An econometric framework to nowcast low-frequency data*

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Abstract

Standard nowcasting frameworks commonly use weekly or monthly variables to monitor quarterly gross domestic product (GDP). However, this method is not suitable for economies that track GDP annually. We modify the state-space representation of an otherwise standard dynamic factor model to represent annual variables as a linear combination of latent monthly indicators for more frequently released variables. Using data from a lower middle-income country, we derive a monthly activity measure that effectively tracks annual GDP growth. These estimates outperform institutional forecasts and competing approaches to estimate low-frequency data. The model offers broader applications to countries facing data limitations, especially lower-income countries.

Keywords: monitoring real activity; Kalman filter; dynamic factor model; annual nowcasting
JEL classification: C38, C53, E37, O11, O47

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1 Introduction

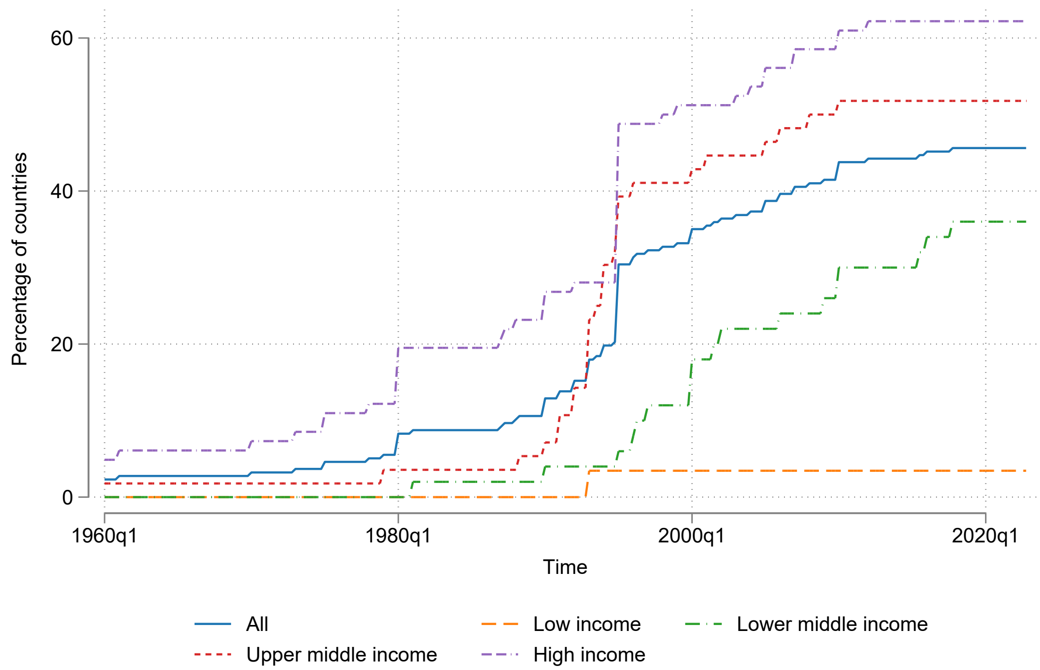
Standard nowcasting frameworks typically utilize high-frequency variables to monitor lower-frequency variables, e.g., weekly or monthly variables to track quarterly indicators. One limitation of the standard frameworks is that these cannot be used directly for monitoring lower-frequency variables, such as semiannual or annual indicators. This is of particular concern in many developing and emerging market economies, where numerous shortcomings often plague gross domestic product (GDP) data, which are typically tracked annually. As Figure 1 illustrates, the measurement of quarterly GDP has received relatively wider attention (around 45% of countries) only in the past decade. While the majority of high-income and upper middle-income countries have been measuring quarterly GDP since around 1999 and 2010, respectively, a significant number still do not track it. Most lower middle-income countries also lack quarterly GDP data, and among low-income countries, only Tajikistan currently publishes such statistics.[1] The low-frequency measurement of GDP makes it challenging to accurately assess the state of the economy in real-time, especially during the periods between official data releases. Consequently, there may be substantial delays in implementing appropriate policies owing to lack of a clear understanding of current economic conditions or trends of the recent past.

The main theoretical purpose of this paper is to develop an econometric framework for predicting and nowcasting low-frequency variables using readily available high-frequency variables. The empirical goal is to apply this econometric framework to track a specific low-frequency variable (annual GDP growth) to highlight its relevance and value addition. We apply the empirical framework to nowcast annual GDP growth in Pakistan, a lower middle-income country, using various indicators to generate a monthly measure of economic activity. Considering that high-frequency measures of economic activity are unavailable for a majority of countries, the proposed econometric framework has broader applications and interests a wider audience.

Nowcasting an emerging market like Pakistan poses two key constraints that many other countries face. The first challenge we face is methodological. The existing nowcasting framework by Giannone et al. (2008) focuses primarily on matching quarterly variables with monthly indicators, creating a quarterly-monthly data linkage. Aruoba et al. (2009)

[1] As of November 2025, illustrative examples of unavailability of quarterly GDP data from CEIC, by income level, include: (i) High income: Andorra, Barbados, Greenland, and Liechtenstein, (ii) Upper middle income: Costa Rica, Fiji, Maldives, and Turkmenistan, (iii) Lower middle income: Algeria, Cambodia, Laos, and Papua New Guinea, and (iv) Low income: Afghanistan, Chad, Malawi, and Uganda.

Figure 1: Availability of quarterly GDP: across economies and over time



Note: The figure plots the percentage of countries for which quarterly GDP is available at CEIC from 1960q1 to 2024q4. The countries are also categorized based on their 2022 income classification by the World Bank.

focuses on the same question but at an even higher frequency. This essentially implies that the state-space framework used in typical nowcasting models needs to be modified to track annual GDP growth rates using mixed frequency variables. Overcoming this challenge is a key contribution of our paper, which is pertinent for most countries, as shown in Figure 1. The second challenge pertains to the quality of data, which contains several missing observations and ragged-ends. We are also constrained by the public unavailability of a broad dataset significantly correlated with GDP growth, but this represents a practical data challenge rather than a methodological one.

To deal with these issues, we use the dynamic factor model (DFM) approach of Giannone et al. (2008) and Banbura et al. (2013). Giannone et al. (2008) highlighted that these models are well-suited for nowcasting and real-time monitoring of macroeconomic conditions. To address the unique challenges faced as a result of the annual frequency of the data, we modify the state-space representation of DFM used in the New York Fed Staff Nowcast, which is presented in Bok et al. (2018) and builds on Giannone et al. (2008).

Modifying the state-space representation enables us to match the targeted annual variable as a linear combination of the latent monthly series for the observed data on monthly, quarterly, semiannual, and annual variables. The estimates are computed iteratively using the Kalman smoother and the expectations-maximization (EM) algorithm until convergence is achieved (Bok et al., 2018). The DFM parsimoniously combines the features and patterns in macroeconomic data to provide a monthly index that tracks annual GDP growth. This approach combines the real-time flow of information, allowing us to assess its impact on current economic conditions as soon as the underlying data are released. Overall, our approach provides a new perspective on applying an existing econometric framework to address the high-frequency data and monitoring constraints encountered by many, if not most, developing and emerging markets.

Our model is estimated using data from January 2000 until June 2023, covering a reasonably long period (Koop et al., 2020). We conduct the evaluation exercise, to ascertain the predictive accuracy of the nowcasts, through a monthly pseudo-real-time forecasting exercise, beginning from the fiscal year 2005-06 and continuing until the end of the fiscal year 2022-23. This is because Pakistan's GDP is assessed over a fiscal year that starts in July and ends in June of the following year. As such, the estimation for the evaluation period's first month utilizes a little over 60 observations. We can increase the observations by starting the evaluation period later, but this would reduce the evaluation period, making it harder to make valid comparisons of predictive accuracy. The pseudo-real-time forecasting exercise entails replicating the data structure that was available for any given month to the econometrician and comparing it with the estimates provided in the macroeconomic monitoring reports by key forecasting agencies, including the Asian Development Bank (ADB) and the International Monetary Fund (IMF), and with the provisional estimate of GDP growth rate released by official authorities in Pakistan. Compared with these benchmarks, our estimates exhibit better predictive accuracy as determined by the Diebold-Mariano test (Diebold and Mariano, 2002).

We also compare our estimates with those generated using a simplified approach to demonstrate the added value of the updated state-space representation for policymakers and practitioners. Similar to the framework in Heng et al. (2024), which is applied to nowcast GDP growth in Cambodia, the simpler approach replaces annual variables with their quarterly interpolations. Then, it applies the standard quarterly-monthly nowcasting framework of Giannone et al. (2008), which may be prone to inaccuracies due to the underlying quarterly interpolates. While convenient, the simpler approach is statistically inferior as it significantly underperforms compared with the nowcasts generated using the updated annual-monthly state-space representation.

This paper is closely related to the seminal work of Stock and Watson (1989), Mariano and Murasawa (2003), Giannone et al. (2008), Camacho and Perez-Quiros (2010), Banbura et al. (2013) and Bańbura and Modugno (2014), who built the first formal and internally consistent statistical framework of this kind by integrating big data models with filtering techniques. It is worth emphasizing that despite this model's simplicity, it has been successfully applied to nowcasting economic activity across a wide range of economies with markedly different characteristics. These include various large, developed, developing, and small open economies: China (PRC) (Giannone et al., 2013),[2] the euro area (Cascaldi-Garcia et al., 2024), India (Bragoli and Fosten, 2018), Indonesia (Luciani et al., 2018), Mexico (Caruso, 2018), and the United Kingdom (UK) (Anesti et al., 2022) to name a few.[3] The key modeling innovation allows us to generalize this approach to nowcast low-frequency variables. Another contribution of this work is the generation of monthly indicators for economic activity. It is flexible enough to be applied to other countries that face data constraints like Pakistan. Furthermore, the applications of this big data framework are not only limited to extracting GDP growth, but could also be used to track other pertinent indicators, e.g., employment and inflation (Ha et al., 2023). A key contribution of our framework is that the state-space representation can generate historical higher-frequency data for countries that measure GDP annually. The new monthly or quarterly data can contribute to a better historical understanding of business cycle dynamics and other important issues.

Our paper is also related to Koop et al. (2020) and Chernis et al. (2020). The former estimates quarterly output growth for regions of the UK that publish economic activity measures annually, and the latter nowcasts annual provincial GDP growth for Canada. However, there are some important differences. First, Koop et al. (2020) develops mixed-frequency vector autoregression (MF-VAR) for the estimations. In contrast, we update the state-space representation of DFM to match the annual variable of interest with a linear combination of latent monthly variables. While Chernis et al. (2020) updates the DFM framework to track the annual target variable using monthly and quarterly indicators, our

[2] Zhang et al. (2023) find that some machine learning (ML) algorithms outperform the benchmark DFM in nowcasting Chinese GDP. However, ML forecasts typically have better predictive accuracy when the frequency of target and predictor variables is aligned.

[3] For an extensive list of economies where the nowcasting framework has been applied, the reader is referred to Cascaldi-Garcia et al. (2023).

framework additionally allows using semiannual and annual variables. Second, Koop et al. (2020) uses quarterly and annual variables, and Chernis et al. (2020) uses monthly and quarterly variables. We, on the other hand, use monthly, quarterly, and annual variables to generate output growth nowcasts at the monthly level. In addition, our framework allows the inclusion of semiannual variables, which may be pertinent for countries with data limitations. Finally, both estimate the regional output growth of countries for which timely national economic activity measures are available at a high frequency (monthly and quarterly).[4] Meanwhile, we use our econometric framework to nowcast the output growth of a lower middle-income country for which economic activity is available at an annual frequency and is subject to significant delays in release.

The next section, Section 2, describes the construction of the instrument and presents the methodology underlying our estimation. Section 3 discusses the underlying data, the transformation of variables, and the baseline results. Section 4 compares our estimates with competing measures and provides some extensions to the baseline results. Section 5 concludes the paper.

2 Low Frequency Nowcasting Framework

This section details the changes we make to the state-space representation of the DFM methodology in Bok et al. (2018) to accommodate the nowcasting of lower-frequency data.

