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Forecasting Inflation in Pakistan Using ARIMA Model

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ABSTRACT

The objective of the study is to forecast CPI inflation for the period 2023 to 2028 using ARMA & ARIMA techniques, which have been extensively used in the previous literature. We used the annual dataset from the ministry of finance from 2002 to 2023. The stationary tests indicated that CPI inflation was integrated of order 1. Therefore, we employed the ARIMA model for forecasting. The results indicated that R-square was 0.819, which implies that the model explains around 81 percent variation in inflation. Further, the F-statistics was 14.51 indicate that the overall model was significant. The ARIMA model ling results indicates that by 2028, the CPI inflation would be around 4.62 percent due to the policy intervention by the state bank of Pakistan aimed at lowering inflation. Moreover, our study forecast that the monetary tithing strategy for controlling inflation by the SBP would be effective in the medium to long term and lead to low and stable inflation in Pakistan. The study has several policy implications, which will enable Pakistan to pursue a path of low inflation, which are also consistent with the IMF requirements.

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Introduction

Inflation forecasts were consistently of great interest to central banks for the management of monetary policy. A dependable inflation forecast wasn't just advantageous for central banks in achieving their objectives, but also aided decision-making for individuals regarding pricing and wage agreements. High unexpected inflation proved to be specifically costly for families relying on long-term pensions and bonds. When inflation exceeded expectations, it led to a reduction in household real purchasing power since income from such assets typically remained fixed.

Consequently, the standard of living for senior citizens was severely impacted as they aged. An unforeseen inflationary surge also tended to diminish labor wages and real purchasing power. Both firms and families were compelled to expend energy and time reducing currency holdings and adjusting to frequent shifts in price levels. While uncertainty remained an inevitable aspect of the future, it was essential to mitigate uncertainties as much as possible. This approach was adopted across various fields of study to enhance the effectiveness and accuracy of decision-making processes (Purwa et al., 2020). Recognizing the significance of forecasting, economic policymakers required models that enabled them to anticipate future scenarios and formulate precise policies. Inflation, being one of the most significant yet unpredictable economic factors, demanded vigilant monitoring, analysis, and prediction to inform timely policymaking (Vesna and Pejovic, 2021). According to Bokil and Schimmelpfennig (2005), p. 10, the International Monetary Fund (IMF) defines inflation as the pace of price increase over a given period of time. Unexpected changes in inflation can have a detrimental effect on the living standard of the general public by decreasing their power to purchase and interference with the planning of manufacturers, retailers, and governments. In order to develop successful monetary, fiscal, and other policies, policymakers must thereby address the uncertainty surrounding future inflation rates (Jiranyakul, 2020).

Previous instances of galloping and hyperinflation in Pakistan were ascribed to either demand-pull or cost-push factors, including depreciating indigenous currency, high energy costs, and oil prices. Although it had been under check for the previous five years, the Central Bank was nonetheless worried about keeping inflation under control (Ghauri et al., 2019). But recent occurrences, like the depreciation of the Pakistani Rupee (PKR) in relation to the US dollar, the increase in oil prices, and Pakistan's disadvantageous TORs from the China-Pakistan Economic Corridor (CPEC), have made authorities concerned about the rate of inflation's unpredictability. Consequently, it became imperative that regulatory agencies create a suitable and precise model for predicting the pace of inflation.

Although there was a dearth of research on the factors influencing inflation and inflation forecasting in Pakistan, there was an abundance of material available elsewhere. Zhang et al. (2020); Štreimikienė et al. (2018); Haider and Hanif (2009); Riaz (2012); Bokil and Schimmelpfennig (2005) Bukhari and Feridun (2006) were among the significant studies conducted in the Pakistani setting. Other research, however, was carried out in the US and Australia; these studies include Stock and Watson (2008); Antipin et al. (2014); Atkeson and Ohanian (2001); Elliott and Timmermann (2008).

Precisely predicting macroeconomic variables particularly inflation is crucial for policymakers and economic and financial experts working in the field of international finance. This makes it possible for financial markets and institutions to decide on financial planning, expenditures, and investments with knowledge (Faust & Wright, 2013; Katona, 1972). In the past, studying economic phenomena has been based on macroeconomic statistics. Macro indicators such as unemployment, inflation, economic growth, imports, and exports have been central to economic theories because of their importance to the economy as a whole. When prices fluctuate and everyone attempts to keep as much control as possible people, businesses, and the government it is one of the most frightening situations. Even if inflation may have little effect on the economy, it may have a greater psychological impact. Inflation affects most economic areas in a noticeable way. Occasionally, price swings could become lethal due to the cascading effects they produce. The growing cost of manufacturing in the industries and sectors they affect drives up the price of finished goods. Empirical studies of inflation have shown a substantial association between inflation and other macroeconomic variables, such as GDP growth, net exports, unemployment, etc. Targeted inflation and price stability are two other important monetary policy objectives of the State Bank of Pakistan. A consistent rise in the average price of goods and services over time is referred to as inflation, and it is commonly calculated using the Consumer Price Index (CPI). Economists frequently debate the correlation between inflation and uncertainty over inflation.

It has been theoretically and empirically proven that monetary policy's transmission mechanisms significantly play vital role in stabilize general prices in an economy. In order to implement monetary policy in an effective manner, inflation forecasts serve as an important tool for the central banks. Central banks develop and adjusts the monetary policies using different instruments for inflation targeting purpose (Batini and Haldane, 1999; Dunbar and Owusu-Amoako, 2023).

The relationship between inflation and uncertainty in inflation forecasts was first explored by Friedman (1977). High inflation had significant welfare costs and indirect impacts on uncertainty, reducing overall wellbeing. As a result, controlling inflation has been a key priority for policymakers since the 1970s, particularly in developing countries like Pakistan, where uncontrolled inflation has devastating effects on lower and middle-income populations.

The Phillips curve demonstrated a negative correlation between inflation and unemployment, with wages also showing an inverse relationship with unemployment (Phillips, 1958). This inverse relationship was further supported by Samuelson and Solow (1960). However, Friedman (1977) argued that this trade-off only holds in the short term, as the vertical aggregate supply curve means that inflationary policies have no long-term impact on unemployment. To address this gap, Phillips introduced the concept of expected inflation. Keynesian economists believe that monetary policy is crucial for controlling unemployment and promoting economic growth, as central banks can influence interest rates, money supply, and subsequently, economic growth and employment levels. The factors influencing inflation have been extensively researched in economics, with the existing literature categorized into five key areas: monetary variables, demand-pull pressures, cost-push dynamics, exchange rate fluctuations, and the role of foreign exchange reserves. This section focuses specifically on the latter, examining the contribution of foreign exchange reserves to inflation management.

