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Inflation Dynamics and Forecasting Performance in Developing Economies: A Cross-Country MIDAS Analysis

Zakia Zafar[1,], Tanweer Ul Islam[1]*

Affiliations
1. School of Economics, National University of Sciences and Technology (NUST), Islamabad

*Corresponding Author Email: zakiazafar.raja@gmail.com

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Abstract
This study examines the inflation dynamics and its forecasting performance for 26 developing economies for the year 2000-2023 using Mixed Data Sampling (MIDAS) regression. The methodological farmwork includes an Augmented Phillips curve approach incorporating asset prices, financial indicators, and macroeconomic indicators. The MIDAS regression technique is used to incorporate the shortcomings of data availability in different frequencies. It incorporates the high frequency indicators, financial indicators, and low frequency macroeconomic indicators in one regression. Hence, the variables are not needed to be aggregated or disaggregated to match the frequencies in same regression. Several MIDAS specifications are estimated such as Beta, PDL/Almon, Exponential Almon, step and UMIDAS to get the RMSE and Theil index for in-sample and out-of-sample forecasts. The results showed the effectiveness of MIDAS models specifying the predominance of Beta method over other specifications for many countries. Inflation occurred as information-rich and multidimensional process which is caused by real economic activity, monetary policy indicators, and other external factors while monetary aggregates are shown as weak predictors of inflation. The relationship between the Phillips curve remained the same in the case of almost all countries but it is more of a hybrid nature and the context (geographical nature of economies) matters. There are cross-country heterogeneity and a need for flexible, data-intensive modeling techniques to effectively predict inflation and design policies in developing economies. This analysis also re-evaluates the Phillips curve relationship and highlights that it is still relevant, but it has now become hybrid and context dependent. The research makes a significant contribution to literature as it gives a more in-depth comparison of the cross-country inflation processes and dynamics in the developing economies.

Keywords: Inflation Dynamics, Forecasting Performance, MIDAS Regression, Developing Economies, Nowcasting, High-Frequency Indicators, Phillip's curve

JEL Classification: C22, C53, C51, C52, E37

1. Introduction

Inflation is one of the key issues among the policy makers of developing economies because of its direct effects on the macroeconomic stability of the economy, income distribution, and financial development. Consistent inflation undermines purchasing power, distorts investment choices and makes it difficult to implement monetary policies. Central banks, especially in the economies that are shifting to inflation-targeting regimes, therefore need to have the capacity to accurately model and predict inflation. Many of the traditional inflation models have been based on the Phillips curve model, which associates inflation with the labor market conditions. Although it sounds theoretically attractive, its empirical results have since deteriorated, particularly in developing economies that have structural rigidities, informal labor markets, and are vulnerable to external shocks. Unemployment alone cannot even explain the dynamics of inflation in these economies.

Recent developments in empirical macroeconomics emphasize the need to include a wide range of indicators in inflation model and inflation forecasting. The forward-looking information on the economic conditions and inflation expectations is included in financial variables such as exchange rates, interest rates, and asset prices. The major difficulty in such estimation is, however, that macroeconomic data are of mixed frequencies, with inflation generally available at a lower frequency and financial variables being measured at higher frequencies. This issue is dealt with in this research by incorporating the MIDAS regression framework that enables one to use variables that are observed at different frequencies without aggregating/disaggregating them. This study incorporates Phillip's curve with information-rich empirical methods and mixed frequency data and extends a thorough analysis of inflation dynamics in 26 developing economies.

The primary objective of the study is to analyze the forecast performance of inflation in developing countries by incorporating financial indicators, asset prices, and macroeconomic indicators. This research includes a mixed-frequency econometric framework to forecast inflation using MIDAS regression specifications that incorporate variables observed at different frequencies. This enables us to investigate how variables such as real economic activity, exchange rates, and commodity prices shape inflation trends in real-time. Moreover, the research aims to evaluate and compare the forecasting performance of several MIDAS specifications, such as Beta, Almon, Exponential Almon, Step, and UMIDAS, employing RMSE and the Theil index as evaluation metrics. Furthermore, this study evaluates the influence of unemployment on the validity of Phillips curve relationship and identifying the most robust and accurate model for inflation forecasting in context of developing economies.

This research investigates several key hypotheses drawn from the theoretical framework and existing literature. First, it aims on the superiority of the MIDAS specification, testing the null hypothesis that these models do not improve the forecasting accuracy against the alternative hypothesis that they significantly enhance the forecasting accuracy by incorporating high frequency information. This study also tests the hypothesis regarding the role of asset prices that whether these indicators have significantly predictive power due to their forward-looking nature. It also investigates if the macroeconomic indicators significantly impact inflation dynamics through demand and supply channels. Furthermore, this study examines and analyzes the MIDAS specification by testing if Beta MIDAS shows better performance due to its flexible lag structure. Finally, the study explores the necessity of including multiple indicators and tests if multi-indicator approach provides improved results and has a better forecasting power than a limited set of variables.

2. Literature Review

Literature has evolved over the years from theoretical structures to extraordinarily complex forms of empirical models that include large sets of information and sophisticated econometric modelling since they have direct implications on economic stability, monetary policy, and welfare. The analysis and prediction of inflation have traditionally held a central place in macroeconomic research. In this section, a systematic literature review is given which follows the development of inflation modeling, starting with the traditional Phillips curve to contemporary data-intensive models. The importance of asset prices and mixed-frequency models (MIDAS) is highlighted.

2.1 The Phillips Curve and its Evolution

The Phillips curve is still the theoretical basis of the dynamics of the inflation process. The Phillips curve was initially presented as an empirical relation between the inflation of wages and unemployment, which implied that there was a trade-off between inflation and unemployment slackness. Its empirical validity was, however, questioned by later events, especially in the stagflation era of the 1970s, where there were high inflation and high unemployment. To overcome these limitations, the expectations-augmented Phillips curve was developed, with inflation expectations and an understanding that the trade-off does not hold in the long run (Friedman, 1968; Phelps, 1967). This relationship was later augmented by the New Keynesian Phillips Curve (NKPC), which was more focused on future expectations and nominal rigidities (Clarida, Galí & Gertler 1999; Woodford, 2003). However, these are theoretical extensions, empirical studies imply that the Phillips curve has become weaker with time, specifically in the case of emerging and developing economies. Researchers like Blanchard (2016) and Mishkin (2007) view globalization and structural labor market shifts and the increase in credibility of monetary policy as motives behind inflation being less sensitive to unemployment. Subsequently, the use of labor market indicators alone gives a partial picture of the dynamics of inflation.