2.1 The Framework

The DFM methodology is based on the work of Giannone et al. (2008) and Banbura et al. (2013), with the former pointing out that these models are well-suited for nowcasting and monitoring macroeconomic conditions in real-time. Their approach is based on the seminal work of Stock and Watson (1989), which applies the Kalman filter to extract a common component from key macroeconomic indicators. The model is dynamic since the common component depends on its lagged values through the transition equation of the Kalman filter. The main drawback of their approach is that it cannot deal with mixed frequencies. This limitation is extended in Mariano and Murasawa (2003) to incorporate monthly and quarterly frequency data. Meanwhile, Camacho and Perez-Quiros (2010)

[4] For Canada, unofficial provincial GDP measures are also available at a monthly and quarterly frequency (Chernis et al., 2020).

resolves both mixed-frequency and ragged-end problems. Kalman filtering techniques provide a convenient and natural framework for handling data irregularities, such as mixed frequencies and asynchronous data releases, and updating the predictions in real time. As Aruoba et al. (2009) demonstrates, the filter is well equipped to deal with missing observations in the data. These features make it desirable to use this framework to nowcast macroeconomic indicators such as real GDP growth.[5]

Section 2.2 shows the treatment of quarterly, semiannual, and annual variables, Section 2.3 provides the state-space representation for the monthly factor model, and Section 2.4 outlines the numerical maximization algorithm to estimate the state-space model.

2.2 Modeling mixed frequencies

Let $Y_{m,t}$, $Y_{q,t}$, $Y_{sa,t}$, and $Y_{a,t}$ be n_m, n_q, n_{sa}, and n_a variate observed monthly, quarterly, semiannual, and annual variables. Define $n = n_m + n_q + n_{sa} + n_a$ as the total number of observed variables with different frequencies. Assume that the variables in $Y_{q,t}$, $Y_{sa,t}$, and $Y_{a,t}$ are observable every 3rd, 6th, and 12th month of the year, respectively, and let $Y^*_{q,t}$, $Y^*_{sa,t}$, and $Y^*_{a,t}$ be the corresponding n_q, n_{sa}, and n_a variate unobserved monthly contributions so that we have the following:

$$
\begin{aligned}
Y_{q,t} &= \sum_{l=0}^{2} Y^*_{q,t-l} \\
Y_{sa,t} &= \sum_{l=0}^{5} Y^*_{sa,t-l} \\
Y_{a,t} &= \sum_{l=0}^{11} Y^*_{a,t-l}
\end{aligned} \tag{1}
$$

Equation (1) shows that the observed quarterly, semiannual, and annual variables can be represented as a sum of their respective unobserved monthly contributions as in Banbura et al. (2010). We define log differences of the observed variables as $y_{q,t} = \ln(\frac{Y_{q,t}}{Y_{q,t-3}})$, $y_{sa,t} = \ln(\frac{Y_{sa,t}}{Y_{sa,t-6}})$, and $y_{a,t} = \ln(\frac{Y_{a,t}}{Y_{a,t-12}})$, and unobserved monthly variables as $y^*_{q,t} = \ln(\frac{Y^*_{q,t}}{Y^*_{q,t-1}})$, $y^*_{sa,t} = \ln(\frac{Y^*_{sa,t}}{Y^*_{sa,t-1}})$, and $y^*_{a,t} = \ln(\frac{Y^*_{a,t}}{Y^*_{a,t-1}})$. Then, using the approximation of Mariano and Murasawa (2003), the observed variables can be linked with their respective unobserved

[5] The reader is referred to Cascaldi-Garcia et al. (2023) for an overview of the evolution of the nowcasting framework.

monthly variables as follows:

$$\begin{aligned} y_{q,t} &= y^*_{q,t} + 2y^*_{q,t-1} + 3y^*_{q,t-2} + 2y^*_{q,t-3} + y^*_{q,t-4} \\ y_{sa,t} &= y^*_{sa,t} + \cdots + 6y^*_{sa,t-5} + \cdots + y^*_{sa,t-10} \\ y_{a,t} &= y^*_{a,t} + \cdots + 12y^*_{a,t-11} + \cdots + y^*_{a,t-22} \end{aligned} \tag{2}$$

2.3 Monthly factor model

For all t, define $y_t = (y'_{m,t}, y'_{q,t}, y'_{sa,t}, y'_{a,t})'$ and $y^*_t = (y'_{m,t}, {y^*_{q,t}}', {y^*_{sa,t}}', {y^*_{a,t}}')'$. Assume that the monthly variables in y^*_t admit the following common factor model representation:

$$\begin{aligned} y^*_t &= \begin{pmatrix} \mu_m \\ \mu^*_q \\ \mu^*_{sa} \\ \mu^*_a \end{pmatrix} + \begin{pmatrix} \Lambda_m \\ \Lambda_q \\ \Lambda_{sa} \\ \Lambda_a \end{pmatrix} f_t + \varepsilon_t \\ f_t &= Af_{t-1} + u_t \\ \varepsilon_{i,j,t} &= \alpha_{i,j}\varepsilon_{i,j,t-1} + e_{i,j,t} \end{aligned} \tag{3}$$

In equation (3), μ_q, μ^*_q, μ^*_{sa}, and μ^*_a are vectors of unconditional means of $y_{m,t}$, $y^*_{q,t}$, $y^*_{sa,t}$, and $y^*_{a,t}$, respectively, Λ's are matrices of factor loadings, f_t is $r \times 1$ vector of common factors, $u_t \sim N(0, Q)$, $e_{i,j,t} \sim N(0, \sigma^2_{i,j})$, and $j \in \{m, q, sa, a\}$. We choose one common factor for our estimation, i.e., we take $r = 1$, because existing literature of factor models shows that it is sufficient to include a small number of factors (Stock and Watson, 2002; Forni et al., 2003) and often includes one factor (Banbura et al., 2013; Luciani and Ricci, 2014; Bragoli et al., 2015). Since $y^*_{q,t}$, $y^*_{sa,t}$, and $y^*_{a,t}$ are unobserved, the above system cannot be directly estimated. Then, using the link between observed and unobserved variables in equation (2), the above common factor model can be rewritten in terms of observed variables as follows:

$$
\begin{aligned}
y_t = \begin{pmatrix} \mu_m \\ \mu_q \\ \mu_{sa} \\ \mu_a \end{pmatrix} + \begin{pmatrix} \Lambda_m f_t \\ \Lambda_q(f_t + \cdots + 3f_{t-2} + \cdots + f_{t-4}) \\ \Lambda_{sa}(f_t + \cdots + 6f_{t-5} + \cdots + f_{t-10}) \\ \Lambda_a(f_t + \cdots + 12f_{t-11} + \cdots + f_{t-22}) \end{pmatrix} \\
+ \begin{pmatrix} \varepsilon_{m,t} \\ \varepsilon_{q,t} + \cdots + 3\varepsilon_{q,t-2} + \cdots + \varepsilon_{q,t-4} \\ \varepsilon_{sa,t} + \cdots + 6\varepsilon_{sa,t-5} + \cdots + \varepsilon_{sa,t-10} \\ \varepsilon_{a,t} + \cdots + 12\varepsilon_{a,t-11} + \cdots + \varepsilon_{a,t-22} \end{pmatrix}
\end{aligned} \tag{4}
$$

where $\mu_q = 9\mu_q^*$, $\mu_{sa} = 11\mu_{sa}^*$, and $\mu_a = 23\mu_a^*$. Based on equation (4), the state-space representation can be written as:[6]

$$
\begin{gathered}
y_t = \mu + A_F F_t + A_\Psi \Psi_t \\
\begin{pmatrix} F_t \\ \Psi_t \end{pmatrix} = \Omega \begin{pmatrix} F_{t-1} \\ \Psi_{t-1} \end{pmatrix} + \eta_t
\end{gathered} \tag{5}
$$

Following Banbura et al. (2010), we partition the common factor into mutually independent global, nominal, real, and international blocks. The global block is loaded with all variables and the three remaining blocks are loaded with only the pertinent variables. These blocks account for local cross-sectional correlations, which is helpful in more efficient extraction of the global factor (Banbura et al., 2010).

Our key innovation in the modeling framework of Banbura et al. (2013) is given in equation (2), which links observed quarterly, semiannual, and annual variables with unobserved monthly variables. This allows us to extend the standard quarterly-monthly state-space representation into a framework that allows tracking lower-frequency variables, such as annual and semiannual, using variables of mixed frequencies. As such, this framework parsimoniously combines the features and patterns in macroeconomic data to provide a monthly index that tracks low-frequency variables. With this approach, we integrate the real-time flow of information and assess its effects on current economic conditions as soon as the new data becomes available.

[6] The detailed expressions for the terms in equation (5) are provided in Appendix A.

2.4 Numerical maximization

Direct numerical maximization of this type of state-space model is efficient if the setup contains only a few variables. However, since the state-space representation often admits a significant number of variables, it is estimated using the EM algorithm of Doz et al. (2011). First, the algorithm is initialized by computing principal components, and the model parameters are estimated by ordinary least squares (OLS) regression, treating the principal components as the true factors. Second, based on the estimated parameters, the estimate of the common factors is updated using the Kalman smoother. Stopping the procedure here gives the two-step common factor estimates used in Giannone et al. (2008) and studied by Doz et al. (2011). Maximum likelihood estimation is carried out by repeating the two steps until convergence, considering the uncertainty related to the estimated factors at each step. Notably, the treatment of missing observations ensures that the filter, through its implicit signal extraction process, does not utilize missing observations in the computation of the factors. Consequently, when no observation of a variable is available, the filter forecasts the common factors using standard autoregressive or splicing techniques.

3 Econometric Application: Nowcasting GDP in Pakistan

3.1 Institutional structure and Data

The Federal Bureau of Statistics (FBS) is an attached department of the Pakistan Statistics Division and is the official statistical organization responsible for compiling national account statistics. In Pakistan, GDP is measured according to the guidelines provided by the United Nations System of National Accounts (UNSNA). Hence, it is computed using a combination of product, income, and expenditure methods.[7] The GDP measure is calculated for the fiscal year, that is, from July to June of the following year. Historically, the delay in GDP's release was approximately 18 months after the fiscal year; this has been brought down to 6 months. At this point, this is the final release of the estimate of (not seasonally adjusted) GDP in domestic currency. To the best of our knowledge, this number

[7]The product method is employed to calculate value added in sectors such as agriculture, mining and quarrying, manufacturing, electricity and gas distribution services, wholesale and retail trade, and ownership of dwellings. The income method is used to estimate income generated from transport, storage and communication, finance and insurance, public administration and defense, and services. Finally, the expenditure method is used to estimate value added in construction based on the investment made and the coefficient of value added.

is often not revised.

The key disadvantage of this data is that the real GDP (along with key inputs such as consumption and investment) is released only at an annual frequency.[8] Therefore, the objective of the nowcasting model is to generate predictions of GDP before official releases by taking advantage of the information embedded in the flow of monthly, quarterly, and annual economic indicators and to update the prediction as new data becomes available.

Table 1 highlights Pakistan's macroeconomic indicators that we use in our estimation, ordered in terms of data frequency and delay in release in months.[9] The majority of the data is acquired from the website of the State Bank of Pakistan (SBP), with our sample ranging from 1st January 2000 to 30th June 2023. The most significant delay is observed in the release of GDP and total tax collection at 6 and 11 months, respectively. Interestingly, rich macroeconomic data is readily available, such as manufacturing quantum index, economic policy uncertainty index (2-newspapers) (Choudhary et al., 2020), exports, imports, interest rates, money supply, and stock market index,[10] among others. These indicators are released more frequently, often with a delay of only a few days after the end of the reference month. However, not all variables are available for the entire sample. For instance, the economic policy uncertainty index became available in August 2010, and the quarterly GDP growth rate from September 2016. Such variables are included in the estimation once at least five observations become available, since estimation with Kalman filter requires at least two observations.

In general, the potential number of series that can be used to nowcast GDP growth is very large. Stock and Watson (1989) relies on a small set of monthly core indicators, including industrial production, total personal income less transfer payments, total sales, and employment as the list of factors. Their main motivation is that these indicators capture the three approaches to calculating GDP through the income, production, and expenditure approaches. Later contributions by Mariano and Murasawa (2010) extend the model to include GDP growth, while Doz et al. (2011) extend it to include weekly unemployment

[8]Quarterly GDP growth rates for Pakistan have only been available since September 2016, providing too few observations for reliable nowcasting, especially in the context of evaluating predictive accuracy. Additionally, as shown in the Appendix C, these quarterly measures offer limited incremental value to the predictive accuracy of the proposed model.

[9]The delay in release is assessed based on the last release date available on SBP and CEIC.