Monetary Factors

Increase in money supply translates in inflation in case if the output remains almost unchanged as explained in the standard theory (Friedman, 1968). In this context, various empirical studies have found this phenomenon at different places round the world. Such as Cecchetti (1994) and Papadamou et al. (2019) reported the same relationship empirically between inflation and money supply expansion. The extent of monetary policy influence in determining aggregate demand and inflation is also reported in various studies such as Taylor (2000).

Demand-Pull Factors

Aggregate demand rise whenever it exceeds the aggregate supply pushes prices upwards and this happens under the common name of demand-pull inflation. Empirical data show that there is a very close relationship between high rates of economic activity and inflation (Blanchard, 2000). Demandpull inflation is attributed to a variety of reasons such as high economic growth, increasing export demand, and increased government spending on inflation expectations (Mankiw, 2006).

Cost Push Factors

These include rising costs of production, which lead to inflation. Straightforward examples of these are rises in wages, energy, and raw materials' prices. Forces in the labor market and workers' capacity to negotiate, as Gal (2015) affirms, can drive wages up, hence driving firms' costs of production up. In the same way, commodity and energy price shocks can create cost shocks that have a ripple effect in the economy, pushing inflation up, as Kilian (2009) found.

Cost-push causes are examples of inflation increases due to an increase in the cost of production. Some examples of such causes include alterations in wages, energy costs, and costs of raw material. Gal (2015) clarifies that labor market tensions and the bargaining power of labor can bring about wage increases and hence production cost increases for firms. Similarly, commodity price changes and energy prices can propagate cost shocks in the economy and lead to increases in inflation (Kilian, 2009).

Exchange Rate Dynamics

Various channels of domestic inflation are influenced by the dynamics of the exchange rate. Devaluation of the household cash can lift the expense of imported labor and products, accordingly adding to higher expansion (Rizvi et al., 2014, 2017). On the other hand, imported deflationary pressure may result from currency appreciation (Baharumshah et al., 2017; Rizvi et al., 2014; Boubaker et al., 2020). Besides, conversion scale unpredictability can affect expansion assumptions and cost setting conduct, in this manner affecting future inflationary patterns (Mirza et al., 2023).

Foreign Exchange Reserves (FX Reserves)

Obstfeld and Rogoff (1996) highlight the importance of adequate foreign exchange reserves in Buffering against external economic shocks, reducing exchange rate volatility, bolstering credibility in maintaining price stability. These reserves, held by central banks, stabilize the domestic currency. Empirical evidence from Edison and Pauls (1993) and Aizenman and Riera-Crichton (2008); Aizenman et al. (2011) shows that sufficient reserves contribute to lower inflation rates. It play a pivotal role in inflation management and they are vital for curbing inflation and maintaining price stability Adequate reserves enable countries to intervene in the foreign exchange market, stabilizing the exchange rate and alleviating inflationary pressures. Sufficient reserves also gives confidence to investors, proving that a nation can support its currency and provide macroeconomic stability, resulting in lower inflation levels.

The classic econometric models like multiple regression, ARMA, ARIMA, and VAR have been the backbone of macroeconomic forecasting for decades. But their limitations have long been understood. They are linear models that may not necessarily reflect the nonlinear complex dynamics of economic systems. In addition, their distributional assumptions can lead to biased estimates, hence compromising their effectiveness and reliability (Chen and Ranciere, 2019).

These considerations made it possible to project future inflation using simple econometric models like ARMA and ARIMA, particularly now that inflation is an issue of concern for the economy. This research aimed at creating an ARIMA econometric model to project inflation between 2002-2023. Further, it created a quantitative framework towards projecting inflation in the Republic of Albania. To the extent of quantitative analysis, this research aimed at providing qualitative explanations to justify some inflation phenomena. The ARIMA model was employed to project future inflation, adding to the debate on the subject of inflation and its implications on the economy. Literature indicates that ARIMA models are one of the most useful and convenient techniques to know and forecast inflationary trends. Forecasting inflation remains an important issue for policymakers worldwide, with ARMA and ARIMA models being common tools. This review reviews recent studies (last 5 years) to evaluate the performance of the models to predict inflation with special reference to studies carried out in Pakistan.

Global Trends in ARMA/ARIMA Inflation Forecasting

Model Selection and Performance

Various studies propose various criteria for selection of ARMA/ARIMA model parameter (p, d, q). Recent work by Wang et al. (2023) proposes information criteria such as AIC and BIC, supplemented by residual analysis, as useful tools for model selection.

Incorporating External Factors

The research works of Aysan et al. (2022) and Adebayo & Akinsola (2020) describes how external variables such as the price of oil, exchange rates, and the money supply need to be incorporated in ARMA/ARIMA models to gain accuracy.

Inflation Forecasting in Pakistan using ARMA/ARIMA

Emphasis on Pakistani studies reveals some essential aspects. Research conducted by Shahbaz et al. (2022) and Maqsood & Maqsood (2019) supports the use of ARIMA models in Pakistani inflation forecasting, especially short-term horizons. Studies conducted by Azhar (2018) and Bokil and Schimmelpfennig (2005) reveal the drawbacks of ARMA/ARIMA models, including sensitivity to outliers and underestimation of volatility. These works investigate the possibility of using GARCH or other models for better forecasting precision. According to research by Hussain et al. (2023), integrating ARIMA models with machine learning methods such as neural networks can produce more precise results, particularly for longer time horizons.

In the context of Pakistan, where inflation is influenced by structural rigidities, political cycles, and external shocks, reliance on purely linear models may not be sufficient. Alternative forecasting approaches are increasingly relevant. For instance, nonlinear time series models such as Threshold Autoregressive (TAR) and Smooth Transition Autoregressive (STAR) can better capture regime shifts during high and low inflation periods. More recently, hybrid models that combine ARIMA with machine learning have been applied in emerging economies to improve out-of-sample forecasting accuracy. While this paper focuses on the ARIMA framework for clarity and comparability with existing SBP and IMF practices, acknowledging and integrating such advanced methods in future research can provide a more holistic understanding of inflation dynamics in Pakistan. This broader methodological horizon would allow policymakers to cross-validate forecasts, reduce model risk, and improve the robustness of inflation-targeting frameworks.