Recent research developments in mixed data forecasting and inflation forecasting also highlights the growing importance of information-rich forecasting frameworks. Ferrara, Mogliani and Sahuc (2022) highlighted the role of high frequency variables in improving the inflation forecasts while Babii, Ghysels and Striaukas (2022) incorporated machine learning technique with mixed frequency regressions. Similarly, Coulombe, Gobel and Klieber (2025) determined the usefulness of modern forecasting framework for macroeconomic indicators forecasting under structural uncertainty.

2.2 The Indicator Approach and Information-Rich Models

To overcome the weakness of single-equation models, scholars have progressively applied an information-based approach to the future of inflation. Undoubtedly, a pivotal contribution in this field is made by Stock and Watson (2002, 2003), who indicate that the inclusion of numerous macroeconomic variables is highly effective in enhancing forecasting results. Their contribution points out that inflation is determined by a wide range of economic factors, such as real activity, financial factors, and external shocks. These findings have been supported by later research. Indicatively, the authors state that factor-augmented models are important in explaining the informational content of massive data (Bernanke and Boivin, 2003). Likewise, Giannone, Reichlin and Small (2008) demonstrate that real-time information and big data sets of information positively influence macroeconomic forecasting.

The significance of a framework that is rich in information is even a more critical issue in the development of economies where structural heterogeneity and external vulnerabilities are more pronounced. Other variables like exchange rates, commodity prices, and monetary aggregates tend to be particularly important in determining the dynamics of inflation (Kose and Prasad, 2010; IMF, 2013). This has given rise to an increasing agreement that inflation models should not only use the traditional variables but also should use various indicators.

2.3 Role of Asset Prices in Inflation Forecasting

As a leading indicator of inflation, financial variables and asset prices have increasingly attracted attention. Asset prices such as exchange rates, interest rates, stock prices, and commodity prices are all forward-looking and react quickly to added information. In this respect, they offer valuable information on what the market anticipates in the future with respect to the economic conditions. Some of the early research, like Fama (1981), emphasizes the connection between the financial markets and the macroeconomic variables. Later works focus on the predictability of inflation by asset prices. As an example, Stock and Watson (2003) discovered that asset prices possess information regarding future inflation, especially when the prices are combined with other macroeconomic variables. Empirical research carried out on the use of asset prices to predict inflation gives inconclusive evidence. Kotze (2005) forecasts inflation using daily financial variables and the results of this forecast show a small improvement in predictive ability. Conversely, Monteforte and Moretti (2012) show that high-frequency financial information enhances the forecasts of inflation in the Euro region. On the same note, Salisu and Ogbonna (2017) demonstrate that oil prices boost the prediction of inflation in OECD countries.

Asset prices are of special importance in the case of developing economies because they are sensitive to foreign shocks and capital flows. Pass-through effects are a major cause of inflation due to the exchange rate fluctuations (Calvo and Reinhart, 2002; Gopinath, 2015). Commodity prices are also a particularly key factor, especially in highly imported or export-oriented economies.

2.4 Mixed-Frequency Data and Econometric Challenges

The key issue of empirical macroeconomic analysis is the mixed-frequency nature of the available data. Financial variables are observed at much higher frequencies, and the macroeconomic variables are generally available at lower frequencies (GDP and inflation). Conventional econometric models involve aggregation of high-frequency data, which may cause loss of information and give biased estimates (Sims, 1978; Granger, 1987). In response to this, several methods have been suggested, such as bridge equations (Baffigi, Golinelli, and Parigi, 2004) and mixed-frequency vector autoregression (MF-VAR). Although these methods offer practical solutions, they can be characterized by complicated estimation processes and can be not flexible to work with large datasets.

2.5 MIDAS Regression and Applications

Ghysels, Santa-Clara, and Valkanov (2004, 2007) have introduced a mixed-frequency econometrics development that has made a major leap: Mixed Data Sampling (MIDAS) regression. The MIDAS models enable high-frequency variables to appear in low-frequency regressions in parsimonious distributed lag forms, hence maintaining the informational content of the data without the need to aggregate the data. MIDAS models have become immensely popular in macroeconomic forecasting due to their flexibility and efficiency. Initial applications were in financial markets, but later researchers applied the model to macroeconomic variables, including GDP and inflation (Clements and Galvão, 2008, 2009).

MIDAS models have performed well in the context of inflation forecasting. Modugno (2011) illustrates that the high-frequency oil prices enhance the inflation forecast in the Eurozone. Marsilli (2017) also incorporates MIDAS into an extended Phillips curve model and concludes that financial variables are a strong predictor. Comparative analysis of the MIDAS specification shows that the performance of the model is related to the selection of the lag structure. Indicatively, Foroni, Marcellino, and Schumacher (2015) observe the benefits of parametric weighting schemes, including the Beta polynomial, in the representation of complicated lag dynamics. Similarly, Breitung and Roling (2015) suggest the use of non-parametric MIDAS, which is more efficient than the conventional specifications in some settings.

2.6 Evidence from developing economies

The literature evidence concerning inflation dynamics for developing countries is still weak as compared to developed economies. The existing studies mainly focus on individual countries rather than using comparative approach. Maji & Das (2016) examined inflation dynamics in India using MIDAS regression and showed that MIDAS show better forecasting performance than other conventional models. Although, Libonatti (2018) showed that incase of Argentina, the results are mixed. He argued that the success of technique depends on the selection of indicators. However, Karagoz & Ergun (2020) taking the case of Turkey and Ooft, Bhagoe & Franses (2021) in case of Suriname, emphasized on necessity of including asset prices and macroeconomic indicators in a broader Phillips curve framework. They highlighted the presence of heterogeneity in developing economies inflation dynamics and suggested a more generalized approach for empirical study. Although there are such contributions in literature regarding MIDAS, the gap in the current study is still significant.

2.7 Research Gap and Contribution

The existing literature provides substantial insights into the inflation forecasting and inflation dynamics but still several critical gaps are there. First, most of the existing literature revolves around individual countries and lack comprehensive, cross-country research which employs an integrated empirical framework and comparative study particularly in case of developing economies. Secondly, a unified impact of asset prices, financial indicators and macroeconomic indicators in forecasting inflation has been overlooked in many cases. Lastly, there is clear evidence of lack of comparative research that evaluates the performance of various MIDAS specifications. This research seeks to bridge the gap by:

- Comparatively evaluating the inflation dynamics across a panel of 26 developing economies.
- Synthesizing macroeconomic indicators, financial indicators, asset prices, and labor market indicators into a cohesive unified framework.
- Investigating different MIDAS specifications to determine which gives the most robust results and accurate forecasting.
- Re-evaluating Phillips curve framework within an information rich environment.