[10]While stock market prices are available at the end of each trading day, we include a one-month delay because: (i) the updated state-space representation does not accommodate daily data and, thus, is unable to account for the daily "release" of the prices, and (ii) the monthly average technically becomes available the next month.

Table 1: Pakistan's economic indicators

Economic Indicator	Frequency	Unit	Start	Months Delay	Source
GDP: Agriculture	a	PKR million	1950m12	6	SBP
GDP: Industry	a	PKR million	1950m12	6	SBP
GDP: Services	a	PKR million	1950m12	6	SBP
GDP: Overall	a	PKR million	1950m12	6	SBP
QGDPG: Agriculture	q	Percent	2016m9	3	SBP
QGDPG: Industry	q	Percent	2016m9	3	SBP
QGDPG: Overall	q	Percent	2016m9	3	SBP
Total tax collection	m	PKR billion	2001m12	11	SBP
Automobile sales	m	Number	2001m1	2	SBP
Economic Policy Uncertainty	m	Index	2010m8	2	SBP
M1: Bank Deposits with SBP	m	PKR million	2005m1	2	SBP
M2: Broad Money	m	PKR million	1988m1	2	SBP
M2: Other Deposits with SBP	m	PKR million	1991m7	2	SBP
Manufacturing Quantum Index	m	Index	1985m7	2	SBP
POL sales	m	Metric Ton	2013m7	2	SBP
Cement: Domestic sale & export	m	1000 Metric Ton	1991m7	1	SBP
Consumer Price Index	m	Index	1991m7	1	SBP
Exports	m	PKR million	1987m12	1	SBP
FDI: Inflow	m	PKR billion	2001m7	1	SBP
FDI	m	PKR billion	1997m7	1	SBP
Imports	m	PKR million	1987m12	1	SBP
Money market rate	m	Percent	1964m1	1	CEIC
Policy Rate	m	Percent	2015m5	1	SBP
Real Effective Exchange Rate	m	Index	2001m7	1	SBP
Remittances	m	PKR million	1972m7	1	SBP
Sales/offtake of fertilizer	m	1000 Metric Ton	2006m7	1	SBP
Sensitive Price Index	m	Index	1995m7	1	SBP
Stock market index	m	Index	1999m3	1	SBP

Note: The table highlights some of the available economic indicators for Pakistan, the monthly delay in the release of the data, the source, and the start date of the indicator. GDP refers to real GDP, QGDPG to quarterly GDP growth rate, PKR to Pakistani Rupee, POL to petroleum, oil, and lubricants, FDI to foreign direct investment. Annual, quarterly, and monthly frequencies are denoted as 'a', 'q', and 'm', respectively.

claims as well. In a recent contribution, Bragoli and Fosten (2018) proxies missing variables for trade in services by introducing international series such as the United States (US) and Eurozone industrial production.

Our approach to selecting the variables for nowcasting is similar to that taken by previous contributions in the literature. However, this is a challenging task for a country like Pakistan, given the natural data constraints - even market platforms infer Pakistan's economic conditions by monitoring a small set of high-frequency indicators.[11] More broadly, many emerging and developing economies face similar data limitations and constraints. Aside from GDP, other important variables such as unemployment, consumption, investment, construction, retail sales, capacity utilization, and inventories are either not measured by any statistical authority in Pakistan or face severe limitations

[11] Bloomberg relies on five key indicators to infer the economic conditions of Pakistan: money supply, industrial production, interest rates, exports, and inflation.

on observations.[12] It is important to mention that key variables, such as manufacturing, have multiple missing observations, but the Kalman filtering approach of Giannone et al. (2008) is equipped to deal with issues of missing observations and ragged-end problems (Camacho and Perez-Quiros, 2010). Another concern is that, since the 1980s, the national accounts have gone through at least three revisions in the base year and, therefore, must be spliced to obtain data series with a common base year.

To further augment the model, we include variables on commodity prices and global economic conditions. These variables often have a major role to play in driving business cycle fluctuations in emerging and developing economies (Drechsel and Tenreyro, 2018). Table 2 provides the particulars of these variables. We acquire commodity price indices for agriculture, energy, fertilizer, metals and minerals, and overall from the World Bank because, being a small open economy, Pakistan is vulnerable to changes in commodity prices. Composite leading indicators for the PRC, the UK, and the US, acquired from the Organisation for Economic Co-operation and Development (OECD), are used since these countries are among the largest trading partners of Pakistan. World Industrial Production (WIP) and Global Economic Conditions (GECON) indices, developed in Baumeister and Hamilton (2019) and acquired from Baumeister's website,[13] are included to capture the global macroeconomic environment, since this may have impacts on Pakistan's economic activity, as a small open economy. Overall, we assemble a mixed-frequency dataset consisting of 31 monthly variables, 3 quarterly variables, and 4 annual variables, including the target variable.

[12] Data on unemployment and labor force are based on an annual labor force survey. This series is available from the 1990s but has long periods of missing data and is released with a substantial delay.

[13] The data can be accessed here: `https://sites.google.com/site/cjsbaumeister/home`

Table 2: Indicators for commodity prices and global economic conditions

Economic Indicator	Frequency	Unit	Start	Months Delay	Source
Commodity prices					
Commodity price – Agriculture	m	Index	1960m1	1	World Bank
Commodity price – Energy	m	Index	1960m1	1	World Bank
Commodity price – Fertilizer	m	Index	1960m1	1	World Bank
Commodity price – Metals/Minerals	m	Index	1960m1	1	World Bank
Commodity price – Overall	m	Index	1960m1	1	World Bank
Global economic conditions					
CLI – China	m	Index	1992m5	3	OECD
CLI – UK	m	Index	1957m12	3	OECD
CLI – US	m	Index	1955m1	3	OECD
WIP	m	Index	1958m1	3	Baumeister's website
GECON	m	Index	1973m2	1	Baumeister's website

Note: The table highlights the indicators for commodity prices and global economic conditions, the monthly delay in the release of the data, the source, and the start date of the indicator. CLI refers to the Composite Leading Indicator, WIP to the World Industrial Production index, and GECON to the Global Economic Conditions indicator.

3.2 Model Specification

Using the variables discussed in the previous section, we estimate five different models: (i) core domestic variables (model A), (ii) extended domestic variables (model B), (iii) domestic variables with commodity prices (model C), (iv) domestic variables with global economic conditions (model D), and (v) a mix of variables from domestic, commodity prices, and global economic conditions (model E). We draw from various country-specific studies to infer a baseline set of variables that might contribute information to our latent indicator. Model A constitutes indicators on manufacturing, trade (exports and imports), total tax collection, consumer price index, remittances, foreign direct investment, stock market index, broad money supply, money market rate, and annual sector-level data on GDP. Therefore, we combine nominal and real variables like those used in previous studies (Boivin and Ng, 2006). Model B augments model A with indicators on automobile sales, domestic sales and export of cement, and sales/offtake of fertilizers. Models C and D include indicators on commodity prices and global economic conditions to model B, respectively. Finally, model E is a mix of different variables from models A, B, C, and D. It is noteworthy that model E does not include the stock market index because financial variables can be quite volatile, resulting in a limited role in nowcasting GDP (Bok et al., 2018). The variables included in each of the models are provided in Table 3, whereas the transformations and block loadings are provided in Table B1 in Appendix B.

Table 3: Variables included in different models

Economic Indicator	Model A	Model B	Model C	Model D	Model E
GDP: Agriculture	✓	✓	✓	✓	✓
GDP: Industry	✓	✓	✓	✓	✓
GDP: Services	✓	✓	✓	✓	✓
GDP: Overall	✓	✓	✓	✓	✓
QGDPG: Agriculture					✓
QGDPG: Industry					✓
QGDPG: Overall					✓
Total tax collection	✓	✓	✓	✓	✓
Automobile sales		✓	✓	✓	✓
Economic Policy Uncertainty					✓
M1: Bank Deposits with SBP					✓
M2: Broad Money	✓	✓	✓	✓	✓
M2: Other Deposits with SBP					✓
Manufacturing Quantum Index	✓	✓	✓	✓	✓
POL sales					✓
Cement: Domestic sale & export		✓	✓	✓	✓
Consumer Price Index	✓	✓	✓	✓	✓
Exports	✓	✓	✓	✓	✓
FDI: Inflow					✓
FDI	✓	✓	✓	✓	
Imports	✓	✓	✓	✓	✓
Money market rate	✓	✓	✓	✓	✓
Policy Rate					✓
Real Effective Exchange Rate					✓
Remittances	✓	✓	✓	✓	✓
Sales/offtake of fertilizer		✓	✓	✓	
Sensitive Price Index					✓
Stock market index	✓	✓	✓	✓	
Commodity prices					
Commodity price – Agriculture			✓		
Commodity price – Energy			✓		✓
Commodity price – Fertilizer			✓		✓
Commodity price – Metals/Minerals			✓		
Commodity price – Overall					✓
Global economic conditions					
CLI – China				✓	
CLI – UK				✓	
CLI – US				✓	
WIP				✓	
GECON				✓	✓

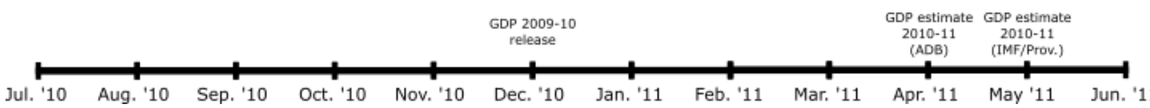
Note: The table indicates the variables used in the different model specifications. GDP refers to real GDP, QGDPG to quarterly GDP growth rate, PKR to Pakistani Rupee, POL to petroleum, oil, and lubricants, FDI to foreign direct investment, CLI refers to the Composite Leading Indicator, WIP to the World Industrial Production index, and GECON to the Global Economic Conditions indicator.

3.3 Nowcasting Pakistan's Gross Domestic Product

One important aim of the proposed nowcast model is to nowcast GDP before the official numbers are published by taking advantage of the information in the preceding data releases. In this section, we evaluate the performance of models A through E. The estimation sample starts from January 2000, whereas the evaluation period starts from the beginning of fiscal year 2005-06, i.e., July 2005, and terminates at the end of fiscal year 2022-23, i.e., June

2023. The evaluation period is set up in this manner to ensure we have a suitable number of observations for the earlier estimations, and fiscal year 2022-23 is the last year for which the GDP data has been released for Pakistan. So, in our context, nowcasting entails estimating the GDP growth rate at the end of the fiscal year based on the data on indicators that become available as the fiscal year progresses. To be more precise, during the months of the fiscal year 2010-11, i.e., from July 2010 to June 2011, nowcasting entails estimating the GDP growth rate for the fiscal year 2010-11 (Figure 2). The estimation in the evaluation period is carried out at a monthly frequency and, for each month, the available data is determined based on the delay in months for each of the variables utilized in the model. Ideally, we should be working with real-time data that mimics the exact information available to the econometrician at the time of the estimation (Croushore and Stark, 2001), however, since such real-time data is not available, we simulate a pseudo-real-time dataset using fully revised data.