While inflation forecasting is a technical exercise, its direct impact on Pakistan's economic stability is profound. Inflation not only erodes purchasing power but also influences wage negotiations, fiscal policy decisions, and private sector investment strategies. In Pakistan's context, persistent inflation has historically contributed to exchange rate volatility, current account deficits, and erosion of real incomes, particularly for vulnerable households. By providing evidence that inflation is likely to decline smoothly in line with SBP's projections, this study highlights the potential for restored investor confidence, reduced cost of borrowing, and improved fiscal planning capacity. Moreover, stable inflation is directly tied to food and energy security two of the most critical determinants of social stability and national security in Pakistan.

While the ARIMA model provides a robust framework for capturing historical inflation patterns and producing reliable short- to medium-term forecasts, it is not without limitations. A key concern is its sensitivity to outliers: sudden political events, natural disasters, or commodity price shocks (such as global oil price spikes) can significantly distort the forecast accuracy, since ARIMA assumes past patterns will persist into the future.

Pakistan has experienced persistent inflation volatility over the last two decades, driven by political instability, external shocks, and structural weaknesses in its economy. Inflation erodes household purchasing power, destabilizes investment decisions, and creates uncertainty for policymakers. Despite repeated policy interventions by the State Bank of Pakistan (SBP), the ability to forecast inflation accurately remains a major challenge. Most existing studies rely on traditional econometric models but do not fully examine their policy relevance or alignment with SBP's inflation-targeting framework. Therefore, the research problem addressed in this study is: How accurately can inflation in Pakistan be forecasted using ARIMA models, and what are the broader implications of such forecasts for monetary policy, and macroeconomic stability?

While ARMA/ARIMA models have been widely applied in prior studies on inflation forecasting, this paper makes several new contributions in terms of data, methodology, and scope. First, it uses a longer and more recent dataset (2002–2022), which incorporates multiple political cycles, oil price shocks, and IMF stabilization programs, thereby offering a more comprehensive picture of Pakistan's inflation dynamics. Second, unlike earlier studies that often focus only on technical accuracy, this study explicitly links ARIMA forecasts to SBP's official inflation targets and IMF's medium-term frameworks, providing a policy-relevant dimension that has been missing from the literature. Third, the study goes beyond producing forecasts by situating results within theoretical frameworks such as the Phillips Curve, Monetarist theory, and New Keynesian insights, thus bridging the gap between statistical modeling and economic theory.

The aim of the present research is to develop an econometric inflation model utilizing ARIMA for the period between 2002 and 2023. Also, it is attempting to create a quantitative approach to forecast inflation in the Republic of Albania. Moreover, the present research tries to clarify different events of inflation by illustrating qualitative information. The ARIMA model is going to be applied to predict future inflation rates. Further, the study adds to the current debate surrounding inflation and its effects on the economy. Academic literature demonstrates that ARIMA models are one of the most potent and feasible methods for explaining the economic phenomenon of inflation.

Literature Review

Empirical Studies

The existing literature review indicates that numerous studies have centered on predicting macroeconomic variables and have labeled the construction of alternative models using out-of-sample prediction (Ghoto, 2021; Ghauri et al., 2019). Inflation prediction has applied influential econometric models, which include Philips curve model, univariate time series (ARIMA) model, interest rate model, and the naive model (Işığıçok et al., 2020). The Philips Curve has been a well-known method for projecting inflation across various time periods, with initial works contributed by Gordon (1982) who formulated the triangle model for projecting decline in inflation during recessions. Alderite and Capili (2020) and Stockton and Glassman (1987) continued to contribute in this field. Subsequent works were dedicated to analyzing volatility in the Philips curve coefficients, with significant contributions made by He et al. (2021) and Canova (2007). There has been recent literature that has compared projections of varying inflation measures, such as studies on the GDP Deflator and long-term expectations of the Harmonized Index of Consumer Price (HICP) by Banbura and Mirza (2013). Scholars have investigated other models for the prediction of inflation, such as univariate and multivariate models.

Fama and Gibbons (1984) established that the interest rate model was more accurate compared to the univariate real interest rate model. Eissa (2020) and Kenny et al. (1998) applied ARIMA models to forecast inflation in Ireland, while Sekine (2001) developed an equilibrium correction model for Japan. Mohamed (2020) and Alles and Horton (1999) evaluated univariate time series and interest rate models, with the latter incorporating public surveys and error correction. The recent research conducted in Pakistan by Drachal (2020); Ghauri et al. (2019), and Štreimikienė et al. (2018) identified ARIMA as the best among other models in their studies. Saman and Pauna (2013) and Lee (2012) demonstrated that the univariate time series model performed better than the naive model and Philips Curve when it comes to forecasting inflation. Moreover, Prüser (2021) and Ang et al. (2007) proved that univariate time series models are more effective than interest rate models or Philips Curve in forecasting US inflation. The review of literature included a wide variety of domestic and foreign research studies in inflation forecasting using different methods and variables. Univariate approaches such as ARMA, ARCH, OLS, VAR, and generalized method of moments were utilized, along with the Philips curve model.

Most studies focused on the Consumer Price Index (CPI), with some also considering the Wholesale Pricing Index (WPI) and other macroeconomic variables. The negative impacts of inflation uncertainty and inflation on economic growth were highlighted by Friedman (1977), emphasizing the importance of managing inflation expectations. Ball (1992) further supported the destabilizing effects of inflation on future expectations, stressing the need for low and stable inflation. Early applications in Pakistan date back to Salam et al. (2007), who laid out a systematic Box–Jenkins framework for monthly CPI forecasting. They concluded that ARIMA models provided strong in-sample and out-of-sample predictive accuracy, making them suitable for shortterm inflation monitoring. Similarly, Bokhari and Feridun (2006) compared ARIMA with Vector Autoregression (VAR) models and showed ARIMA's superior forecasting performance in Pakistan, noting that simpler ARIMA specifications often outperformed more complex alternatives Moving into the 2010s, Rahim (2013) examined ARIMA against decomposition techniques for forecasting CPI and industrial growth (LSM). Again, ARIMA models shone, showing lower mean absolute deviation and sum of squared errors.