The development in inflation forecasting has incurred a significant shift towards more data intensive and complex models over time. The Phillips curve remained a foundation in theoretical concepts but in modern research, its shortcomings have pushed researchers to look for a broad category of indicators. In this regard, asset prices and financial indicators have emerged as dynamic and robust predictors due to their forward-looking nature. Alongside, the progression of model specific models has provided a sophisticated way to manage mixed frequency data, portraying the rich details of high frequency variables without losing information by aggregating the data. However, these developments are yet to be applied to the challenges given in developing countries. Based on these diverse strands of literature, this study demonstrates a more complete picture of inflation dynamics and provides a rigorous and robust empirical model for the forecasting of stability of prices across developing economies.

3. Theoretical Framework

This study is theoretically grounded on an augmented Phillips curve that involves the use of macroeconomic indicators and financial variables. Financial markets and macroeconomic indicators in contemporary economies have a major influence on inflationary pressures. The movements of asset prices, interest rate, credit conditions, and real economic activity indicators are usually a useful source of information on the future trend of inflation. Consequently, modern empirical studies are becoming more information-intensive, one that uses a high number of economic indicators.

In their seminal 2003 article on inflation forecasting, James H. Stock and Mark W. Watson showed that model-based predictions of inflation are significantly better when models are based on a wide range of macroeconomic variables, as opposed to using only the conventional variables, including unemployment. The main conclusion of their study is that inflation represents the aggregate impact of various spheres of the economy. Based on these observations, the current research identifies a theoretical framework on which inflation, unemployment, asset prices, and macroeconomic indicators are connected in one empirical framework. Moreover, the framework uses Mixed Data Sampling (MIDAS) regression to overcome the issues related to the variables that are measured on varying frequencies. The normal expectations-enriched Phillips curve can be written as follows:

$$\pi_t = \pi_t^e - \alpha \left(U_t - U_n \right) + \gamma_{zt} \qquad (1)$$

According to this model, inflation relies on the anticipated inflation, the variation between unemployment and the natural level, and a group of other variables, which capture the supply shocks or other macroeconomic factors. Even though this specification represents important theoretical mechanisms, empirical studies have increasingly revealed that unemployment is not the sole factor that can be used to understand the dynamics of inflation, especially in recent decades, where the Phillips Curve relationship seems to have broken down in most economies. To capture broader inflation dynamics, the model is extended as:

$$\pi_t = \beta_0 + \beta_1 \left(U_t - U_n\right) + \beta_2 X_t + \beta_3 A_t + \mathcal{V}_t \tag{2}$$

Under this formulation, macroeconomic indicators, labor market conditions, and asset prices affect inflation. Macroeconomic indicators are usually offered at varied frequencies. Monthly, inflation, and unemployment are normally reported, and quarterly, the GDP data are normally released. Monetary variables like stock prices or bond yields can be obtained at much greater frequency, e.g., daily. Conventional econometric models usually demand that all the variables are brought to the same frequency. Nevertheless, this aggregation can lead to the loss of useful information that exists in the high-frequency financial data. Recent empirical studies have embraced mixed-frequency econometric methods to deal with this problem.

3.1 MIDAS Regression Framework

Mixed Data Sampling (MIDAS) regression offers a less restrictive approach to the inclusion of high-frequency variables in models involving lower-frequency dependent variables. Instead of combining high-frequency data, MIDAS models enable the latter to be reflected into the regression using weighted lag forms.

$$\pi_{i,t} = \beta_0 + \beta_1 U_{i,t} + \beta_2 X_{i,t} + \sum_{k=0}^{K} \omega_k\left(k;\ \theta i\right) [A_{t--\frac{k}{m}}] + \varepsilon_t \tag{3}$$

π_t: Inflation at the time t

β_0: Constant term

$\beta_1 u_t$: Effect of unemployment

$\beta_2 X_t$: Vector of macroeconomic indicators (e.g., industrial production, CPI components, credit variables)

$A_{t-\frac{k}{m}}$: High-frequency asset price variable (e.g., daily stock prices)

$w_k(\theta)$: MIDAS weighting function (parameterized, often Beta polynomial)

K: Number of high-frequency lags

m: Frequency ratio (e.g., twenty-two trading days per month)

ε_t: Error term

Time t inflation is conditioned by the state of the labor market, macroeconomic indicators, and a weighted aggregate of high-frequency financial variables. The MIDAS element is introduced via a distributed lag model on the high-frequency variable $A_{t-\frac{k}{m}}$.

Unemployment, a group of macroeconomic indicators, and weighted lags of high-frequency asset prices are used to explain inflation in this specification. The weighting function is used to calculate the effect of past observations of the high frequencies on the dependent variable. In this way, the model can ensure that the financial markets have been captured without any form of restrictive aggregation processes.

There are three key channels that affect inflation in the proposed framework. The first channel is the labor market channel, which includes the unemployment and employment indicators. The second channel has macroeconomic factors like industrial production, commodity prices, and credit conditions that represent the forces of demand and supply in the economy. The third channel is a financial market channel that captures the developments in the financial markets, especially the prices of assets, like stock market indices, property prices, and the yield of bonds, which incorporate forecasts regarding future economic conditions.

Mixed Data Sampling (MIDAS) regression is used to integrate information from these various sources in the empirical model. The method enables the inclusion of high-frequency financial variables along with the lower-frequency macroeconomic variables without any significant information being lost within financial market data.

3.2 Implications for Empirical Research

The suggested framework carries several methodological implications:

1) The models of inflation need to incorporate wider macroeconomic information.
2) The financial market indicators include forward-moving signals that are applicable in the dynamics of inflation.
3) Mixed-frequency econometric models enable researchers to use high-frequency financial data without aggregation bias.
4) The combination of labor market, financial and macroeconomic indicators can be enhanced in terms of explanatory and forecast performance.

