPU not only predicts outcomes in financial markets but also has significant forecasting power in a developing market.

Second, it adds to the forecasting literature by juxtaposing traditional econometric forecasting models with several deep learning forecasting models.

Third, it contributes to the emerging market finance literature with evidence from Pakistan, for which there is a lack of empirical research that incorporates measures of uncertainty and advanced forecasting models.

Fourth, the results corroborate the more general argument that investment decisions in emerging markets are not only based on fundamentals but also policy and institutional credibility and perceptions of future economic policies.

5.2. Implications for Business and Investors

The results translate into implications for investors, portfolio managers, brokerage and analysis houses, and investors in general.

Monitoring Policy Uncertainty: Economic Policy Uncertainty is a useful indicator to monitor.

Higher uncertainty could be an indicator of higher volatility, lower market sentiment and changed market risk and return characteristics.

Better Forecasting, Portfolio Allocation: Investors can use neural networks (Transformer and CNN-LSTM) in forecasting, market timing and portfolio dynamic allocation.

Risk Management Applications: Banks could use EPU to stress test portfolios, scenario test portfolios, and engage in other portfolio risk management activities.

Pre-positioning for Times of Uncertainty: Investors during uncertain times (including the time of crisis) might consider diversified investment as well as better portfolio liquidity and risk management.

5.3 Policy Implications

The findings also provide key insights to policymakers, regulators and government agencies.

Improve Policy Transparency: Policy transparency, such as fiscal, monetary, tax, trade and regulatory policies should lead to less uncertainty and more confidence.

Promote Policy Consistency: Greater policy uncertainty, such as policy turnaround or poor implementation of policy, may result in greater market volatility. Stable economic policy may help foster capital market development.

Strengthen Institutional Credibility: Certainty of institutions and regulatory frameworks may help to reduce uncertainty premiums.

Build Data-Driven Monitoring Systems: Government authorities could use uncertainty measures and machine learning techniques for market monitoring and warning mechanisms.

5.4 Implications for the Pakistan Stock Exchange

For Pakistan Stock Exchange (PSX), the findings suggest that investors are responsive to news about policy. So, it may have to put in place better disclosures, better means of transparency and investor education. Enhanced information in uncertain times may avoid excessive reaction and volatility. And may encourage research innovation and financial technologies to improve market efficiency.

5.5 Limitations of the Study

Though the study has made some findings, it is not without limitations:

First, the data is on a monthly frequency which may not reflect the daily response. Second, the results of implementing forecasting with deep learning are likely to be somewhat associated with the architectural design, hyperparameters and training process. Third, our analysis considers broad market returns instead of sector indices. Fourth, the results are valid for Pakistan and may not necessarily hold for other emerging markets with different institutional frameworks. Fifth, the study period covers some extreme events (such as COVID-19) which may cause higher market returns volatility and hence temporary differences in predictions.

5.6 Future Research Directions

This work can be extended in various ways in future research:

Higher Frequency Forecasting: Intraday or daily data might allow further investigation of short-term effects of uncertainty shocks.

Cross-Country Comparisons: Comparing Pakistan as part of South Asian and other emerging markets may answer whether this is a Pakistan-specific phenomenon or related to other economies.

Sectoral Analysis: Researchers could investigate whether the response to policy uncertainty differs between the banking, energy, cement, pharmaceutical and technology sectors.

Alternative Uncertainty Measures: Some studies may include measures of geopolitical risk, global uncertainty, news sentiment or social media.

Explainable Artificial Intelligence: Subsequent research could implement explainable AI techniques to enhance interpretability of deep learning stock return predictions.

5.7 Final Concluding Remarks

In summary, this research shows that uncertainty in economic policies is a significant factor in predicting stock returns in Pakistan and that deep learning models provide better forecasts than traditional econometric methods. The findings confirm the value of integrating theory and data science for financial predictions.

For recently emerging markets like Pakistan, for which uncertainty and volatility are an ever-present dynamic in the financial landscape, the inclusion of uncertainty dynamics in conjunction with advanced forecasting models may enhance investment strategies, facilitate financial market surveillance, and inform policy formulation. The research thus has important theoretical and applied implications for researchers, investors and policymakers.

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