This reaffirmed ARIMA's consistency and reliability, even under the structural shifts often seen in Pakistan's economy. The determinants of inflation were extensively examined, including monetary factors, demand-pull factors, cost-push factors, exchange rate dynamics, and foreign exchange reserves. Empirical studies consistently showed a positive relationship between money supply growth and inflation, with monetary factors being crucial determinants. Demand-pull factors result from excessive aggregate demand, while cost-push factors arise from increased production costs. Exchange rate dynamics impact domestic inflation through various channels, and foreign exchange reserves play a vital role in managing inflationary pressures and maintaining price stability.

Different researchers have utilized various models to forecast inflation, with studies comparing the forecasting performance of models like the Philips curve and the naive model. While the Philips curve has historically been a significant tool for guiding monetary policy, recent studies suggest varying performance compared to alternative models such as the naive model or univariate time series models. Inflation forecasting has been done by a variety of researchers using various models. The relative accuracy of interest rate-based models and univariate models in predicting inflation was evaluated by Hafer and Hein (1990). Around the world, the Philips curve has been an important tool for guiding monetary policy to control price levels. However, numerous recent studies demonstrate that the integrated moving average (1, 1) model, naive model, and an unobserved stochastic volatility model performed better over the past twenty years than inflation forecasts based on the Philips curve. As a result, the question arises as to whether or not the Philips curve should continue to hold a significant position in policy discussions. Atkeson and Ohanian (2001) composed the principal paper that estimates vulnerability about the adequacy of Philip's bend.

For inflation forecasting, their findings demonstrated that the naive model outperforms the Philip's curve model. Since then, many papers have looked into the relative forecasting performance, especially those by Stock and Watson (2008). In this way, from the above discussion, we can conclude that inflation forecasting from Philips cure model is not authentic as some time Philips curve predict accurate than naive model and sometime naive model predict better than Philip curve model. Further research is needed to clarify the effectiveness of the Philips curve in inflation forecasting.

Hypotheses development

This study is grounded in two complementary theoretical perspectives.

Phillips Curve

This framework suggests a trade-off between inflation and unemployment, where inflationary pressures are influenced by demand conditions and inflation expectations. In Pakistan's case, persistent inflation reflects both structural rigidities and weak anchoring of expectations. By using lagged values of inflation in the ARIMA model, the study captures the inertia and expectation-driven dynamics central to the Phillips Curve.

Monetarist Theory

Building on Friedman's view that "inflation is always and everywhere a monetary phenomenon," Pakistan's inflationary episodes can also be traced to money supply growth, fiscal deficits, and external borrowing. ARIMA's autoregressive structure indirectly reflects these monetary imbalances by showing how past inflation (driven by money supply expansion) feeds into future outcomes. Together, these frameworks provide the conceptual foundation for evaluating inflation dynamics and for interpreting forecasts within a broader macroeconomic and policy context.

Based on the theoretical grounding, the study proposes the following hypotheses:

H1: Inflation in Pakistan exhibits strong persistence, meaning past inflation significantly influences future inflation trends.
H2: Forecasted inflation using ARIMA aligns with SBP's official inflation targets, suggesting that monetary policy stance has medium- to long-term credibility.

Methodology

In this section, first, we will discuss the theoretical underpinnings related to AR, MA, ARMA and ARIMA while later on, we will explain the process of data collection, data smoothening and the econometric techniques for forecasting.

Theoretical Framework

The theoretical foundation of inflation forecasting can be better understood by situating it within established economic theories. One of the classical frameworks is the Phillips Curve, which posits an inverse relationship between inflation and unemployment. In Pakistan's case, high inflation episodes often coincide with rising unemployment and reduced real wages, challenging the trade-off originally described by Phillips and highlighting structural rigidities in the labor market. This study's results align with the modified expectations-augmented Phillips Curve, which emphasizes that credible monetary policy and anchored expectations are crucial to sustaining low and stable inflation.

In addition, Monetarist theory, particularly Friedman's assertion that "inflation is always and everywhere a monetary phenomenon," is highly relevant in Pakistan where money supply growth, fiscal deficits, and external borrowing have historically driven inflationary pressures. The ARIMA model's ability to capture persistent inflation trends reflects the medium-run influence of monetary expansion and policy interventions. Furthermore, elements of New Keynesian economics especially the role of expectations and price rigidities help explain why SBP's credibility in maintaining inflation targets can influence long-term outcomes. Anchoring expectations through transparent inflation targeting reduces uncertainty and mitigates the impact of random shocks such as political instability or global commodity price swings.

Autoregressive (AR) Models

Imagine a time series representing monthly sales figures for a company. An AR model assumes that the current value Y_t is influenced by a linear combination of its own past values $(Y_{t-1}, Y_{t-2}, Y_{t-p})$ along with a random error term (ϵ_t). This is mathematically represented as:

$$Y_t = \alpha_0 + \alpha_1 * Y_{t-1} + \alpha_2 * Yt - 2 + ... + \alpha_p * Y_{t-p} + \epsilon_t$$

Here:

- Y_t: The value of the time series at time t
- α_0: The constant term (intercept)
- α_i: Coefficients for the lagged values $(i = 1, 2, ..., p)$ representing the impact of past values (p is the order of the AR model)
- ϵ_t: The random error term at time t, capturing the unexplained portion of the current value

The coefficients α_i are estimated using statistical methods like least squares to determine the extent to which past values influence the current value.

Moving Average (MA) Models

MA models take a different approach. They assume the current value Y_t is influenced by the current error term ϵ_t and a weighted sum of past error terms ϵ_{t-1}, ϵ_{t-2}, ..., ϵ_{t-q}. This is expressed as:

$$Y_t = \mu + \epsilon_t + \beta_1 * \epsilon_{t-1} + \beta_2 * \epsilon_{t-2} + ... + \beta_q * \epsilon_{t-q}$$

Here:

- μ: The mean of the time series
- β_i: Coefficients for the lagged error terms $(i = 1, 2, ..., q)$ representing the impact of past errors (q is the order of the MA model)

The MA model suggests that past errors can influence current and future values. Positive coefficients (β_i) indicate a positive correlation with past errors, while negative coefficients imply a negative correlation.