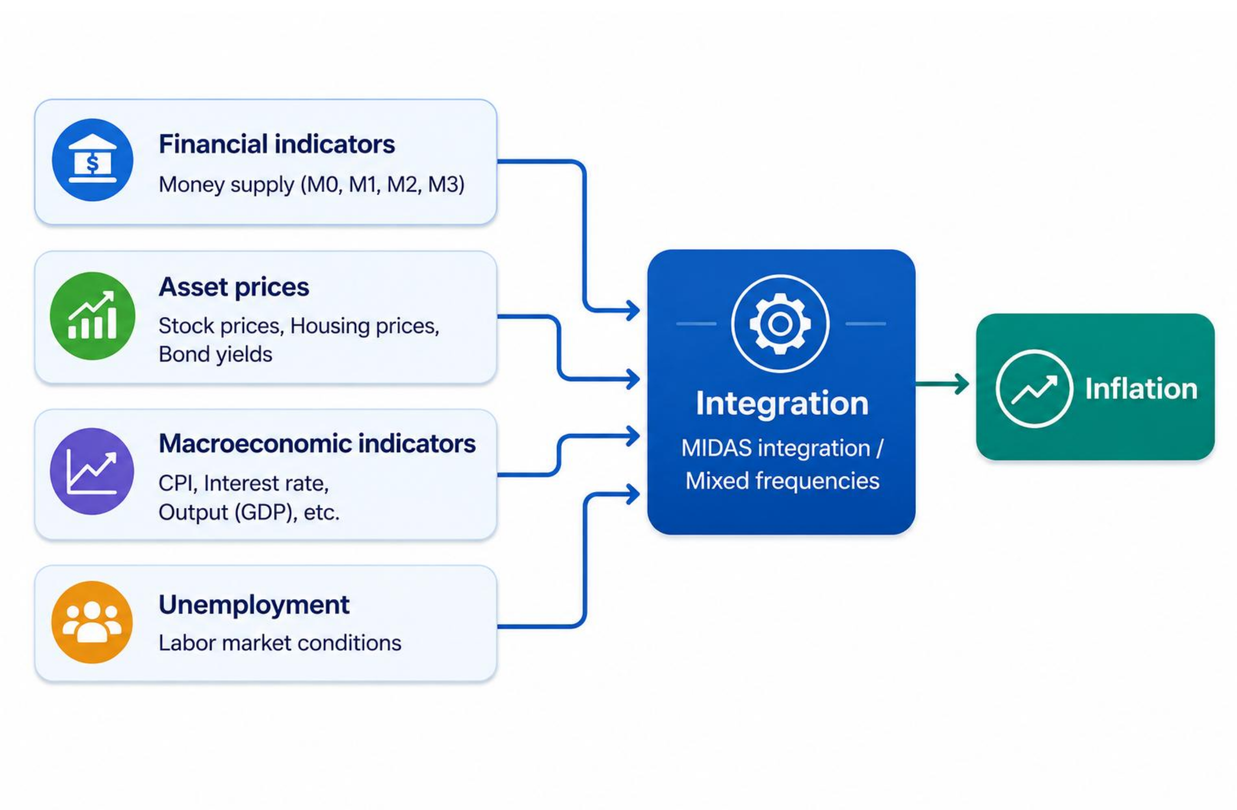

Figure 1: Conceptual Framework Guiding the Empirical Analysis

4. Data and Methodology

The paper employs a mixed-frequency econometric model to predict the inflation rate in developing economies by incorporating labor market factors, macroeconomic and financial variables. The empirical approach is based on an augmented Phillips curve model, which is further developed to include a wider range of data as proposed by the indicator approach developed by Stock and Watson (2003). By so doing, the inflation is not only modeled as a form of labor market slack, but also in the form of real activity, monetary conditions, and forward-looking asset prices.

One of the main difficulties of the implementation of this framework is the heterogeneous frequency of data. Although the frequency of inflation and unemployment is quarterly, a majority of financial and macroeconomic variables are of a higher (monthly) frequency. The conventional time-series methods would involve temporal aggregation that could result in loss of information and aggregation bias. To overcome the limitation, the study uses the Mixed Data Sampling (MIDAS) regression, which enables one to directly incorporate the high-frequency variables into a low-frequency regression without prior aggregation. The analysis incorporates a sample of 26 developing economies during the year 2000-2023. The dependent variable is inflation, and the explanatory variables are unemployment, macroeconomic variables (GDP growth, CPI components, credit variables) and financial variables (interest rates, bond yields, and exchange rates).

4.1 Baseline MIDAS Specification

The empirical model is specified as follows:

$$\pi_{i,\,t} = \beta_0 + \beta_i U_{i,t} + \sum_{k=1}^{K} \gamma_{i,\,k}\; Z_{i,t}^{k} + \sum_{j=0}^{J} \omega_k\left(j;\ \theta i\right) X_{i,t-\frac{j}{m}} + \varepsilon_{i,\,t} \tag{4}$$

Where:

- $\pi_{i,\,t}$: Quarterly inflation rate for country i at time t
- $U_{i,t}$: Unemployment rate (labor market channel)
- $Z_{i,t}^{k}$: Vector of low-frequency macroeconomic indicators (e.g., GDP growth, employment)
- $X_{i,t-\frac{j}{m}}$: High-frequency explanatory variables (monthly asset prices, monetary variables, price indices)
- m: Frequency ratio (e.g., m=3 for monthly to quarterly data)
- $\omega\left(j;\, \theta i\right)$: MIDAS Weighing function.
- θi : Parameters governing the lag distribution.
- J : Maximum number of high-frequency lags
- $\varepsilon_{i,\,t}$: Error term

This specification is a panel MIDAS model whereby the inflation of country i at time t is specified as a form of labor market state, a collection of macroeconomic indicators, and high-frequency financial variables. U(i, t) represents unemployment, which is the Phillips Curve channel, and that Z(i, t) 3 (k) is a macroeconomic and financial variable of monetary aggregates, commodity prices, and interest rates. MIDAS component is represented by the weighted average of the high-frequency variables, X(i, t-j/m), and the weighting factor w(j; 0 i) is used to define the effect of past high-frequency observations on the current inflation. This method enables the model to use information of the variables observed at varying frequencies without summing the data hence retaining the informational content on financial market indicators. The lag length 'J' used in the MIDAS specification is selected using a combination of AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion). Alternative lag structures are estimated for every country and every specification to ensure that the model is parsimonious. The final lag structure for each indicator (and each country) is selected based on its forecasting performance and statistical efficiency.