Figure 2: Timeline of the release of data and estimates of GDP

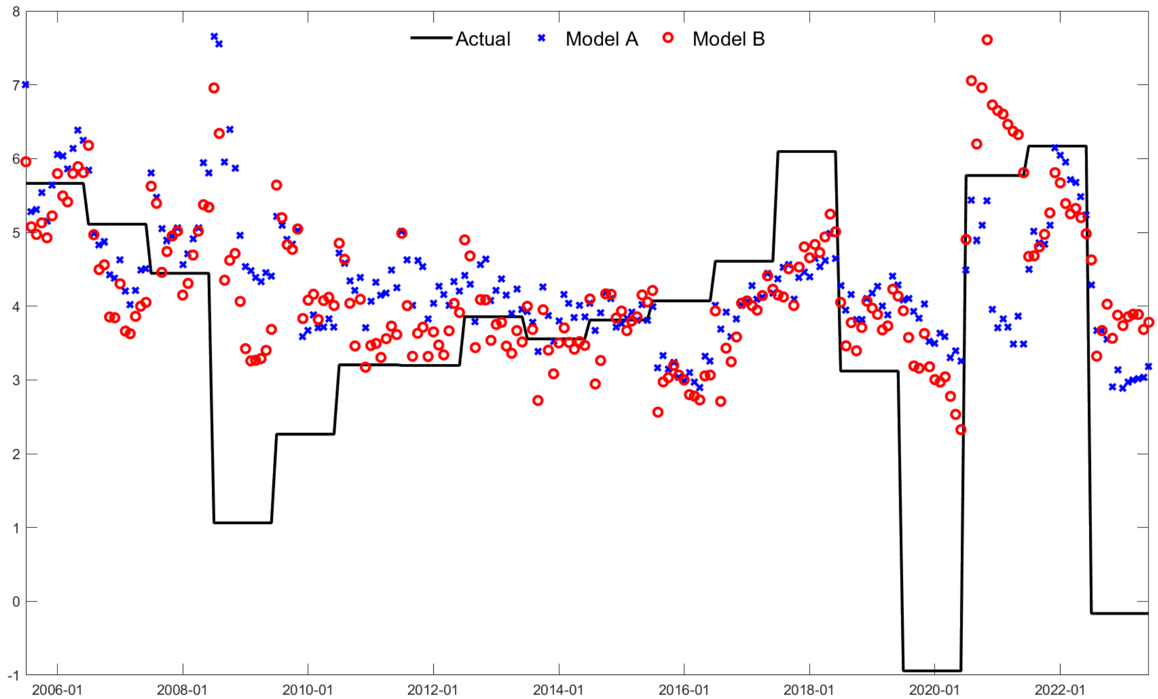


Note: The figure plots the timeline of the release of actual GDP and GDP growth rate estimates by the Asian Development Bank (ADB) and the International Monetary Fund (IMF), and provisional (Prov.) estimates released by Pakistani officials using fiscal year 2010-11 as an example.

Figure 3 plots the nowcasts from models A and B against the actual GDP growth rate for the period July 2005 to June 2023. Each scatter point represents the nowcast of GDP growth for the corresponding fiscal year, based on the data available in that month. The figure shows that models A and B do not perform remarkably well during periods of low economic growth, which is evident from the nowcasts in fiscal years 2008-09, 2019-20, and 2022-23. However, we note that model B generally performs better than model A as the nowcasts are closer to the actual GDP growth rates for fiscal years 2008-09 and 2019-20. Model B also better tracks the recovery after the COVID-19 pandemic, i.e., in fiscal year 2020-21, compared to model A. Another notable feature is that the nowcasts are relatively noisier before 2010.

Figure 3 shows how well domestic variables can nowcast the GDP growth rate in Pakistan. However, we expect commodity prices to be an important driver of economic activity in small open economies like Pakistan. So, we compare the nowcasts of models B

Figure 3: Nowcasts from models A and B against actual GDP growth rate

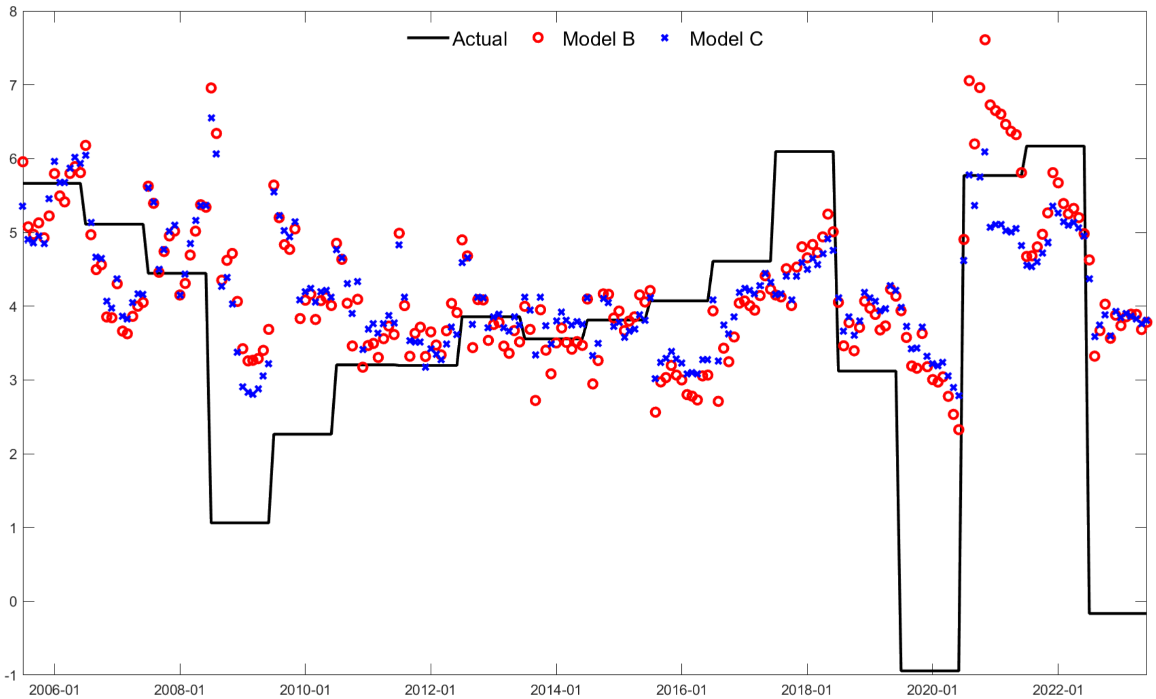


Note: The figure plots the actual annual GDP growth rate and the nowcasts from models A and B for the evaluation period from July 2005 to June 2023.

and C in Figure 4. We find that the nowcasts from the two models are quite similar. Model C is better at estimating the decrease in economic activity in 2008-09, but the performance in 2019-20 and 2022-23 is comparable for the two models. Both models capture the recovery after COVID-19; however, model B overestimates, whereas model C underestimates the growth rate for fiscal year 2020-21. Overall, there is pertinent informational content in commodity prices, but their inclusion does not considerably improve the nowcasts for Pakistan's GDP growth rate.

Figure 5 compares the nowcasts from models B and D to assess how global economic conditions might add value to the estimates for Pakistan's GDP growth rate. Since Pakistan is a small open economy, global economic conditions are expected to impact its economic performance, especially the economic conditions of its largest trading partners, which are included using the composite leading indicators for the PRC, the UK, and the US. Figure 5 shows that model D is better at tracking the economic slowdown in 2008-09 and 2022-23 compared with model B. Moreover, after COVID-19, the nowcasts from model D are a

Figure 4: Nowcasts from models B and C against actual GDP growth rate

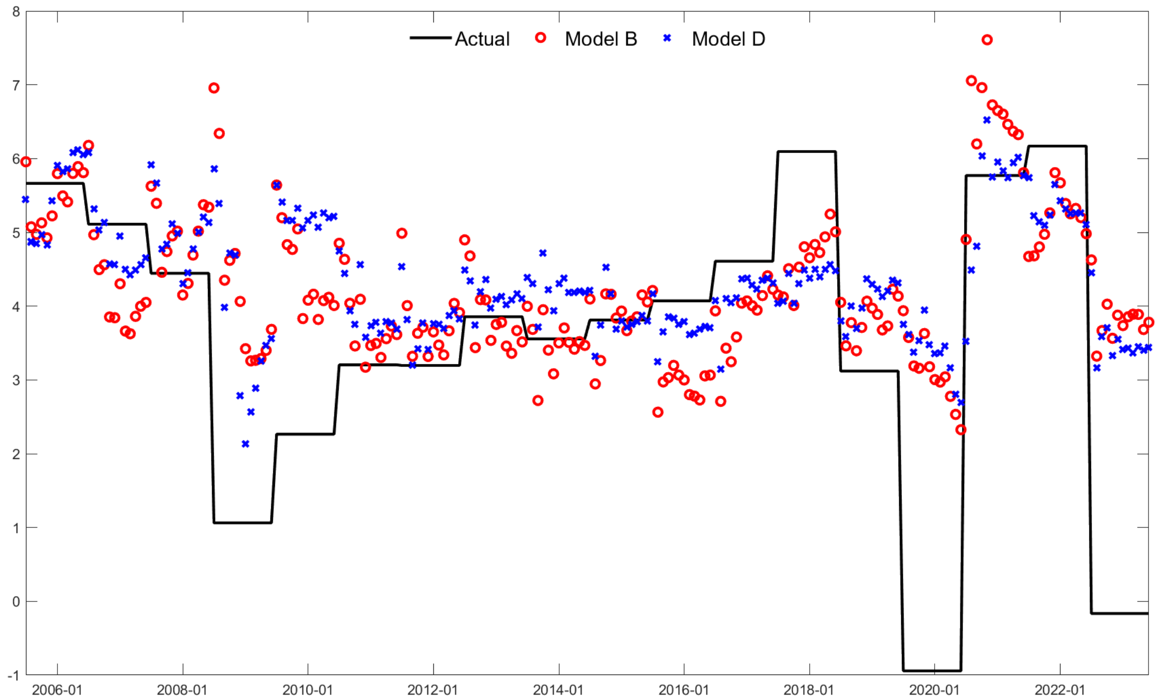


Note: The figure plots the actual annual GDP growth rate and the nowcasts from models B and C for the evaluation period from July 2005 to June 2023.

lot closer to the actual growth rate than model B. This shows that the inclusion of global economic conditions indicators considerably improves the nowcasting performance of our framework and suggests that these indicators significantly increase the informational content in the DFM estimation.

Based on models A through D, we come up with a mix of variables from domestic, commodity prices, and global economic conditions that constitute model E. Figure 6 shows that model E considerably improves on model B, especially in tracking the economic slowdowns in fiscal years 2008-09, 2019-20, and 2022-23. This is particularly interesting because 2019-20 and 2022-23 constitute periods of extreme declines in economic activity owing to the COVID-19 pandemic and political turmoil, respectively. Nevertheless, the nowcasts from model E are quite close to the observed GDP growth rates for these periods. Another notable feature is that the estimates for model E are not as volatile as those from model A before 2010. This could be attributed to the removal of the stock market index from model E (Bok et al., 2018). Overall, we can conclude that model E outperforms

Figure 5: Nowcasts from models B and D against actual GDP growth rate

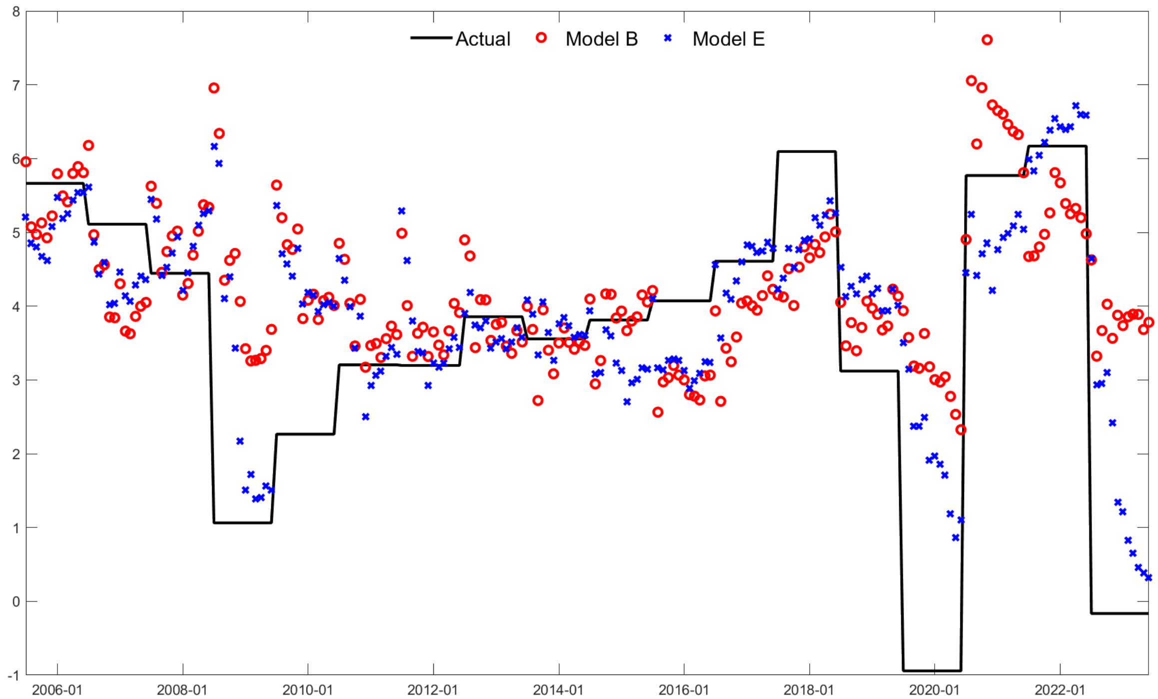


Note: The figure plots the actual annual GDP growth rate and the nowcasts from models B and D for the evaluation period from July 2005 to June 2023.

models A through D, models B through D are comparable, and model B outperforms model A.