ARMA Models

ARMA models combine the strengths of AR and MA models. The current value Y_t is influenced by both past values of itself Y_{t-i} and past error terms ϵ_{t-j}:

$$Y_t = \alpha_0 + \alpha_1 * Y_{t-1} + \alpha_2 * Y_{t-2} + ... + \alpha_p * Y_{t-p} + \beta_1 * \epsilon_{t-1} + \beta_2 * \epsilon_{t-2} + ... + \beta_q * \epsilon_{t-q} + \epsilon_t$$

This equation incorporates both the autoregressive component (AR) and the moving average component (MA) to capture the influence of past observations and past errors on the current value.

Stationarity and ARIMA Models:

For ARMA models to be effective, the time series data needs to be stationary. Stationarityimplies that the mean, variance, and autocorrelation (correlation between observations at different time lags) remain constant over time. If the data exhibits trends or seasonality, differencing is required to achieve stationarity.

The ARIMA (p, d, q) model incorporates differencing (d) into the ARMA framework. The data is differenced "d" times to achieve stationarity. Differencing involves subtracting the previous value from the current value, essentially removing trends or seasonality.

Methodology of ARIMA Model for Inflation Forecasting

The following methods are used in ARIMA model forecasting for inflation.

Stationarity Analysis

Check if the time series data of inflation is stationary. Stationarity implies that the statistical properties of the time series like mean and variance are constant over time. If not stationary, the nonstationarity needs to be addressed through differencing.

Differencing

If the data is non-stationary, take differences between consecutive observations to make it stationary. This is known as differencing and can be done multiple times until stationarity is achieved.

Identification of AR and MA Orders

Determine the orders of the autoregressive (AR) and moving average (MA) components of the ARIMA model through Autocorrelation Function (ACF), to identify the order of the MA component and Partial Autocorrelation Function (PACF), to identify the order of the AR component.

Model Fitting

Fit the ARIMA model with the identified orders. The general form of ARIMA model is ARIMA(p, d, q) where:

p: The order of the autoregressive (AR) component.
d: The degree of differencing.
q: The order of the moving average (MA) component.

$$Y_t = \alpha_0 + \alpha_1 * Y_{t-1} + \alpha_2 * Y_{t-2} + ... + \alpha_p * Y_{t-p} + \beta_1 * \epsilon_{t-1} + \beta_2 * \epsilon_{t-2} + ... + \beta_q * \epsilon_{t-q} + \epsilon_t$$

Parameter Estimation

Estimate the parameters ϕ_i and θ_i using methods like maximum likelihood estimation (MLE).

Model Diagnosis:

Check the residuals of the fitted model for autocorrelation to ensure that the model captures all the temporal dependencies in the data.

Forecasting

After the model has been fitted and tested, it may be applied for the prediction of future inflation rates. Predictions are typically produced recursively by recycling previously forecasted values into the model.

Data Preprocessing: Preparing the Data for Analysis

Before unleashing the power of the ARIMA model, data preprocessing becomes crucial. This stage ensures the data quality and suitability for model fitting:

Missing Values

Missing data points can disrupt your analysis. If these points represent a negligible portion of the data, you can remove them. Alternatively, consider imputation techniques to fill the gaps with statistically sound estimates. In our case, no values were missing in the official data sheet.

Outliers

Extreme data points, or outliers, can significantly influence model performance. Analyze the data for outliers and decide on a course of action. You can choose to keep them, remove them, or apply transformations (e.g., winsorizing) to lessen their impact. Winsorizing replaces extreme values with values closer to the central tendency of the data. The data used in the study had no outliers.

Transformation

The distribution of your inflation data might require transformation. If the data exhibits nonnormality (doesn't follow a bell-shaped curve), consider applying a log transformation. This transformation can improve model performance by making the data more suitable for ARIMA model assumptions. We employed the inflation data without transformation since it was rate (inflation rate) and relatively smooth data naturally.

Data Collection:

Inflation Data for Pakistan We have employed the annual dataset of Inflation based on Consumer Price Index from Ministry of Finance[2]. It was divided into three different basis. Data from 2002 to 2012 used 2000 as base year, from 2009 to 2019 was based on 2008, 2017 - 2023 is based on 2016. First, we converted all the data to the base 2016 and proceed for stationarity testing as a pre-requisite for ARMA/ ARIMA procedure.

Results and Discussion

This section explains the result and analysis of stationary, ARMA & ARIMA models

[2] https://finance.gov.pk/survey_2023.html

Table 1: Test for Stationarity

	ADF		PP	
	Level	1st Difference	Level	1st Difference
Constant	-0.862	-3.448	-0.820	-3.448
Constant and Trend	-0.994	-3.391	-0.994	-3.391

Note: Critical values (Constant) at 10%, 5%, and 1% are -2.650, -3.020, and -3.808, respectively.
Critical values (Constant and Trend) at 10%, 5%, and 1% are -3.268, -3.658, and -4.498, respectively.

According to ADF test, Inflation is found to be stationary at the first difference at 10 percent level of significance. These results are also re-confirmed from PP-test and the finding regarding integration of order one is also endorsed from PP-test. Having established the level of stationarity, we can proceed for estimating and forecasting inflation series from 2023 to 2028 through ARMA.

Table 2: ARMA Estimation Results

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	2.132521	0.03537	60.29123	0.0000
AR(1)	1.749859	0.047735	36.65773	0.0000
AR(2)	-0.9831	0.041016	-23.9689	0.0000
MA(1)	-1.96453	3522.477	-0.00056	0.9996
MA(2)	0.999991	3585.756	0.000279	0.9998
SIGMASQ	0.061086	108.4004	0.000564	0.9996

