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Asif Mahmood* and Hina Masood†

Abstract

Evaluating the current state of the business cycle is of crucial importance to policymakers for making effective decisions. However, economic data are often noisy and available with a substantial lag. Determining the underlying state of an economy is thus very difficult in practice as traditional national accounts data are often available on quarterly or annual basis. To overcome these gaps, policymakers, especially at the central banks, started to closely track the changes in high-frequency economic activity indicators. In this paper, learning from global best practices, we attempt to develop a composite monthly measure of real economic activity for Pakistan using available high-frequency data. Our constructed measure closely tracks the trend in the real GDP, which is available with relatively large lags from Pakistan Bureau of Statistics. Provided this important characteristic, we test and found a reasonable power of our monthly measure to nowcast real GDP growth for a reference quarter.

JEL Classification Numbers: E01, E23

Keywords: Economic Activity, High-frequency data, GDP

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I. Introduction

Evaluating the current state of the business cycle is of crucial importance to policymakers for making effective decisions. However, economic data are often noisy and available with a substantial lag. Determining the underlying state of an economy is thus very difficult in practice as traditional national accounts data are often available on quarterly or annual basis. Realization of this data shortcomings amongst the policymakers become more prominent when the COVID-19 pandemic hit the world economy in early 2020. The health emergency created by the pandemic led to a sudden stop in economic activity all over the world. Global supply disruptions due to containment measures were magnified by large-scale demand destruction across major countries. This effect largely caused by employment and income losses, weakening of consumer and business confidence, heightened uncertainty, contraction in global trade and especially in tourism, and behavioral restrictions like social distancing measures.

To overcome these data gaps, especially during the COVID, policymakers started to closely track the changes in high-frequency economic activity indicators. Moreover, the availability of digital data such as the google mobility indices were also proved to be very useful to detect the economic activity during the COVID peak and subsequent recovery afterwards (Sampi and Jooste, 2020). These data helped policymakers and researchers to understand the state of the economy and its underlying path. Many of the national statistics offices in countries like the United Kingdom, Canada, Argentina, Netherlands and Colombia started to produce a composite measure of monthly economic growth using available high-frequency economic indicators. Similarly, central banks in the countries like Chile, Brazil, South Africa and Armenia also developed such composite indices that help track economic activity on monthly basis (Stanger, 2020). In fact, central bank in the US has even developed weekly economic activity indices (Lewis et al., 2022).

Although the use of such high-frequency indicators become more in-fashion after the COVID, such tracking of real-time economic activity is not new amongst the policymakers. Indeed, the theoretical literature on constructing economic activity indicators dates back to the seminal work on measurement of business cycles (Burns and Mitchell, 1946). Empirically, it has, however, slowly progressed over time in terms of data selection and estimation methodologies. For instance, Stock and Watson (1989) first introduced the empirical use of leading economic indicators to policymakers to help understand the state of business cycles. Other examples for the development of such indicators includes Mariano and Murasawa (2003), Proietti and Moauro (2006) and Aruoba et al. (2009). For emerging economies, despite its importance, the empirically literature still remain scant. For example, Dahlhaus et al. (2017) constructed such activity indicators for BRICS countries, Bragoli and Fosten (2018) for India and Aruoba and Sarikaya (2013) in case of Turkey.

Apart from tracking economic activity, high-frequency indicators also help predict near-term growth by filling the data gaps. Many of the researchers attempted to predict GDP growth for a

given quarter using such high-frequency economic activity indicators. This method of gauging the present state of the economy using information from high-frequency indicators is known as 'nowcasting.' It was first introduced by central banks in the advanced economies about two decades ago. The approach initially adopted was the Bridge Model (BM) where quarterly frequency national accounts variables were regressed on their lagged values and other high-frequency indicators, converted to quarterly frequency (Baffigi et al., 2004). Subsequently, with availability of large datasets, more advanced techniques and methods, including machine-learning were developed (Giannone et al., 2008) to perform such analysis. The results from such studies broadly indicate the high predictive power of composite indicators that help policymakers to understand the underlying state of the economy and detect turning points in the business cycles.

In this backdrop, the objective of this note is to build a composite indicator of real economic activity (IREA) for Pakistan using available high-frequency indicators. To our knowledge, this attempt is first of its kind in case of Pakistan. In a country, where economy is prone to frequent internal and external shocks, this is an important study that strives to distinguish a noise from an underlying trend. Moreover, this exercise will also provide the basis for projecting economic growth over the near-term. In particular, from the central bank's perspective, the importance of such economic activity indicator(s) becomes much more prominent due to increase in frequency of monetary policy decisions from six to eight in recent years. Given the large lags involved in official reporting of national accounts, the increasing frequency of monetary policy decisions certainly require a more comprehensive and frequent analysis of the state of Pakistan's economy and where does it stands in terms of business cycle. Thus, availability of such composite measure of economic activity will help policymakers to undertake timely and informed decisions.

The rest of the article is divided in four sections. The next section details the current state of high-frequency economic activity indicators available to economic policymakers in Pakistan and their use at the State Bank of Pakistan (SBP). Third section describes the methodology used in this study to construct a high-frequency measure(s) of economic activity for Pakistan. Fourth section discusses the results, compare the constructed measures with official benchmarks, and demonstrate the usefulness of these measures to nowcast real GDP growth. The last section concludes and discusses the way forward.