Aside from a visual comparison among the five models, we also compare their predictive accuracy using the Diebold-Mariano test (Diebold and Mariano, 2002). We choose the lags for the Diebold-Mariano test using the Schwert criterion, and the uniform kernel is used to calculate the long-run variance. Table 4 presents the predictive accuracy of models A-D in predicting Pakistan's GDP growth rate compared with model E. The reported numbers are root mean squared errors (RMSEs) of the respective models and the results can be interpreted as follows: a better model has a lower RMSE at the specified horizon and the statistical significance of the difference from model E is indicated with ***, **, or * to represent that p-value is less than 1, 5, or 10%, respectively. The table shows that the predictive accuracy of all models increases as we move further into the fiscal year. Furthermore, Table 4 formalizes the conclusions drawn from figures 3-6: model B has lower RMSEs compared to model A, models B through D have comparable RMSEs, and

Figure 6: Nowcasts from models B and E against actual GDP growth rate



Note: The figure plots the actual annual GDP growth rate and the nowcasts from models B and E for the evaluation period from July 2005 to June 2023.

model E generally outperforms all the other models and, in the majority of the comparisons, the better performance is deemed to be statistically significant. This can be quantified by comparing average RMSEs for the different models. On average, model E has about 28% better forecast accuracy compared to models B through D, models C and D have less than 1% better accuracy compared to model B, and model B has about 8% better accuracy compared to model A.[14]

[14] Appendix C explores the drivers of the considerable gains in predictive accuracy drivers of model E. It shows that the additional monetary and external sector indicators play a critical role in model E's performance, especially monetary indicators. This appendix also shows that the performance gains of model E are not solely driven by the extreme declines in economic activity due to COVID-19 (2019-20) and political turmoil (2022-23).

Table 4: Comparison of predictive accuracy of models A-E

Fiscal Month	Model E	Model A	Model B	Model C	Model D
1	2.29	2.55**	2.48***	2.39***	2.32
2	1.94	2.38***	2.21***	2.17**	2.05
3	1.56	2.09***	1.82**	1.86**	1.78*
4	1.57	2.17***	1.90*	1.88*	1.91***
5	1.46	2.05***	1.95***	1.87**	1.96***
6	1.16	1.79***	1.70**	1.68	1.66**
7	1.05	1.75***	1.60*	1.62	1.62**
8	1.04	1.79***	1.63*	1.64	1.65**
9	0.96	1.77***	1.63*	1.63	1.66**
10	0.86	1.73***	1.60*	1.61	1.68***
11	0.81	1.78***	1.55**	1.59*	1.64***
12	0.83	1.78***	1.56**	1.60*	1.64***

Note: The table presents the accuracy of models A-D in predicting Pakistan's GDP growth rate compared to model E. ***, **, and * represent p values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.

4 Comparison and Extensions

4.1 Testing against competing forecasts

The main purpose of this paper is to propose a nowcasting framework that can track low-frequency variables. To exhibit the applicability of this framework, we use it to nowcast the economic activity of a lower middle-income country that measures its GDP annually. So far, we have established that nowcasts from model E have the best predictive accuracy for nowcasting Pakistan's GDP among the five models presented in this paper. Now, we compare the performance of the proposed model (model E) with other institutional estimates for Pakistan's GDP growth.

ADB releases nowcasts of year-on-year real GDP growth for individual countries based in Asia and the Pacific, including Pakistan, in its Asian Development Outlook (ADO), which is released in early April, with a supplement in July (ADOS), an update in September (ADOU), and a final supplement in December of each year. The ADO contains an estimate of the current fiscal year's real GDP growth rate. Similarly, the IMF releases the year-on-year GDP growth rate of the current year for all countries of the world in May every year in its World Economic Outlook (WEO).

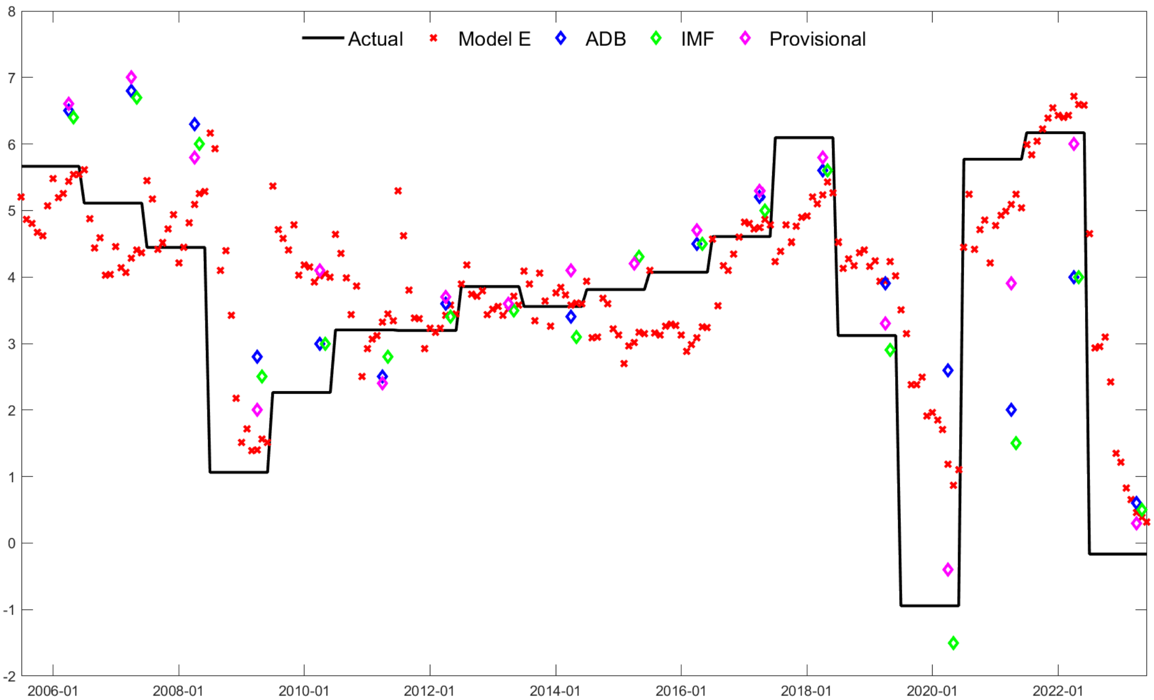
ADB and IMF publish updated numbers in September and October, respectively, each year. However, these estimates are generally based on the provisional estimate of the GDP growth rate for Pakistan that is announced in the meetings of the National Accounts Committee (NAC), which is normally held around the end of May. This is evident from the fact that the updated numbers from ADB and the IMF have been essentially identical since

2008 (Table B2). Some of the press releases from NAC are available from the Pakistan Bureau of Statistics (PBS) for the evaluation period, and these numbers are more in line with the estimates published by ADB in September. Therefore, we use the estimates reported in ADOU as a proxy for provisional estimates of GDP growth rates for Pakistan. The estimates for Pakistan's GDP growth rate by ADB and the IMF, and those announced by NAC are reported in Table B2 in Appendix B. Overall, we compare model E's nowcasts in March with ADB's estimates released in April and nowcasts in April with the IMF's estimate and the provisional estimate released in May. The motivation behind using the previous month's nowcast for model E is that the ADB, IMF, and provisional estimates might be based on the data available in the month before the release month. The timeline of the release of provisional GDP growth rate and estimates by ADB and the IMF is provided in Figure 2, which uses fiscal year 2010-11 as an example.

Figure 7 gives a visual comparison of model E nowcasts against institutional estimates of Pakistan's GDP growth rate. The figure shows that model E nowcasts perform considerably better than the institutional estimates before 2010, where the institutional estimates appear to overestimate the GDP growth rate. This is evident from model E tracking the decline in economic activity in 2008-09 better than the institutional estimates. After 2010, there does not appear to be any distinctive pattern of over- or under-estimation across any of the estimates. The IMF and provisional estimates track the economic slowdown in 2019-20 better than model E, which in turn performs better than ADB's estimate. However, model E outperforms the institutional estimates in tracking the recovery in 2020-21 compared with all the institutional estimates. Finally, all estimates are comparable for the decline in GDP growth rate for 2022-23. Overall, we can conclude that the institutional estimates have improved over time, but nowcasts from model E exhibit comparable performance and, in some cases, even better performance.

We can formally compare the predictive accuracy of model E with the institutional estimates for Pakistan's GDP growth rate using the Diebold-Mariano test with the same specification as before. Table 5 presents the predictive accuracy of model E and GDP growth rate estimates from ADB, the IMF, and provisional GDP growth rates. The table shows numbers only for March and April since those are the months assigned to the different institutional estimates. The table shows that model E RMSEs are considerably lower than the RMSEs for ADB and IMF estimates, and this difference is statistically significant. The RMSE for the provisional GDP growth rate is considerably lower than the RMSEs of ADB and IMF estimates; however, the provisional GDP growth rate and ADB estimates are not

Figure 7: Comparing model E nowcasts against institutional estimates of GDP growth rate



Note: The figure plots the actual annual GDP growth rate, the nowcasts model E, and estimates from ADB, the IMF, and a proxy for provisional growth rates for Pakistan announced in the meetings of the National Accounts Committee (NAC) for the evaluation period from July 2005 to June 2023.

directly comparable since the two estimates are based on data available at different times. The RMSE for the provisional GDP growth rate is higher than the nowcasts for model E, but the difference is not statistically significant. It is noteworthy that the RMSE of the provisional GDP growth rate is closer in magnitude to March nowcasts from model E.

Overall, this subsection highlights the ability of the proposed DFM framework to track Pakistan's annual GDP growth rate better than institutional forecasts. However, this framework offers broader and more general applicability as most countries do not track quarterly economic activity (Figure 1) and can be used for other important economic indicators, for example, employment, that are typically subject to low-frequency coverage even in higher-income countries.

Table 5: COMPARISON OF PREDICTIVE ACCURACY OF MODEL E WITH INSTITUTIONAL FORECASTS

Fiscal Month	Model E	ADB	IMF	Provisional
9	0.96	1.58**		
10	0.86		1.36*	0.97

Note: The table compares the predictive accuracy of Pakistan's GDP growth estimates from ADB, the IMF, and a proxy for provisional growth rates for Pakistan announced in the meetings of the National Accounts Committee (NAC). ***, **, and * represent p-values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.

Table 6: INDICATORS INCLUDED IN DIFFERENT CATEGORIES TO EXAMINE THEIR CONTRIBUTION TO CHANGE IN THE NOWCASTS

External Sector	Policy Variables	Prices	Real Sector
Exports	Total tax collection	Consumer Price Index	GDP: Agriculture
FDI: Inflow	Economic Policy Uncertainty	Sensitive Price Index	GDP: Industry
Imports	M1: Bank Deposits with SBP	Commodity price – Energy	GDP: Services
Real Effective Exchange Rate	M2: Broad Money	Commodity price – Fertilizer	GDP: Overall
Remittances	M2: Other Deposits with SBP	Commodity price – Overall	QGDPG: Agriculture
GECON	Money market rate		QGDPG: Industry
	Policy Rate		QGDPG: Overall
			Automobile sales
			Manufacturing Quantum Index
			POL sales
			Cement: Domestic sale & export

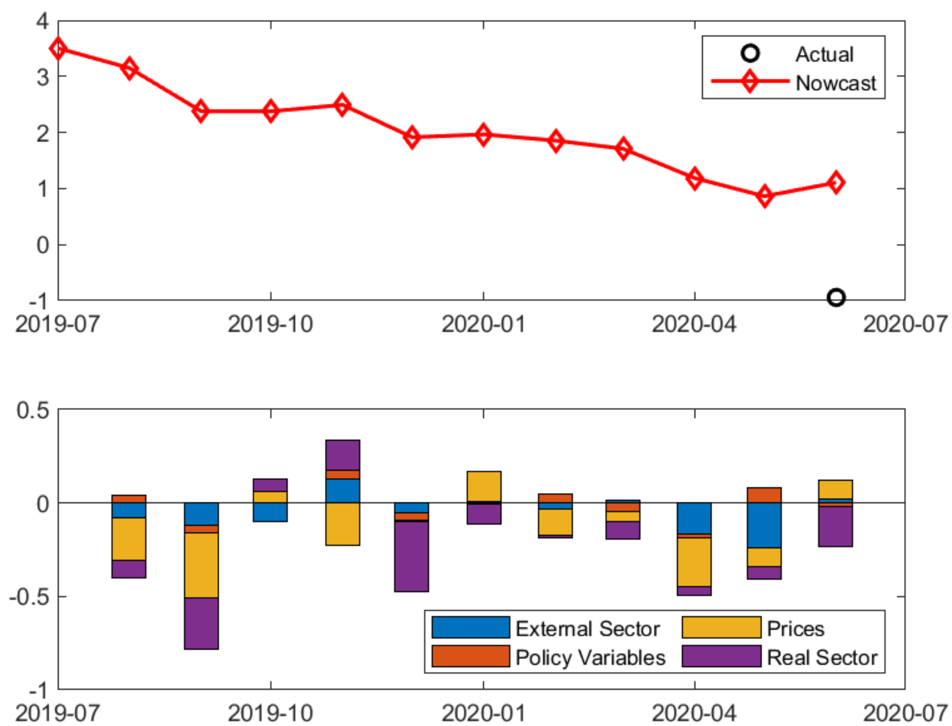
Note: The table shows how model E indicators are categorized to examine the contribution of each category to changes in nowcasts for Pakistan's GDP growth rate.