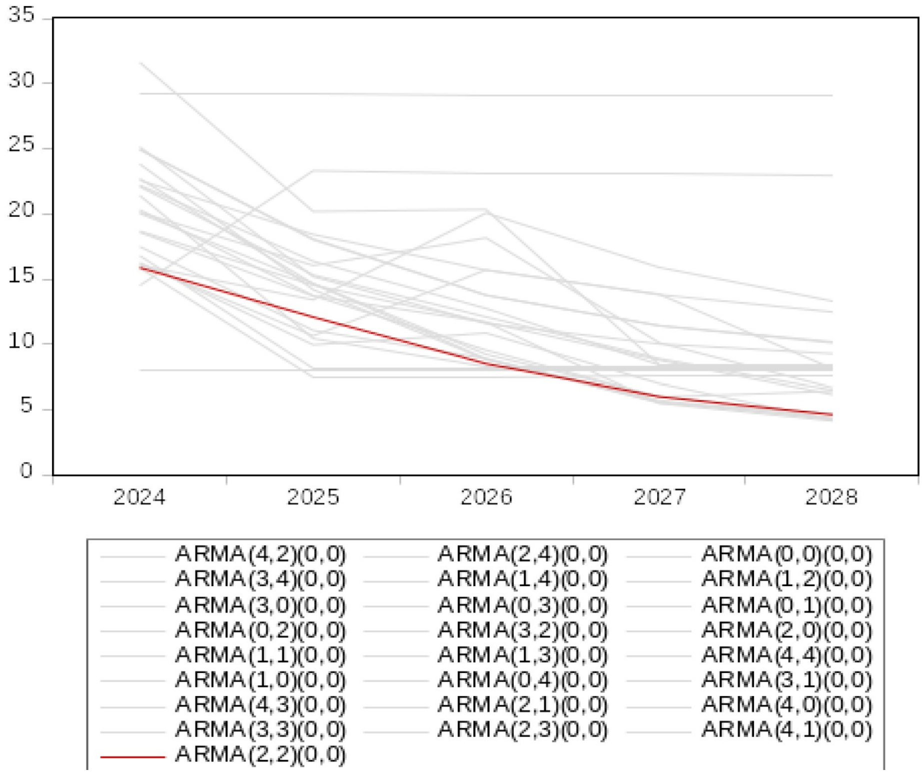
R-squared: 0.819397	**Mean dependent var:** 2.084966
Adjusted R-squared: 0.762959	**S.D. dependent var:** 0.595267
S.E. of regression: 0.289817	**Akaike info criterion:** 1.039893
Sum squared resid: 1.343903	**Schwarz criterion:** 1.337450
Log likelihood: -5.438820	**Hannan-Quinn criter.:** 1.109988
F-statistic: 14.51844	**Durbin-Watson stat:** 1.723000
Prob(F-statistic): 0.000018	
Inverted AR Roots: $0.87 \pm 0.47i$	**Inverted MA Roots:** $0.98 \pm 0.19i$

We utilized Autoregressive Integrated Moving Average (ARIMA) modeling to forecast inflation in Pakistan for the period spanning from 2024 to 2028. The ARIMA model was constructed using historical inflation data spanning from 2002 to 2023. As shown, R-square is 0.819 implies that the variation in ARMA process explain around 81 percent variation in inflation. Also, a significant F-statistic of 14.51 indicating the model's overall goodness of fit.

Notably, the autoregressive (AR) component of the model revealed insightful dynamics: the firstorder autoregressive coefficient (AR 1) emerged as positive and statistically significant, suggesting a strong influence of past inflation on future values. Conversely, the second-order autoregressive coefficient (AR 2) displayed a negative and significant relationship, indicating a damping effect on inflation momentum. However, both the first-order moving average (MA 1) and second-order moving average (MA 2) coefficients were found to be statistically insignificant, implying that the influence of recent forecast errors on inflation was not significant. This comprehensive ARMA analysis provides valuable insights into the dynamics of inflation in Pakistan, offering a robust framework for forecasting future inflation trends. Before moving further, the following figure compares different ARIMA models (having different lag orders) to find out the best specification for forecasting inflation.

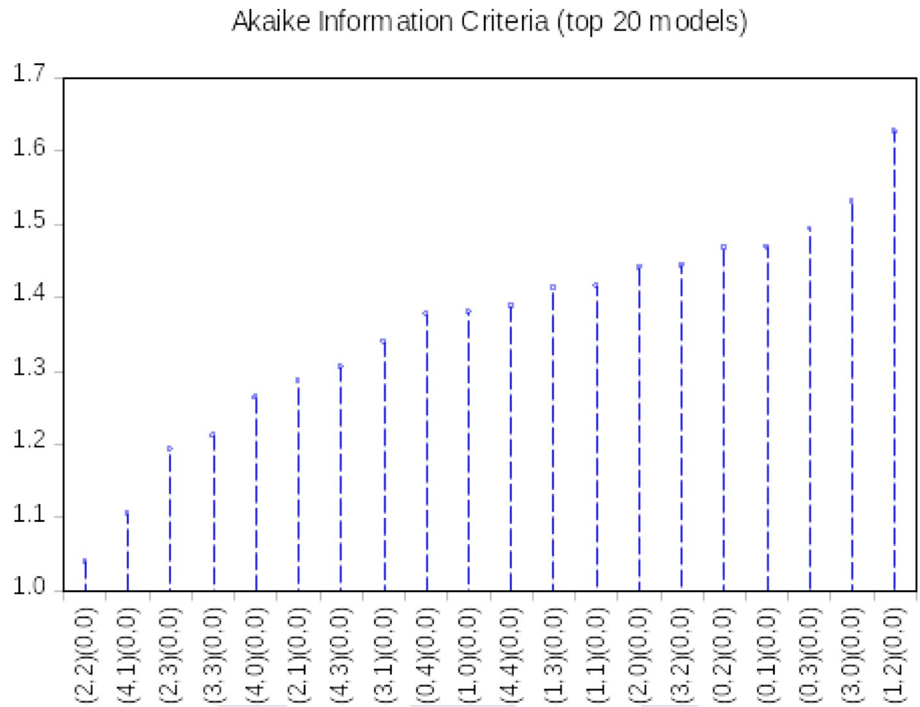
As shown in figure 1, the red line represents the most efficient lag order AR(2,2)(0,0), selected using the Akaike Information Criterion. This indicates that inflation in Pakistan is best explained by its first and second lags, confirming the strong persistence and inertia in price dynamics. The dominance of these lags reflects how past inflationary pressures rather than random shocks—are the primary drivers of future inflation, underscoring the importance of consistent monetary policy to anchor expectations.

Figure 1: Forecast Comparison Graph



As shown in figure 2, the AR(2,2) and MA(0,0) are the lags selected through the Akaike Information Criterion, indicating that the most efficient inflation forecasts for Pakistan rely on the first and second lags of inflation, without including lagged error terms in the estimating equation. This suggests that inflation in Pakistan is heavily path-dependent, with past inflation levels (particularly over the last two years) being the strongest predictors of future outcomes. In other words, inflationary expectations and inertia play a central role in driving price dynamics, consistent with both monetarist views and New Keynesian emphasis on expectations. The historical data (2002-2022) in the figure further demonstrates that while inflation has been volatile due to shocks such as political transitions, global oil price fluctuations, and fiscal imbalances, the long-run trend reveals a gradual stabilization effect. This reflects the medium- to long-run influence of SBP's inflation-targeting framework, as well as structural adjustments aligned with IMF programs.