4.2 MIDAS Weighting Scheme

To ensure parsimony while capturing potentially complex lag structures, the study employs parametric weighting functions. Five MIDAS specifications are estimated:

1) Beta MIDAS
2) Polynomial Distributed Lag (PDL/Almon)
3) Exponential Almon
4) Step MIDAS
5) UMIDAS

4.3 Model Evaluation and Forecasting Strategy

To assess the performance of the forecast, in-sample and out-of-sample metrics are used to guarantee strength and generalization. Two important indicators are used:

1) Root Mean Squared Error (RMSE)
2) Theil Inequality Coefficient (Theil Index)

The average magnitude of forecasting errors is estimated through Root Mean Squared Errors (RMSE) while Theil index is used to calculate the relative forecasting accuracy in terms of the comparison of predicted and actual values. These measures together make certain that scale effects alone do not lead to the performance of all models.

Model performance is evaluated using:

$$RMSE = \sqrt{(1/T\ \Sigma(y_t - \hat{y}_t)^2)} \tag{5}$$

$$Theil\ Index = \frac{RMSE}{(\sqrt{mean(y_t^2)} + \sqrt{mean(\hat{y}_t^2)})} \tag{6}$$

Recursive estimation is used to get both the in-sample and out-of-sample forecasts in which the model is estimated with a primary sample, and the model is applied to make forecasts of the inflation in the next periods. This approach also simulates real-time forecasting situations and can be used to realistically evaluate the performance of the model.

4.4 Data:

This research uses a comprehensive panel dataset encompassing quarterly and monthly observations for developing countries, spanning from January 2000 (Q1/M1) through June 2023 (Q2/M6). The analytical framework consists of 21 distinctive indicators for each country, which are categorized into financial metrics, asset prices, macroeconomic indicators, and labor market indicators. The data is primarily taken from the International Monetary Fund (IFS), World Development Indicators (WDI), and Refinitiv Eikon. The sample was filtered based on the World Bank's 2022 classifications, focusing on the 137 countries identified as developing economies. To capture environments of considerable economic volatility, we further restricted the analysis to countries maintaining a five-year average inflation rate above 5% (2019–2023). The selected economies reflect regional diversity and contrasting macroeconomic structures, therefore providing a suitable framework for comparative evaluation of inflation dynamics.

The analysis was conducted using country specific estimation instead of fully pooled panel estimation. This approach was adopted to cater structural heterogeneity across developing economies, including variations in exchange rate regimes, monetary policy frameworks and institutional structures.

To ensure a robust ground for forecasting, the raw data underwent several systematic treatments. We addressed missing values through linear interpolation or extrapolation, while significant outliers were replaced with the average of the surrounding observations. For variables available only at lower frequencies—such as GDP growth—we employed the Chow-Lin temporal disaggregation method to convert annual or quarterly figures into monthly series. This approach keeps the movement of original low frequency series while incorporating information from associated high frequency indicators and therefore minimize aggregation bias..

Table 1 Data Description

Series label	**Sampling frequency**	**Description**	**Data Source**
Asset Prices			
IR	M	Lending Rate	IFS/ Refinitive Eikon
REER	M	Exchange Rates, Real Effective Exchange Rate Based on Consumer Price Index, Index	IFS/ Refinitive Eikon
ER	M	Exchange Rate	IFS/ Refinitive Eikon
IGP	M	International Gold Prices	IFS/ Refinitive Eikon
TR_B	M	Treasury Bill Rate: Six Months	IFS/ Refinitive Eikon
IRES	M	International Reserves	IFS/ Refinitive Eikon
GOVT_BOND	M	Government Bond Yield	IFS/ Refinitive Eikon
Activity			
EMP	Q/M	Employment level	Refinitive Eikon
UNEMP	Q	Unemployment Level	Refinitive Eikon
IPI	M	Industrial Production Index	Refinitive Eikon
GDP	M	GDP Growth rate (annual data disaggregated into monthly)	IFS/ world bank
Wages, Goods and Commodity Prices			
CPI	Q/M	Prices, Consumer Price Index, All Items, Index	IFS
PP	M	Oil Prices (Petrol Price)	IFS/ Refinitive Eikon
PPI	M	Producer Price Index	Refinitive Eikon
COP	M	Wholesale Prices, All Commodities	Refinitive Eikon
Money			
MON_BASE	M	Monetary Base	Refinitive Eikon
M0	M	M0	Refinitive Eikon
M1	M	M1	Refinitive Eikon
M2	M	M2	Refinitive Eikon
M3	M	M3	Refinitive Eikon
Pol_Rate	M	Policy Rate	Refinitive Eikon
Notes: M indicates that the original data are monthly, Q indicates that they are quarterly. Additional details are given in the appendix. *The above descriptions slightly vary from country to country according to the availability of the data.			

Furthermore, we applied seasonal adjustments based on diagnostic pre-tests to remove periodic noise. To stabilize variance and account for scale disparities, logarithmic transformations were applied to high-magnitude series. Finally, all variables were subjected to unit root testing; non-stationary series were differenced to achieve stationarity, ensuring all inputs were integrated of order zero I(0) for the subsequent empirical analysis. Following table 1 shows the description of the variables which are taken for estimation

5. Results and Discussions

5.1 Introduction

The chapter includes an in-depth discussion of the empirical results of the estimation of the inflation models in 26 developing economies during the period 2000-2023. The model is analyzed in an augmented Phillips curve model based on Mixed Data Sampling (MIDAS) tools. Root Mean Squared Error (RMSE) and Theil index are used to measure forecast performance during in-sample and out-of-sample periods. The discussion incorporates three major dimensions, which are model performance in accordance with the MIDAS specifications, country and region-specific inflation, and the comparative significance of the macroeconomic, financial, and external variables to explain inflation. Such a combined method can be used to understand the behavior of inflation in structurally heterogeneous developing economies more deeply.

5.2 Forecast Performance across Countries

The main aim of this research was to determine whether there is an improvement in the forecasting of inflation with the help of mixed-frequency models. The findings give substantial and coherent reasons that support the belief that MIDAS-based models are more effective than more constrained specifications in most countries. Findings indicated that Beta MIDAS prevails i.e., 80-85 percent with exceptions of Uzbekistan (UMIDAS) and Sierra Leone (Exp Almon). RMSE and Theil rankings are fully consistent, which proves strength of the forecast.