4.2 Contribution of surprises

This section examines how surprises in the released data each month contribute to the change in the nowcasts for model E. We conduct this exercise at a monthly level for the fiscal years 2019-20 and 2022-23 because exact dates of data releases are unavailable for Pakistan. These fiscal years are selected due to the notably stronger performance of model E compared to models A-D during periods of economic slowdown. For ease of interpretation, model E indicators are grouped into four categories: External Sector, Policy Variables, Prices, and Real Sector. The specific indicators included in each category are listed in Table 6.

The contribution of each indicator within the categories listed in Table 6 is determined by the deviation between its prediction and the actual value and the weight the model assigns to the surprise (Bok et al., 2018). Figures 8 and 9 illustrate the evolution of model E's nowcasts for Pakistan's GDP growth rate during fiscal years 2019-20 and 2022-23, along with the actual annual growth rates. The figures also show the monthly contribution of data releases to changes in the nowcast, aggregated by the categories provided in Table 6. In both years, initial nowcasts are considerably optimistic, 3.50% in July 2019 and 4.65% in July 2022, compared to the actual growth rate of -0.94 and -0.17%, respectively. However, as more data becomes available over the course of each fiscal year, the nowcasts go through downward revisions, reaching 1.10% in June 2020 and 0.32% in June 2023. This shows that the nowcasts from the proposed DFM framework improve as more data becomes available.

Figure 8: Contribution of surprises in series in different categories to the changes in nowcasts for 2019-20



Note: The top panel of the figure plots the month nowcasts of model E from July 2019 to June 2020 along with the actual annual GDP growth rate. The bottom panel shows the monthly contribution of data releases to changes in the nowcast aggregated by the following categories: External Sector, Policy Variables, Prices, and Real Sector.

The bottom panels of figures 8 and 9 illustrate the contribution of surprises in data releases, which are grouped by indicator category, to monthly changes in nowcasts. In fiscal year 2019-20, Real Sector and Prices indicators contributed to downward revisions, reflecting the adverse effects of the COVID-19 pandemic on Pakistan's economy. This period was marked with widespread lockdowns, a sharp contraction in industrial and services activity, and elevated prices due to supply chain disruptions. The uncertainty surrounding this period is evident from both positive and negative contributions, over the fiscal year, from indicators in Prices and Real Sector. Meanwhile, for 2022-23, indicators in the Prices and External Sector categories played a prominent role in lowering the nowcast. This fiscal year was characterized by heightened political uncertainty following the dissolution of the government in April 2022 after a vote of no-confidence and the lead-up to general elections. The indicators in the Prices category considerably decrease the nowcast over the fiscal year, which likely reflects the high levels of year-on-year consumer price index and sensitive price index inflation of 29.4 and 34.9%, respectively, between June 2022 and June 2023. Meanwhile, the downward revision from the External Sector indicators aligns with the year-on-year decline in cement dispatches (-23%), worker remittances (-13.7%), and exports (-19.1%) over the same period.

4.3 Measuring monthly economic activity

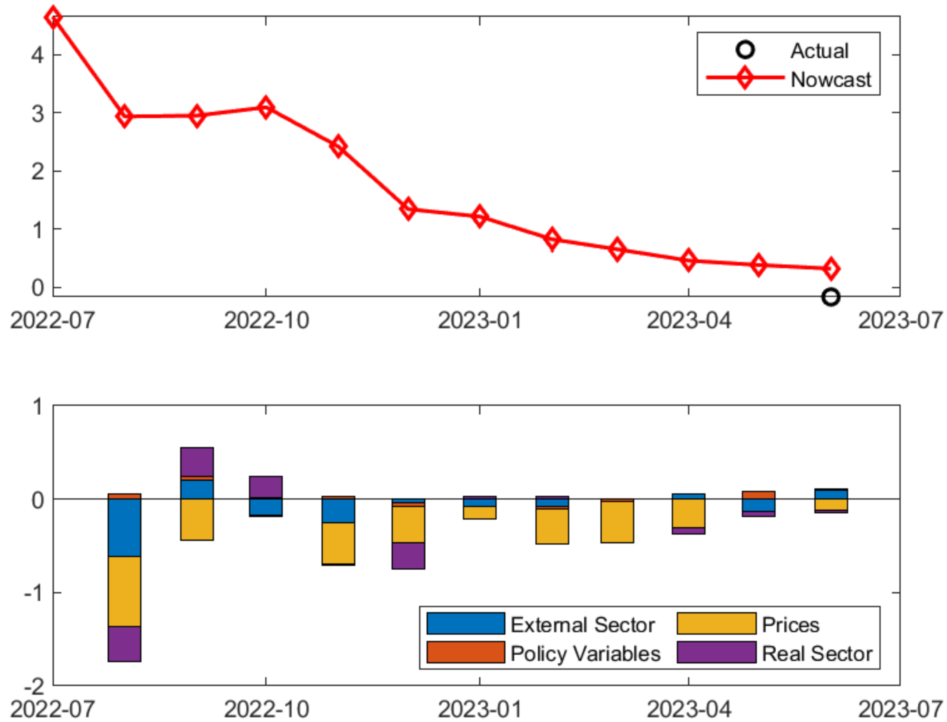
Another application of the proposed DFM framework is that the state-space representation can generate historical higher-frequency data for countries that track GDP annually. The estimated monthly data can contribute to a better understanding of historical business cycle dynamics. This is similar to Koop et al. (2020) using MF-VAR to produce consistent estimates of quarterly regional output growth in the UK dating back to 1970.

For this exercise, we use the data on model E variables from January 2000 to June 2023 without imposing any release delays. Figure 10 presents the monthly estimates for year-on-year GDP growth rates for Pakistan. The estimates are consistent with actual GDP growth rates, as the estimates coincide with the actual rates in the last month of the fiscal year.

4.4 Backcasting GDP growth rate

In applying the DFM framework, the paper focuses primarily on nowcasting economic activity that is tracked at a low frequency. This entailed nowcasting the GDP growth rate of Pakistan, i.e., estimating the growth rate of the GDP of the fiscal year as data becomes available during that fiscal year. However, the GDP data is not released until after the fiscal year is finished, so GDP data is not available to policymakers until a few months after the fiscal year ends. As such, we also estimate backcasts using the five models proposed in this paper, wherein the data that becomes available from July to November is used to estimate

Figure 9: Contribution of surprises in series in different categories to the changes in nowcasts for 2022-23

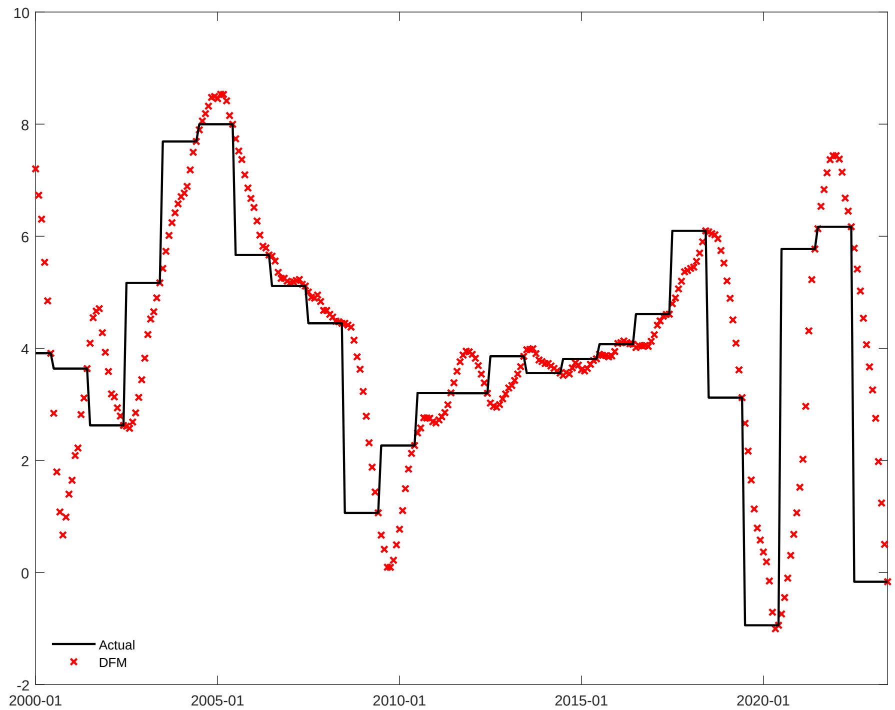


Note: The top panel of the figure plots the month nowcasts of model E from July 2022 to June 2023 along with the actual annual GDP growth rate. The bottom panel shows the monthly contribution of data releases to changes in the nowcast aggregated by the following categories: External Sector, Policy Variables, Prices, and Real Sector.

the GDP growth rate of the previous fiscal year because GDP data for Pakistan becomes available in December.

Table 7 presents the RMSEs for the backcasts from models A through E and the Diebold-Mariano test is conducted to compare the predictive accuracy of estimates from models A through D with those from model E. The table shows that RMSEs for the backcasts generated from model E are statistically significantly lower than those from models A through D. On average, model E has 34%, 24%, 27%, and 29% better forecast accuracy compared to models A, B, C, and D, respectively. Another noticeable feature is that, as we progress further into the new fiscal year, the accuracy of the backcasts decreases. This is the converse of our observation for nowcasts, where the accuracy increases as more

Figure 10: Estimates of monthly economic activity from model E against actual GDP growth rate



Note: The figure plots the monthly estimates for year-on-year GDP growth rates for Pakistan from model E against the actual annual GDP growth rate from January 2000 to June 2023.

data becomes available. One potential reason for this is that, as we progress through the new fiscal year, even though more data from the previous fiscal year is released, which adds information to the model, information related to the new fiscal year also becomes available that may not be pertinent to the previous fiscal year. Overall, it is comforting to note that backcasts and nowcasts from model E outperform those from models A through D so that policymakers can rely on one model for both nowcasting and backcasting the GDP growth rate of Pakistan.

Table 7: Comparison of predictive accuracy of backcasts from models A-E

Fiscal Month	Model E	Model A	Model B	Model C	Model D
1	1.06	1.68**	1.43***	1.48***	1.57***
2	1.05	1.68***	1.44***	1.5***	1.56***
3	1.11	1.68***	1.46***	1.54***	1.56***
4	1.15	1.68**	1.47***	1.55**	1.55***
5	1.16	1.67**	1.46***	1.54**	1.56***

Note: The table presents the accuracy of models A-D in backcasting Pakistan's GDP growth rate compared to model E. ***, **, and * represent p values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.