Figure 2: Akaike lag selection criteria



The red values in the graph shows the actual while the blue values are forecasted values for inflation. As shown in the graph, based of lag order (2,2) (0,0), our model has predicted that in the upcoming years, there would be a smooth and consistent decline in inflation. This forecast not only validates the robustness of SBP's inflation-targeting stance but also highlights its consistency with the IMF's medium and long-term frameworks.

Beyond the statistical forecast, the broader policy implications are critical. Sustained reduction in inflation enhances macroeconomic stability, which directly impacts investor confidence, exchange rate stability, and fiscal discipline. A predictable inflation environment encourages both domestic and foreign investment, supports credit expansion, and stabilizes the cost of doing business. Moreover, for Pakistan's socio-economic context, lower inflation translates into greater purchasing power for households, improved poverty alleviation outcomes, and reduced vulnerability of lowincome groups to price shocks-factors that contribute to social cohesion and national security. The historical pattern, where inflation was heavily influenced by exogenous shocks such as political instability, global oil price volatility, and structural reforms, the importance of policy continuity. If Pakistan maintains consistency in its inflation-targeting framework, it can build credibility in international markets, reduce reliance on emergency stabilization packages, and better integrate with global trade and investment flows. In the long run, anchoring inflation expectations strengthens Pakistan's resilience against external shocks, thereby advancing not only economic growth but also strategic security interests in an increasingly volatile global economic environment.

Conclusion

In this study, our objective was to forecast CPI inflation for the next 5 years (2023-2028) using ARMA / ARIMA method. This is a very powerful tool for inflation forecasting mostly employed by the central Banks around the globe. For this, the study used the annual dataset from official website of Ministry of Finance from 2022 to 2022. Prior to move for ARMA / ARIMA, we found the CPI inflation to be integrated of order one so ARIMA was most appropriate for forecasting. We found that in the upcoming years, inflation would decline in a smooth and consistent manner, which is as per the roadmap laid down by State Bank of Pakistan for the upcoming years. This shows that the strategies for controlling inflation by SBP are effective in the medium and long run so there is a need to continue the current stance (monetary tightening) for controlling inflation and reaching to a single digit, low inflation.

Directions for Further Research

This analysis can be further enhanced by using CPI sector wise data in order to observe the difference in price paths of different categories. Moreover, in order to have a more detailed view, along with the sectors of CPI, the WPI inflation data along with its subsectors would increase the significance of the analysis manifolds.

Policy implications

The study has several policy implications. It will help by providing an accurate and timely forecast of inflation, which will help regulators in devising suitable macroeconomics policies. Moreover, our study will equip policymakers with essential information to make informed decisions, which will be ensuring economic stability, growth, and welfare of the public.

The smooth and consistent decline in inflation predicted over the next five years, in line with SBP's official targets, suggests that the central bank's stance on inflation targeting is both credible and effective. For monetary policymakers, this implies that continued commitment to a tight but flexible monetary policy stance can anchor inflation expectations and reinforce macroeconomic stability. More specifically, reliable forecasts enable SBP to calibrate the policy rate more effectively, avoiding overly aggressive tightening (which can slow growth) or premature loosening (which can reignite inflation). By aligning interest rate decisions with forecasted inflation trends, SBP can maintain a balance between price stability and growth. In addition, inflation forecasts can guide exchange rate management by signaling when external shocks, such as commodity price hikes or depreciation pressures, may feed into domestic inflation.

References

Aizenman, J., Edwards, S., and Riera-Crichton, D. (2011). Adjustment patterns to commodity terms of trade shocks: The role of exchange rate and international reserves policies. nber working paper no 17692.

Aizenman, J. and Riera-Crichton, D. (2008). Real exchange rate and international reserves in an era of growing financial and trade integration. *The Review of Economics and Statistics*, 90(4):812–815.

Alderite, A. A. and Capili, A. F. (2020). Comparison of ARIMA and singular spectrum analysis in forecasting the Philippine inflation rate. *Advances and Applications in Statistics*, 65(1):19–31.

Alles, L. and Horton, D. (1999). An evaluation of alternative methods of forecasting Australian inflation. *The Australian Economic Review*, 32(3):237–248.

Ang, A., Bekaert, G., and Wei, M. (2007). Do macro variables, asset markets or surveys forecast inflation better? *Journal of Monetary Economics*, 54(4):1163–1212.

Antipin, J. E., Boumidiene, F. J., and Osterholm, P. (2014). Forecasting inflation using constant gain least squares. *Australian Economic Papers*.

Atkeson, A. and Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation? *Quarterly Review*, 25(1):2–11.

Baharumshah, A. Z., Sirag, A., and Mohamed Nor, N. (2017). Asymmetric exchange rate pass-through in sudan: Does inflation react differently during periods of currency depreciation? *African Development Review*, 29(3):446–457.

Banbura, M. and Mirza, H. (2013). Forecasting Euro area inflation with the Phillips curve. Mimeo manuscript. European Central Bank.

Batini, N. and Haldane, A. G. (1999). Forward-looking rules for monetary policy. *Bank of England Working Paper*, (91).

Bokhari, S. M. H. and Feridun, M. (2006). Forecasting inflation through econometric models: An empirical study of Pakistani data. *Doğuş Üniversitesi Dergisi*, 7(1):39–47.

Bokil, M. and Schimmelpfennig, A. (2005). Three attempts at inflation forecasting in Pakistan. Technical Report WP/05/105, International Monetary Fund.

Boubaker, H., Canarella, G., Gupta, R., and Miller, S. M. (2020). Long-memory modeling and forecasting: Evidence from the U.S. historical series of inflation. *Studies in Nonlinear Dynamics & Econometrics*, 24(2).

Canova, F. (2007). G-7 inflation forecasts: Random walk, Phillips curve or what else? *Macroeconomic Dynamics*, 11(1):1–30.

Chen, S. and Ranciere, R. (2019). Financial information and macroeconomic forecasts. *International Journal of Forecasting*, 35(3):1160–1174.

Drachal, K. (2020). Forecasting the inflation rate in Poland and U.S. using dynamic model averaging (DMA) and Google queries. *Romanian Journal of Economic Forecasting*, 23(2):18–34.