The Beta MIDAS specification becomes the notable model, with the smallest values of RMSE and Theil index in in-sample and out-of-sample forecasts. This is because of its superiority in capturing smooth, flexible, and non-linear lag structures, which are critical in the modelling of inflation dynamics, which have delayed transmission mechanisms. In developing economies, the inflation transmission mechanism appears through exchange rate pass-through effects, monetary policy channels, expectation formation, and delayed responses to external shocks. The Beta MIDAS specification effectively captures these non-linear and persistent adjustment processes while avoiding abrupt lag truncation and excessive parameterization.

On the other hand, the Step MIDAS model is not highly effective, as it has a strict lag structure, which cannot reflect progressive changes. Likewise, UMIDAS, being flexible, tends to be over-parameterized, which results in a decrease in efficiency, especially with small samples. Nonetheless, there are some exceptions in some economies (e.g., Uzbekistan and Suriname) where less restrictive models are also competitive, which suggests structural variance in lag dynamics. In general, the results indicate that parametric lag structures with flexible parameters are essential in modeling inflation in developing economies correctly, which justifies the methodological soundness of the use of MIDAS-based techniques.

Table 2: In-Sample vs. Out-of-Sample Performance

Region	Country	Best Model (In)	Best Model (Out)	RMSE Range	Theil Range	Rank
South Asia	Bangladesh	Beta	Beta	3.5–6	0.9–1.4	High
South Asia	India	Beta	Beta	3.5–6	0.9–1.4	High
South Asia	Pakistan	Beta	Beta	3.5–6	0.9–1.4	High
Africa	Kenya	Beta	Beta	8–13	1.8–2.7	Low
Africa	Zambia	Beta	Beta	8–13	1.8–2.7	Low
Africa	Nigeria	Beta	Beta	8–13	1.8–2.7	Low
Africa	Ghana	Beta	Beta	8–13	1.8–2.7	Low
Africa	Sierra Leone	Exp Almon	Exp Almon	8–13	1.8–2.7	Low
Central Asia	Uzbekistan	UMIDAS	UMIDAS	1–8	0.7–1.8	Medium
Central Asia	Kyrgyzstan	Beta	Beta	1–8	0.7–1.8	Medium
Central Asia	Tajikistan	Beta	Beta	1–8	0.7–1.8	Medium
Central Asia	Kazakhstan	Beta	Beta	1–8	0.7–1.8	Medium
Caribbean	Jamaica	Beta	Beta	4–7	1.0–1.5	Medium
Caribbean	Venezuela	Beta	Beta	4–7	1.0–1.5	Medium
Latin America	Uruguay	Beta	Beta	4–7	1.0–1.5	Medium
Middle East and North Africa	Iran	Beta	Beta	4–7	1.0–1.5	Medium
Southern Africa	Zimbabwe	Beta	Beta	4–7	1.0–1.5	Medium
North America	Haiti	Beta	Beta	4–7	1.0–1.5	Medium
North Africa	Tunisia	Beta	Beta	4–7	1.0–1.5	Medium
North Africa	Egypt	Beta	Beta	4–7	1.0–1.5	Medium
Southern Africa	Angola	Beta	Beta	4–7	1.0–1.5	Medium
Transition	Ukraine	Beta	Beta	4–7	1.0–1.5	Medium
Transition	Suriname	Beta	Beta	4–7	1.0–1.5	Medium
Asia	Myanmar	Beta	Beta	4–7	1.0–1.5	Medium
South Asia	Sri Lanka	Beta	Beta	4–7	1.0–1.5	Medium
Europe & Central Asia	Kyrgyz Republic	Beta	Beta	4–7	1.0–1.5	Medium

5.3 Regional Discussion of Results

The empirical results indicate that there are evident regional trends of inflation dynamics. The South Asian countries such as India, Bangladesh, and Pakistan have relatively low values of RMSE and consistent forecasting capability in in-sample and out-of-sample estimates. This implies that inflation in such economies is predictable and highly influenced by the macroeconomic conditions of the nation. The prevalence of the Beta MIDAS specification in this part of the world is indicative of the relevance of smooth lag forms in reflecting gradual transmission of policies and demand side effects.

However, it is observed that African economies, like Zambia, Nigeria, and Ghana, have much higher RMSE and Theil index values, which is more volatility and poor predictability of inflation. These findings are in line with the structural weakness and openness to the external world that these economies have. Sierra Leone is an exception with the Exponential Almon specification doing better than the rest of the models indicating that the dynamics of inflation are more responsive to the swiftly decaying lagging structures perhaps because of the volatile monetary conditions. The economies in Central Asia are mixed. Uzbekistan is one of the few examples when UMIDAS is better than Beta MIDAS, which means that inflation can be explained by smooth lag effects that occur in the short run. However, Kyrgyzstan and

Tajikistan trend towards the general pattern, where Beta MIDAS is doing best, albeit with greater forecast errors than more stable economies. These results indicate that structural rigidities and external shocks affect inflation in this region.

The economies of Latin America, especially Uruguay and Haiti, exhibit stable inflation dynamics, low forecast errors, and high model consistency. However, Zimbabwe displays more RMSE values indicating continuous inflationary pressures and macroeconomics instabilities. Tunisia and Egypt in North Africa follow the same pattern, being stable as South Asia, and moderately more volatile in Egypt. Stable inflation patterns and superior performance of the Beta MIDAS model are also exhibited in transition economies like Ukraine and Suriname. Myanmar, on the contrary, is a high volatility example with the largest RMSE values in the sample, indicating extreme macroeconomic instability.

Table 3 Regional Forecast Performance Comparison

Region	Avg RMSE (In)	Avg RMSE (Out)	Avg Theil (In)	Avg Theil (Out)	Stability
South Asia	4.2	5.3	0.95	1.25	High
Africa	8.5	11.2	1.8	2.4	Low
Central Asia	5.8	7.5	1.3	1.8	Medium
Latin America	4.0	5.2	1.0	1.3	High
Caribbean	5.5	7.2	1.2	1.6	Medium
North Africa	4.5	5.8	1.1	1.4	High