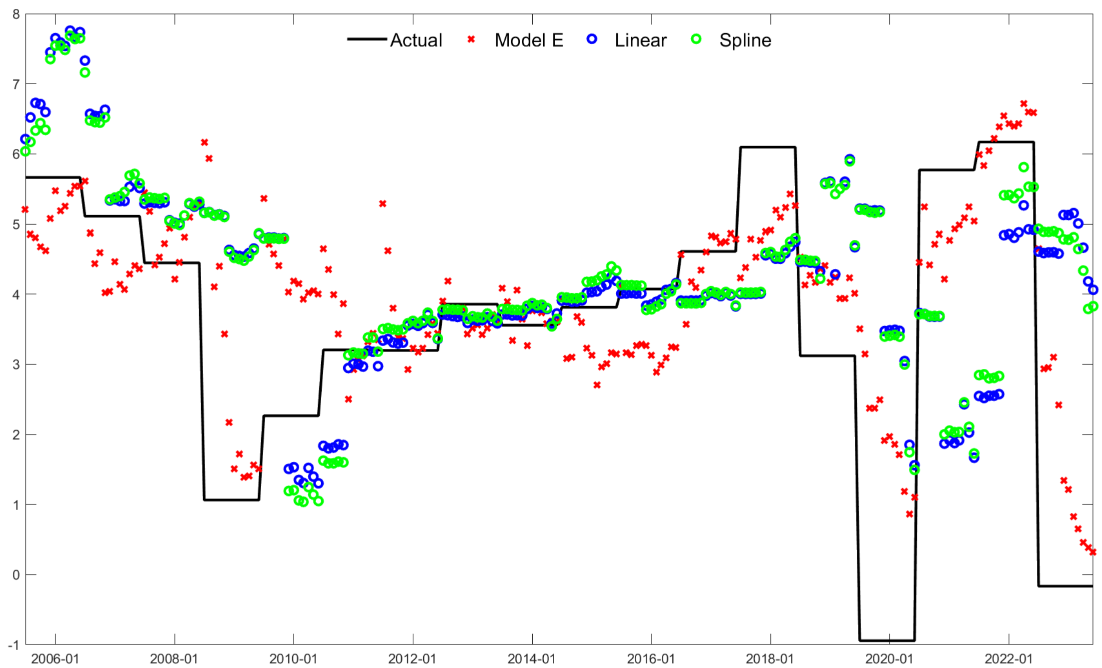
4.5 Quarterly interpolation of annual variables

As a final exercise, we compare our estimates with those generated using a simplified approach to demonstrate the added value of the updated state-space representation for policymakers and practitioners. Similar to the approach in Heng et al. (2024) to nowcast GDP growth in Cambodia, the simpler approach replaces annual variables with their quarterly interpolations and then applies the standard nowcasting framework of Giannone et al. (2008). The estimation utilizes a standard quarterly-monthly state-space representation of DFM, but may be prone to inaccuracies due to the quarterly interpolation of annual variables. While convenient, the two-step approach exhibits inferior performance as it significantly underperforms the nowcasts generated using the updated annual-monthly state-space representation.

Empirically, we rely on linear and spline interpolation methods to extract a pseudo quarterly series for GDP. After calculating the quarterly interpolates of the annual variables, we then utilize the quarterly-monthly DFM framework of Giannone et al. (2008) to estimate nowcasts. We use the same variables as in model E, but our key point remains the same if we use other model specifications. Figure 11 shows that the two-step nowcasts using linear and spline interpolations show very similar performance, but appear to underperform compared with model E. This is particularly evident for periods with sharp decreases (2008-09, 2018-19, 2019-20, and 2022-23) and increases (2017-18 and 2020-21) in Pakistan's economic activity. This indicates that the two-step nowcasts cannot suitably track economic activity during periods of extreme changes.

Table 8 echoes the conclusions drawn from Figure 11. The RMSEs from the two-step nowcasts are considerably higher than those for model E, especially after the first two fiscal months. Moreover, the difference is statistically significant in terms of the Diebold-Mariano test. Model E, on average, has around 43% better forecast accuracy compared to the two-step

Figure 11: Comparing model E nowcasts against two-step nowcasts using linear and spline interpolation



Note: The figure plots the actual annual GDP growth rate, the nowcasts model E, and the nowcasts from the two-step estimation that uses linear or spline interpolation to convert annual variables to have a quarterly frequency.

estimation with linear and spline interpolations. This exercise further highlights the value addition from the updated state-space representation of the DFM framework that allows expressing annual variables as a linear combination of latent monthly series for the observed monthly, quarterly, semiannual, and annual variables.

5 Conclusion

Standard nowcasting techniques often utilize weekly or monthly indicators to monitor quarterly variables, such as real GDP growth, using the DFM methodology developed by Giannone et al. (2008) and Banbura et al. (2013). However, in most countries, important variables like real GDP growth are only tracked annually. This results in delays in obtaining current economic information and even recent historical data, making policymaking particularly challenging. The issue becomes more pronounced when dealing with other crucial macroeconomic indicators, such as unemployment and fiscal data, and when

Table 8: Comparison of predictive accuracy of model E with linear and spline interpolations

Fiscal Month	Model E	Linear	Spline
1	2.29	2.54	2.55
2	1.94	2.51	2.52
3	1.56	2.51**	2.52*
4	1.57	2.51**	2.52*
5	1.46	2.50**	2.50**
6	1.16	2.24*	2.16*
7	1.05	2.24*	2.16*
8	1.04	2.19*	2.16*
9	0.96	2.22*	2.14*
10	0.86	2.09**	2.03**
11	0.81	1.99**	1.92**
12	0.83	1.95**	1.90**

Note: The table presents the accuracy of two-step nowcasts using linear and spline interpolation in predicting Pakistan's GDP growth rate compared to model E. ***, **, and * represent p values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.

monitoring social variables like poverty, inequality, and related statistics.

To address this concern, we modify the state-space representation of DFM used in Giannone et al. (2008), Banbura et al. (2013), and Bok et al. (2018). This modification enables us to incorporate monthly, quarterly, semiannual, and annual indicators to track the annual real GDP growth rate. The growth rate is represented as a linear combination of the latent monthly series for the indicators observed at their respective frequencies. By extending the modeling framework of Bok et al. (2018), we transition from the usual quarterly-monthly state-space representation to an annual-monthly representation.

As an application, we use this framework and data on monthly, quarterly, and annual indicators to nowcast Pakistan's annual GDP growth rate using five different models and demonstrate that model E best tracks Pakistan's economic activity. Our analysis shows that the proposed model outperforms estimates from key forecasting agencies, specifically ADB and the IMF, and exhibits performance comparable to provisional estimates from the Government of Pakistan. Therefore, we conclude that the proposed model is suitable for tracking Pakistan's annual GDP growth rate. We also examine how data releases of different indicators contribute to changes in nowcasts over the fiscal years 2019-20 and 2022-23 at the monthly level. We also show that the updated DFM framework can produce high-frequency historical economic activity measures that can help us better understand the dynamics of business cycles. Finally, we showcase the value added by the updated state-space representation by comparing nowcasts from our best-fit model with two-step nowcasts that utilize the more standard quarterly-monthly nowcasting approach. Overall, the

DFM framework with the updated state-space representation offers broader applicability to countries that do not monitor economic activity at high frequency and warrants evaluation in additional country contexts.

References

Anesti, N., A. B. Galvão, and S. Miranda-Agrippino (2022): "Uncertain Kingdom: Nowcasting gross domestic product and its revisions," *Journal of Applied Econometrics*, 37, 42–62.

Aruoba, S. B., F. X. Diebold, and C. Scotti (2009): "Real-time measurement of business conditions," *Journal of Business & Economic Statistics*, 27, 417–427.

Banbura, M., D. Giannone, M. Modugno, and L. Reichlin (2013): "Nowcasting and the real time data flow In Handbook of Economic Forecasting, vol. 2," .

Banbura, M., D. Giannone, and L. Reichlin (2010): "Nowcasting," *ECB working paper*.

Bańbura, M. and M. Modugno (2014): "Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data," *Journal of applied econometrics*, 29, 133–160.

Baumeister, C. and J. D. Hamilton (2019): "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks," *American Economic Review*, 109, 1873–1910.

Boivin, J. and S. Ng (2006): "Are more data always better for factor analysis?" *Journal of Econometrics*, 132, 169–194.

Bok, B., D. Caratelli, D. Giannone, A. M. Sbordone, and A. Tambalotti (2018): "Macroeconomic nowcasting and forecasting with big data," *Annual Review of Economics*, 10, 615–643.

Bragoli, D. and J. Fosten (2018): "Nowcasting indian gdp," *Oxford bulletin of economics and statistics*, 80, 259–282.

Bragoli, D., L. Metelli, and M. Modugno (2015): "The importance of updating: Evidence from a Brazilian nowcasting model," *Journal of Business Cycle Research*, 2015, 5.

Camacho, M. and G. Perez-Quiros (2010): "Introducing the euro-sting: Short-term indicator of euro area growth," *Journal of Applied Econometrics*, 25, 663–694.

Caruso, A. (2018): "Nowcasting with the help of foreign indicators: The case of Mexico," *Economic Modelling*, 69, 160–168.

Cascaldi-Garcia, D., T. R. Ferreira, D. Giannone, and M. Modugno (2024): "Back to the Present: Learning about the Euro Area through a Now-casting Model," *International Journal of Forecasting*, 40, 661–686.

Cascaldi-Garcia, D., M. Luciani, and M. Modugno (2023): "Lessons from Nowcasting GDP across the World," *International Finance Discussion Paper*.

Chernis, T., C. Cheung, and G. Velasco (2020): "A three-frequency dynamic factor model for nowcasting Canadian provincial GDP growth," *International Journal of Forecasting*, 36, 851–872.

Choudhary, M. A., F. Pasha, and M. Waheed (2020): "Measuring economic policy uncertainty in Pakistan," .

Croushore, D. and T. Stark (2001): "A real-time data set for macroeconomists," *Journal of econometrics*, 105, 111–130.

Diebold, F. X. and R. S. Mariano (2002): "Comparing predictive accuracy," *Journal of Business & economic statistics*, 20, 134–144.

Doz, C., D. Giannone, and L. Reichlin (2011): "A two-step estimator for large approximate dynamic factor models based on Kalman filtering," *Journal of Econometrics*, 164, 188–205.

Drechsel, T. and S. Tenreyro (2018): "Commodity booms and busts in emerging economies," *Journal of International Economics*, 112, 200–218.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin (2003): "Do financial variables help forecasting inflation and real activity in the euro area?" *Journal of Monetary Economics*, 50, 1243–1255.

Giannone, D., S. M. Agrippino, and M. Modugno (2013): "Nowcasting China real GDP," *Working Paper*.

Giannone, D., L. Reichlin, and D. Small (2008): "Nowcasting: The real-time informational content of macroeconomic data," *Journal of monetary economics*, 55, 665–676.

Ha, J., M. A. Kose, and F. Ohnsorge (2023): "One-stop source: A global database of inflation," *Journal of International Money and Finance*, 137, 102896.

Heng, D., F. Han, S. Chey, R. Uch, D. Kuchsa, and P. Phork (2024): "Nowcasting and Near-Term Forecasting Cambodia's Economy," Tech. rep., International Monetary Fund.

Koop, G., S. McIntyre, J. Mitchell, and A. Poon (2020): "Regional output growth in the United Kingdom: More timely and higher frequency estimates from 1970," *Journal of Applied Econometrics*, 35, 176–197.

Luciani, M., M. Pundit, A. Ramayandi, and G. Veronese (2018): "Nowcasting Indonesia," *Empirical Economics*, 55, 597–619.

Luciani, M. and L. Ricci (2014): "Nowcasting Norway," *International Journal of Central Banking*.

Mariano, R. S. and Y. Murasawa (2003): "A new coincident index of business cycles based on monthly and quarterly series," *Journal of applied Econometrics*, 18, 427–443.

——— (2010): "A coincident index, common factors, and monthly real GDP," *Oxford Bulletin of economics and statistics*, 72, 27–46.

Stock, J. H. and M. W. Watson (1989): "New indexes of coincident and leading economic indicators," *NBER macroeconomics annual*, 4, 351–394.

——— (2002): "Macroeconomic forecasting using diffusion indexes," *Journal of business & economic statistics*, 20, 147–162.

Zhang, Q., H. Ni, and H. Xu (2023): "Nowcasting Chinese GDP in a data-rich environment: Lessons from machine learning algorithms," *Economic Modelling*, 122, 106204.