Dunbar, G. and Owusu-Amoako, K. (2023). Inflation forecasting in developing economies: A comparison of model-based approaches. *Journal of Economic Studies*, 50(1):1–23.

Edison, H. J. and Pauls, B. D. (1993). A re-assessment of the relationship between real exchange rates and real interest rates: 1974–1990. *journal of Monetary Economics*, 31(2):165–187.

Eissa, N. (2020). Forecasting the GDP per capita for Egypt and Saudi Arabia using ARIMA models. *Research in World Economy*, 11(1):247–258.

Elliott, G. and Timmermann, A. (2008). Economic forecasting. *Journal of Economic Literature*, 46(1):3–56.

Fama, E. F. and Gibbons, M. R. (1984). A comparison of inflation forecasts. *Journal of Monetary Economics*, 13(3):327–348.

Friedman, M. (1968). The role of monetary policy. *The American economic review*, 58(1):1–17.

Friedman, M. (1977). Nobel lecture: inflation and unemployment. *Journal of political economy*, 85(3):451–472.

Ghauri, S. P., Ahmed, R. R., Vveinhardt, J., Štreimikienė, D., and Qureshi, K. S. (2019). The effects of remittances on inflation (CPI and WPI) and exchange rate: A case of Pakistan. *Romanian Journal of Economic Forecasting*, 22(2):146–165.

Ghoto, A. A. (2021). Estimation and forecasting of the inflation, interest, literacy and unemployment rate of Pakistan using nonlinear regression models. *Indian Journal of Science and Technology*, 14(3):251–258.

Gordon, R. J. (1982). Inflation, flexible exchange rates, and the natural rate of unemployment. In Baily, M. N., editor, *Workers, Jobs and Inflation*, pages 89–158. The Brookings Institution, Washington, DC.

Haider, A. and Hanif, M. N. (2009). Inflation forecasting in Pakistan using artificial neural networks. *Pakistan Economic and Social Review*, 47(1):123–138.

He, M., Hao, X., Zhang, Y., and Meng, F. (2021). Forecasting stock return volatility using a robust regression model. *Journal of Forecasting*.

Işığıçok, E., Öz, R., and Tarkun, S. (2020). Forecasting and technical comparison of inflation in Turkey with Box-Jenkins (ARIMA) models and artificial neural network. *International Journal of Energy Optimization and Engineering*, 9(4):84–103.

Jiranyakul, K. (2020). The linkages between inflation and inflation uncertainty in selected Asian economies: Evidence from quantile regression. *Journal of Advanced Studies in Finance*, 11(2):74–80.

Kenny, G., Meyler, A., and Quinn, T. (1998). Forecasting Irish inflation using ARIMA models. Technical Report 3/RT/98, Central Bank of Ireland.

Lee, U. (2012). Forecasting inflation for inflation-targeted countries: A comparison of the predictive performance of alternative inflation forecasting models. *Journal of Business & Economic Studies*, 18(1):75–95.

Mankiw, N. G. (2006). The macroeconomist as scientist and engineer. *Journal of economic perspectives*, 20(4):29–46.

Mohamed, J. (2020). Time series modeling and forecasting of Somaliland consumer price index: A comparison of ARIMA and regression with ARIMA errors. *American Journal of Theoretical and Applied Statistics*, 9(4):143–153.

Obstfeld, M. and Rogoff, K. (1996). *Foundations of international macroeconomics*. MIT press.

Phillips, A. W. (1958). The relation between unemployment and the rate of change of money wage rates in the united kingdom, 1861-1957. *economica*, 25(100):283–299.

Prüser, J. (2021). Forecasting US inflation using Markov dimension switching. *Journal of Forecasting*, 40(3):481–499.

Purwa, T., Nafngiyana, U., and Suhartono, S. (2020). Comparison of ARIMA, transfer function and VAR models for forecasting CPI, stock prices, and Indonesian exchange rate: Accuracy vs. explainability. *Media Statistika*, 13(1):1–12.

Rahim, A. (2013). Forecasting inflation and economic growth of Pakistan by using two time series methods. *International Journal of Business and Economics Research*, 2(6):174–178.

Riaz, M. (2012). Forecast analysis of food price inflation in Pakistan: Applying rationality criterion for VAR forecast. *Developing Country Studies*, 2(1):63–72.

Rizvi, S., Naqvi, B., Mirza, N., and Bordes, C. (2017). Fear of floating in asia and the credibility of true floaters? *Research in International Business and Finance*, 42:149–160.

Rizvi, S. K. A., Naqvi, B., and Mirza, N. (2014). From fear of floating to benign neglect: The exchange rate regime roller coaster in pakistan. *Lahore Journal of Economics*, 19(special Edition):17–34.

Salam, M. A., Salam, S., and Feridun, M. (2007). Modeling and forecasting Pakistan's inflation by using time series ARIMA models. Technical Report 2007(1), Economic Analysis.

Saman, C. and Pauna, B. (2013). New Keynesian Phillips curve for Romania. *Romanian Journal of Economic Forecasting*, 16(2):159–171.

Samuelson, P. A. and Solow, R. M. (1960). Analytical aspects of anti-inflation policy. *The American economic review*, 50(2):177–194.

Sekine, T. (2001). Modeling and forecasting inflation in Japan. Technical Report WP/01/82, International Monetary Fund.

Stock, J. H. and Watson, M. W. (2008). Phillips curve inflation forecasts. *Conference Series [Proceedings]*, 53.

Stockton, D. J. and Glassman, J. E. (1987). An evaluation of the forecast performance of alternative models of inflation. *The Review of Economics and Statistics*, 69(1):108–117.

Vesna, K. and Pejovic, B. (2021). Inflation forecasting in the Western Balkans and EU: A comparison of Holt-Winters, ARIMA and NNAR models. *Amfiteatru Economic*, 23(57):517–532.

Zhang, B., Chan, J. C. C., and Cross, J. L. (2020). Stochastic volatility models with ARMA innovations: An application to G7 inflation forecasts. *International Journal of Forecasting*, 36(4):1218–1238.

Štreimikienė, D., Ahmed, R. R., Vveinhardt, J., Ghauri, S. P., and Zahid, S. (2018). Forecasting tax revenues using time series techniques: A case of Pakistan. *Economic Research-Ekonomska Istraživanja*, 31(1):722–754.