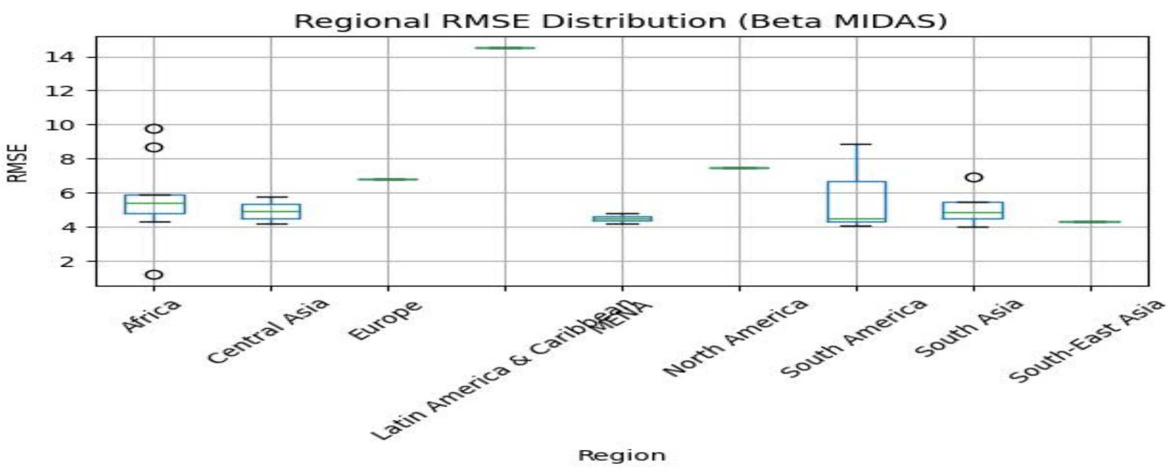

Figure 2: Regional RMSE Distribution

The existence of significant heterogeneity in dynamics of inflation is further evidenced by a comparison of results, which is presented in Table 3 of the results of the region. The South Asian and Latin American economies have lower values of RMSE and Theil, and it means that the inflation process is more stable and predictable. Conversely, the African economies have greater forecast errors, which are indicators of structural weaknesses and susceptibility to external shocks. Central Asian economies are in the middle ground with moderate levels of stability though with some recurrent external factors.

The heterogeneity in inflation dynamics is drawn by the regional distribution of RMSE. Economies in Africa and Latin America have a greater dispersion and greater median errors indicating structural instability and external vulnerability. On the other hand, the South Asian economies show lower and more concentrated values of RMSE, which means that the inflation processes are stable and predictable.

5.4 Model Performance Discussion

Across all countries, a clear hierarchy of MIDAS models emerges:

Beta MIDAS > PDL/Almon > Exponential Almon > Step / UMIDAS

This trend is also observed in in-sample and out-of-sample predictions, and it is Importance of smooth lag structures, Ability to capture gradual inflation transmission, Avoidance of overfitting. An exception is that UMIDAS is more effective in capturing adaptive inflation dynamics in Uzbekistan, and that exponential Almon is more effective in Sierra Leone because of its volatile monetary dynamics.

5.5 Cross-Country Heterogeneity

Three distinct inflation regimes emerge:

1) **High-Volatility Economies (Zimbabwe, Venezuela, Suriname, Angola**)
   - Extremely high RMSE and Theil index values
   - Inflation driven by monetary instability and exchange rate shocks.
2) **Moderate-Stability Economies (Pakistan, Nigeria, Kenya, Egypt, Ghana**)
   - Mixed drivers: policy + external + structural factors
3) **Stable Economies (India, Bangladesh, Sri Lanka, Uruguay**)
   - Inflation primarily demand-driven
   - Strong Phillips Curve relationship
4) **Externally Driven Economies (Zambia, Tajikistan, Kyrgyz Republic, Ukraine**)
   - Dominance of exchange rate and external shocks

5.6 Variable-Level Discussion of Inflation Determinants

The analysis of key determinants conducted in Table 5 shows that the monetary policy variables, especially the policy interest rates, always have the best predictive power in all countries. This observation justifies the need to pay attention to expectations and policy credibility in the dynamics of inflation. Variables of real economic activity, including the GDP growth, are also noteworthy especially in comparatively stable economies where the demand-side strains are more intense. Open economies are particularly sensitive to exchange rates and prices of commodities, with foreign shocks and external prices of imports having a direct effect on local inflation.

Table 4: Summary of Key Determinants of Inflation

Variable Group	**Predictive Strength**	**Representative Countries**
Policy Rate	Very High	All countries
GDP Growth	High	India, Bangladesh, Uruguay
Exchange Rate	High	Zambia, Jamaica, Tajikistan
Commodity Prices	Moderate	Zambia, Kyrgyzstan
Wages	Moderate-Low	Most countries
Monetary Aggregates	Weak	Most countries

The Phillips curve relationship remains applicable, but it seems to have transformed into a hybrid and context-specific relationship. Inflation is mostly related to domestic demand conditions in some economies and mostly external factors and monetary policy in others. In general, findings indicate that inflation in the developing economies can be most appropriately described as a multi-dimensional process that needs a modeling approach that incorporates information.

5.7 Monetary Policy Variables

The performance of various countries in terms of variables indicates that the monetary policy variables, real economic activity, and external sector indicators are the major drivers of inflation. The policy interest rates are the most predictable and influential factors of inflation. In all countries, the model with policy rates provides the minimal value of the RMSE and Theil index, which points to the pivotal role of monetary policy in developing inflation expectations and outcomes. Policy rates in Iran, Pakistan, Tunisia, and Egypt substantially decrease the forecast errors. The significance of central bank credibility and expectations management is manifested in them. Nonetheless, in very volatile economies like Zimbabwe and Venezuela, Policy rates are not highly effective because of Institutional fragility, Dollarization and Policy transmission breakdown.

5.8 Real Economic Activity

The real economic activity variables, especially the growth of the GDP, are also observed to have a high explanatory power especially in stable economies like India, Bangladesh, and Uruguay. The inflation in these nations seems to be strongly correlated with demand-side forces, which prove the classical concept of output-based inflation. Nevertheless, in more volatile economies, the role of real variables is less, which suggests that the role of structural and external factors is more significant. In Pakistan, there are mixed evidence because of the structural rigidities in economies like Zambia, Nigeria and Sudan, the real activity variables are not particularly important meaning that inflation is not a demand-driven process.

5.9 Exchange Rate Variables

The variables of the exchange rate come out as imperative determinants in open and externally vulnerable economies. Exchange rates are highly effective predictors of country performance in countries like Zambia, Jamaica, and Tajikistan, indicating a prominent level of exchange rate pass-through effects. This means that imported inflation and inflation through changes in the currency are significant factors in causing inflation in these economies. These findings substantiate the existence of an exchange rate pass-through in which the depreciation of the currency is a direct cause of inflation as determined by Calvo and Reinhart (2002). Conversely, the exchange rate effects are less effective in India and Bangladesh, owing to the comparatively controlled exchange rate regimes.