Appendix A State-Space Representation

$$\mu = \begin{pmatrix} \mu_m \\ \mu_q \\ \mu_{sa} \\ \mu_a \end{pmatrix}$$

$$A_F = \begin{pmatrix} \Lambda_m & 0_{n_m \times 22r} \\ (1 \cdots 3 \cdots 1) \otimes \Lambda_q & 0_{n_q \times 18r} \\ (1 \cdots 6 \cdots 1) \otimes \Lambda_{sa} & 0_{n_{sa} \times 12r} \\ (1 \cdots 12 \cdots 1) \otimes \Lambda_a & \end{pmatrix}$$

$$A_\Psi = \begin{pmatrix} I_{n_m} & & 0_{n_m \times (5n_q + 11n_{sa} + 23n_a)} \\ 0_{n_q \times n_m} & (1 \cdots 3 \cdots 1) \otimes I_{n_q} & 0_{n_m \times (11n_{sa} + 23n_a)} \\ 0_{n_q \times (n_m + 5n_q)} & (1 \cdots 6 \cdots 1) \otimes I_{n_{sa}} & 0_{n_m \times 23n_a} \\ 0_{n_q \times (n_m + 5n_q + 11n_{sa})} & & (1 \cdots 12 \cdots 1) \otimes I_{n_a} \end{pmatrix}$$

$$\Psi_t = (\varepsilon'_{m,t}, \varepsilon'_{q,t}, \cdots, \varepsilon'_{q,t-4}, \varepsilon'_{sa,t}, \cdots, \varepsilon'_{sa,t-10}, \varepsilon'_{a,t}, \cdots, \varepsilon'_{a,t-22})'$$

$$\eta_t = (u'_t, e'_{m,t}, e'_{q,t}, 0'_{4n_q \times 1}, e'_{sa,t}, 0'_{10n_{sa} \times 1}, e'_{a,t}, 0'_{22n_a \times 1})'$$

$$\Omega = \begin{pmatrix} \begin{pmatrix} A & \cdots & 0_{r \times r} & 0_{r \times r} \\ I_r & \cdots & 0_{r \times r} & \vdots \\ \vdots & \ddots & \vdots & \vdots \\ 0_{r \times r} & \cdots & I_r & 0_{r \times r} \end{pmatrix} & 0_{23r \times (5n_q + 11n_{sa} + 23n_a)} \\ 0_{(5n_q + 11n_{sa} + 23n_a) \times 23r} & \begin{pmatrix} \psi_m & & 0_{n_m \times (5n_q + 11n_{sa} + 23n_a)} \\ 0_{5n_q \times n_m} & \psi_q & 0_{5n_q \times (11n_{sa} + 23n_a)} \\ 0_{11n_{sa} \times (n_m + 5n_q)} & \psi_{sa} & 0_{11n_{sa} \times 23n_a} \\ 0_{23n_a \times (n_m + 5n_q + 11n_{sa})} & & \psi_a \end{pmatrix} \end{pmatrix}$$

$$\psi_m = \text{diag}(\alpha_{1,m}, \cdots, \alpha_{n_m,m})$$

$$\psi_q = \begin{pmatrix} \text{diag}(\alpha_{1,q}, \cdots, \alpha_{n_q,q}) & 0_{n_q \times 4n_q} \\ \text{diag}(I_{n_q}, I_{n_q}, I_{n_q}, I_{n_q}) & 0_{4n_q \times n_q} \end{pmatrix}$$

$$\psi_{sa} = \begin{pmatrix} \text{diag}(\alpha_{1,sa}, \cdots, \alpha_{n_{sa},sa}) & 0_{n_{sa} \times 10n_{sa}} \\ \text{diag}(I_{n_{sa}}, \cdots, I_{n_{sa}}) & 0_{10n_{sa} \times n_{sa}} \end{pmatrix}$$

$$\psi_a = \begin{pmatrix} \text{diag}(\alpha_{1,a}, \cdots, \alpha_{n_a,a}) & 0_{n_a \times 22n_a} \\ \text{diag}(I_{n_a}, \cdots, I_{n_a}) & 0_{22n_a \times n_a} \end{pmatrix}$$

In the above expressions, I represents the identity matrix, $\otimes$ is the Kronecker product, and diag refers to the diagonal matrix of the specified terms.

Appendix B Tables

Table B1: Transformation and block loadings for the variables

Economic Indicator	Transformation	Global	Nominal	Real	International
GDP: Agriculture	% change	✓		✓	
GDP: Industry	% change	✓		✓	
GDP: Services	% change	✓		✓	
GDP: Overall	% change	✓		✓	
QGDPG: Agriculture	Linear	✓		✓	
QGDPG: Industry	Linear	✓		✓	
QGDPG: Overall	Linear	✓		✓	
Total tax collection	% change	✓		✓	
Automobile sales	% change	✓		✓	
Economic Policy Uncertainty	% change	✓		✓	
M1: Bank Deposits with SBP	% change	✓	✓		
M2: Broad Money	% change	✓	✓		
M2: Other Deposits with SBP	% change	✓	✓		
Manufacturing Quantum Index	% change	✓		✓	
POL sales	% change	✓		✓	
Cement: Domestic sale & export	% change	✓		✓	✓
Consumer Price Index	% change	✓	✓		
Exports	% change	✓		✓	✓
FDI: Inflow	% change	✓		✓	✓
FDI	% change	✓		✓	✓
Imports	% change	✓		✓	✓
Money market rate	Linear	✓	✓		
Policy Rate	Linear	✓	✓		
Real Effective Exchange Rate	% change	✓		✓	✓
Remittances	% change	✓		✓	✓
Sales/offtake of fertilizer	% change	✓		✓	
Sensitive Price Index	% change	✓	✓		
Stock market index	% change	✓	✓		✓
Commodity prices					
Commodity price – Agriculture	% change	✓	✓		✓
Commodity price – Energy	% change	✓	✓		✓
Commodity price – Fertilizer	% change	✓	✓		✓
Commodity price – Metals/Minerals	% change	✓	✓		✓
Commodity price – Overall	% change	✓	✓		✓
Global economic conditions					
CLI – China	% change	✓		✓	✓
CLI – UK	% change	✓		✓	✓
CLI – US	% change	✓		✓	✓
WIP	% change	✓		✓	✓
GECON	% change	✓		✓	✓

Note: The table indicates the blocks variables are loaded on. Each variable is loaded on the global block. GDP refers to real GDP, QGDPG to quarterly GDP growth rate, PKR to Pakistani Rupee, POL to petroleum, oil, and lubricants, FDI to foreign direct investment, CLI refers to the Composite Leading Indicator, WIP to the World Industrial Production index, GECON to the Global Economic Conditions indicator, % change is percentage change based on the frequency of the variable, and Linear refers to no transformation of the indicator.

Table B2: GDP growth rate estimates released in ADB's ADO, IMF's WEO, and announced by NAC

Fiscal Year	ADB-ADO		IMF-WEO		NAC
	Apr.	Sep.	May	Sep./Oct.	May
2005-06	6.5	6.6	6.4	6.2	
2006-07	6.8	7	6.7	6.4	
2007-08	6.3	5.8	6	5.8	
2008-09	2.8	2	2.5	2	
2009-10	3	4.1	3	4.8	
2010-11	2.5	2.4	2.8	2.6	
2011-12	3.6	3.7	3.4	3.7	3.20
2012-13	3.6	3.6	3.5	3.6	3.59
2013-14	3.4	4.1	3.1	4.1	
2014-15	4.2	4.2	4.3	4.2	4.24
2015-16	4.5	4.7	4.5	4.7	4.71
2016-17	5.2	5.3	5	5.3	5.30
2017-18	5.6	5.8	5.6	5.8	5.79
2018-19	3.9	3.3	2.9	3.3	3.29
2019-20	2.6	-0.4	-1.5	-0.4	-0.38
2020-21	2	3.9	1.5	3.9	3.94
2021-22	4	6	4	6	5.97
2022-23	0.6	0.3	0.5	-0.5	0.29

Note: The table presents the estimates for Pakistan's GDP growth released in ADB's ADO, IMF's WEO, and provisional GDP growth rates announced by the National Accounts Committee (NAC) of Pakistan. ADB, ADO, IMF, and WEO stand for Asian Development Bank, Asian Development Outlook, International Monetary Fund, and World Economic Outlook, respectively.

Appendix C Assessing Gains in Predictive Accuracy of Model E

Section 3.3 demonstrates that model E significantly outperforms models A-D. To identify the sources of this improvement, we construct four variants of model E, listed in Table C1, each excluding a subset of variables that differentiate model E from models A-D. These variants allow us to assess how the omission of specific variable groups affects predictive accuracy, thereby isolating the contributions of different data categories to the enhanced performance of model E.

Table C1: Variants of model E

Variants	Variables excluded from model E
Economic activity	QGDPG: Agriculture, QGDPG: Industry, QGDPG: Overall, POL Sales
Monetary	M1: Bank deposits with SBP, M2: Other deposits with SBP, Policy rate, Sensitive price index
External	Real effective exchange rate, FDI inflow
Uncertainty	Economic Policy Uncertainty

Note: The table lists the variables that are excluded from Model E for each of its variants.

Table C2 compares the predictive accuracy of model E and its variants using the Diebold-Mariano test (Diebold and Mariano, 2002). The results indicate that excluding economic activity variables leads to a modest increase in RMSE during the initial fiscal months; on average, 2.3% higher in the first six fiscal months. However, for later fiscal months, the difference in predictive accuracy is not statistically significant. Similarly, excluding Economic Policy Uncertainty (EPU) does not materially affect predictive accuracy in a statistical sense, likely due to the limited historical availability of quarterly GDP and EPU data, which begin in September 2016 and August 2010, respectively. In contrast, the exclusion of monetary and external variables results in a substantial and statistically significant deterioration in predictive accuracy across all fiscal months. These findings suggest that both monetary and external indicators play a critical role in enhancing the predictive accuracy of model E, with monetary variables appearing particularly important, as evidenced by the larger RMSE increases observed when they are omitted.

Table C2: Comparison of predictive accuracy of model E with its variants

Fiscal Month	Model E	Model E Variant			
		Economic activity	Monetary	External	Uncertainty
1	2.29	2.31*	2.39***	2.32***	2.29
2	1.94	1.97	2.21**	2.02***	1.94
3	1.56	1.6*	1.88*	1.66**	1.57
4	1.57	1.61*	1.89**	1.68**	1.58
5	1.46	1.5*	1.88***	1.6***	1.46
6	1.16	1.2	1.65**	1.34***	1.16
7	1.05	1.11	1.53*	1.27***	1.07
8	1.04	1.1	1.52*	1.25***	1.05
9	0.96	1.05	1.49*	1.17**	0.96
10	0.86	0.94	1.43**	1.13***	0.87
11	0.81	0.88	1.39**	1.11***	0.81
12	0.83	0.91	1.38**	1.09***	0.84

Note: The table presents the accuracy of model E and four of its variants in predicting Pakistan's GDP growth rate compared to model E. ***, **, and * represent p values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.

Another notable feature is that model E is its superior ability to track economic downturns, particularly during the fiscal years 2019-20 and 2022-23. This raises the question of whether its improved predictive accuracy is primarily driven by these episodes. To investigate this, we compare the predictive accuracy of models A-E after excluding these two fiscal years, as reported in Table C3. As expected, the predictive accuracy of all models improves substantially once these periods are removed. Moreover, the performance gap between model E and models A-D narrows. Nonetheless, model E continues to outperform models A-D according to the Diebold-Mariano test, suggesting that the better performance of model E is not solely attributable to these episodes of economic downturn.

Table C3: Comparison of predictive accuracy of models A-E Excluding 2019-20 and 2022-23

Fiscal Month	Model E	Model A	Model B	Model C	Model D
1	1.79	2.11*	2.00**	1.91**	1.82
2	1.61	1.96*	1.86***	1.75***	1.65
3	1.21	1.59**	1.32***	1.32**	1.23
4	1.20	1.73***	1.38***	1.32***	1.39**
5	1.11	1.61**	1.45***	1.30***	1.43***
6	0.92	1.3***	1.09	1.00	1.01
7	0.77	1.27**	0.97**	0.93*	1.00*
8	0.82	1.29**	1.01**	0.96	1.05
9	0.74	1.27**	0.98***	0.94**	1.05*
10	0.72	1.27***	0.99**	0.95**	1.14*
11	0.71	1.32***	1.01**	0.98**	1.17**
12	0.71	1.33***	1.05***	1.02***	1.18**

Note: The table presents the accuracy of models A-D in predicting Pakistan's GDP growth rate compared to model E. ***, **, and * represent p values being less than 1%, 5%, and 10%, respectively. The reported numbers are the RMSEs of the nowcasts from the respective models.