5.10 Factors of Commodity Prices and Cost-Push.

The secondary, not the least important, is attributed to commodity prices and cost-push factors especially in resource-dependent economies. Nevertheless, they are not as consistent in their predictive power across countries, meaning that they have a contingent effect on the macroeconomic setting. In the commodity-dependent economies, there is Strong influence e.g., Angola, Nigeria, and Zambia. Whereas moderate in diversified economies e.g., India and Tunisia.

5.11 Monetary Aggregates

On the contrary, monetary aggregates are always weak in all countries, and the values of RMSE and Theil index are high. This result implies that there is a weak and unstable correlation between money supply and inflation, and this indicates the fading applicability of monetarist models in contemporary developing economies. This is contrary to popular monetarists' thinking and upholds new perspectives on interest rate mediums rather than money supply.

5.12 Reassessing the Phillips Curve

With the addition of unemployment, one can test the relation of the Phillips curve on an international level. The findings show that although the Phillips curve is still applicable, it has developed into a hybrid and context-specific model. Three regimes emerge:

1) Conventional Demand-based Phillips curve e.g., Bangladesh, India, Uruguay.
2) Hybrid Phillips curve that is influenced by policy e.g., Pakistan, Kenya, Tunisia.
3) Weak or externalized Phillips curve e.g., Zambia, Kyrgyzstan, Tajikistan, Zimbabwe

The Phillips curve, in most instances, has been observed to be flattened implying that the slack in the labor market alone cannot be used to explain the dynamics of inflation. In comparatively stable economies like India, Bangladesh and Uruguay, the inflation is responsive to the demand-side conditions which implies that the Phillips curve relationship is operating. When this occurs, increased output and reduced unemployment are accompanied by increased inflation which is in line with the conventional theory.

The Phillips curve however, in most developing economies, is said to be weakened or flattened. Inflation in other countries like Zambia and Tajikistan is caused by external shocks and monetary conditions as opposed to labor market slack. This implies that the historical trade-off between unemployment and inflation is not as strong. In Kenya and Tunisia, where the economy is hybrid, inflation is affected by a joint combination of demand conditions, monetary policy, and external factors, meaning augmented Phillip's curve framework.

5.13 Inflation as an Information-Rich Process

The empirical findings clearly suggest that the process of inflation in developing economies is an informational and multi-dimensional process. These findings are consistent with Stock & Watson (2003) who determined that inflation is an information rich process and is influenced by multiple financial and macroeconomic indicators. Predictability is also greatly enhanced by the fact that a wide range of macroeconomic and financial variables is used to predict the future, as indicated by the low values of RMSE and Theil indexes in different models. These results contradict the classical single-variable or small-framework models and suggest the implementation of indicator-based models, in which inflation displays the interplay of:

- Aggregate demand conditions
- Monetary policy stance
- Financial market developments
- External and cost-push factors.

These findings therefore confirm the central hypothesis that inflation cannot be explained by a small number of variables but rather a comprehensive modeling framework is needed to explain it.

5.14 The Role of Monetary Aggregates

In most of the nations, monetary aggregates have poor and unstable associations with inflation. Even when using flexible MIDAS specifications, high RMSE and Theil index values are observed. In rare instances (such as Suriname), monetary aggregates still have a predictive value. This observation indicates structural modifications in monetary systems such as:

- Greater dependence on interest rate-based policy frameworks.
- Financial deepening and innovation.

- Unsteadiness in money velocity.

5.15 Concluding Remarks

Overall, the findings show that inflation in the developing economies is a multi-dimensional process that is caused by the interaction of monetary policy, the demand conditions, and the external factors. The whole dominance of the Beta MIDAS model indicates the value of flexibility in the lag structure, and the analysis on the variable level reveals the primary role of the policy rates and exchange rates in the determination of the inflation dynamics. The Phillips curve is still applicable, but it needs to be viewed in the context of a much more persistent and hybrid model that considers structural and external effects.

6 Conclusion & Policy implications

6.1 Conclusion

This paper aimed to examine the determinants and prediction performance of inflation in a panel of developing economies between 2000 and 2023 using an augmented Phillips curve model in a mixed-frequency MIDAS model. The analysis provides a well sounded and empirically sound evaluation of the dynamics of inflation in several structural conditions by incorporating macroeconomic indicators, asset prices, and monetary variables. The conclusions indicate that flexible and more informative models require a better forecast for inflation. Beta specification proved as the most stable and reliable model specification among developing nations.

Cross-country heterogeneity is prominent with inflation dynamics in almost all countries. Phillip's curve is still valid but looks more like a conditional and complex relationship. The value of using large datasets, extensive econometric techniques and useful information in modelling inflation is also brought out especially in externally exposed and structurally diverse economies in developing economies.

This study is also eminent to literature because it extends to a single empirical model that can connect classical Phillip's curve and contemporary mixed frequency models. It contributes to the literature by providing one the few broad cross-country evaluations of inflation forecasting using mixed frequencies models in developing economies. Contrasting to previous single country analysis shown in literature, this study integrates macroeconomic indicators, labor market indicators and financial variables within a unified mixed frequency framework.

Lastly, the findings of this study highlight the fact that information rich inflation modelling for developing economies needs to be mindful of structural diversity, information intensive and be more flexible. Policy wise, the results showed that it is important to track broad set of indicators which enhance the credibility of the monetary policy and consider external exposures and vulnerabilities while developing inflation management policies. Finally, the study provides practical and methodological outcomes which contribute to the knowledge of the inflation dynamics and inflation forecasting.

6.2 Policy implications

This study has eminent implications for monetary policy in developing economies. The higher predictive ability of interest rate implies that central banks must emphasize interest based framework and must accentuate on the credibility to fix inflation expectations. The stability of exchange rates is also essential particularly in economies that are externally vulnerable, however, the exchange rate can certainly turn into inflationary pressures. The weak performance of monetary aggregates indicates that they are not reliable indicators to be used as major policy tools (especially in the case of developing countries). Despite, policy makers ought to integrate data intensive methods that incorporate financial metrics and high frequency data.

It also has implications for inflation management in developing economies. The satisfactory performance of policy interest rates explains that the central banks must prioritize interest rate-based frameworks and emphasize the maintenance of credibility in anchoring inflation expectations. Stability of the exchange rate is also paramount, especially in open economies, where currency depreciation can easily be converted to increased inflation. The actual economic activity must be closely monitored so that it does not overheat in stable economies, and more attention should be given to controlling external weaknesses in volatile economies.

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