II. High-frequency economic activity indicators: Availability and stylized facts

Fortunately, there is a good amount of high-frequency activity indicators available to policymakers in Pakistan that can help track economic activity with some precision. Especially on the monthly basis, several indicators from public and private sources are available with different lags. These indicators cover key sectors of the economy like agriculture, industry, services, trade and financial markets. In addition to these hard indicators, qualitative survey-based monthly responses from households and business are also providing valuable insights to policymakers. Besides monthly frequency, indeed some of the indicators from key sectors are available on daily and weekly basis having underlying important implications for broader economic activity. Specifically, these dataset includes port traffic data, activities at the stock exchanges, monetary

survey indicators and cotton crop arrivals. **Table 1** below list down high-frequency activity indicators along with other important official economic activity data.

Table 1: Key High-frequency Economic Activity Indicators - Pakistan

Indicator	Frequency	Lags	Source	
Port traffic	Daily	Next day	BRecorder.com	
PSX index	-do-	Day end	Pakistan Stock Exchange	
Exchange rates	-do-	Day end	State Bank of Pakistan	
Interest rates	-do-	-do-	-do-	
Monetary survey indicators	Weekly	12-14 days	-do-	
Cotton crop arrivals	Fortnightly	2-3 days	-do-	
Credit to private sector, detailed	Monthly	18-20 days	-do-	
Consumer credit	-do-	18-20 days	-do-	
Mining & quarrying data	-do-	45 days	-do-	
External trade data, detailed	-do-	18-20 days	-do-	
Bank deposits	-do-	12-14 days	-do-	
Foreign direct/portfolio investment	-do-	-do-	-do-	
Remittances	-do-	-do-	-do-	
Household and Business surveys	-do-	After MPC meeting	-do-	
Uncertainty index	-do-	2-3 days	Policyuncertainty.com	
POL sales	-do-	-do-	Oil Companies Advisory Council	
Fertilizer sales	-do-	-do-	National Fertilizer Development Centre	
Cement sales	-do-	-do	All Pakistan Cement Manufacturers Association	
Auto sales	-do-	8-10 days	Pakistan Automotive Manufacturers Association	
Large-scale manufacturing	-do-	45 days	Pakistan Bureau of Statistics	
Prices	-do-	1-2 days	-do-	
Electricity generation	-do-	15-16 days	National Electric Power Regulatory Authority	
# of Companies registered & dissolved	-do-	2-3 days	Securities & Exchange Commission of Pakistan	
Capital expenditure releases	-do-	10-12 days	Planning Commission	
Water availability	-do-	40 days	Space & Upper Atmosphere Research Commission	
Temperature & rainfall	-do-	2-3 days	Pakistan Meteorological Department	
Tax collection	-do-	1-2 days	Federal Bureau of Revenue	
Memorandum items:				
Financial soundness indicators	Quarterly	60 days	State Bank of Pakistan	
Payment system data	-do-	-do-	-do-	
Listed non-financial firms data	-do	60-90 days	Pakistan Stock Exchange, Capital Stake	
External trade indices	-do-	90 days	Pakistan Bureau of Statistics	
Quarterly national accounts	-do-	-do-	-do-	
Annual national accounts	Annual	End of May*	-do-	
Labour force survey	-do-	As and when	-do-	

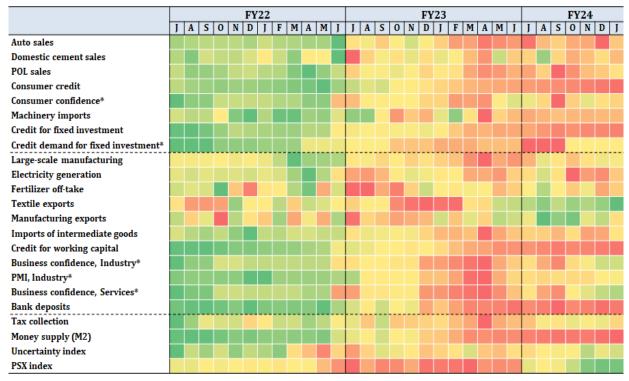
^{*} Provisional estimates for the ongoing fiscal year – that starts from July 1st till June 30th, with revisions in subsequent quarters Note: Monetary Policy Committee (MPC) meetings held 8 times in a year with a lag about 45 days between two successive meetings.

Despite some detail data available on key sectors, there is still exist a significant data gap which could potentially clouds the effectiveness of policy decisions. For example, central banks around world closely track the developments in the labour markets as an important input for their monetary policy decisions. However, in Pakistan, no such comprehensive quantitative labour data is available at high-frequency from official sources. Indeed, the availability of annual labour force data doesn't follow the proper timelines. In absence of this, though SBP's survey-based indicators provide some good qualitative analysis of the labour market conditions in Pakistan, they are still not the substitute for measuring actual ground conditions. Apart from labour data, SBP (2023) identified several other important data gaps in case of Pakistan - such as in the housing markets. These data gaps not only create hurdles for monetary policy decisions at the SBP but also for the implementation of country's broader economic policy and reform agenda.

Notwithstanding the presence of such data gaps, the available high-frequency indicators also provide a reasonable state of economic activity. However, since there are several indicators from different sectors that one can track on weekly or monthly basis, their ocular representation becomes very important for the policymakers. This is important in order to extract an underlying coherent message about the state of economic activity. Generally, these indicators are presented in the form of heat map, where one can separate the period of stress from that of progress through designated color schemes. **Table 2** below presents a typical heat map of 23 high-frequency activity indicators for Pakistan.

Table 2: Heat Map of Economic Activity Indicators

(deviations from monthly average during FY18-22, inflation and seasonally adjusted data)



^{*} Survey-based diffusion indices, deviation from 50 benchmark, where above (below) 50 means expansion (contraction) Sources: Various sources, SBP staff estimates

Note: Yellow and green shade boxes indicate the respective indicator is moving near or above its monthly average during FY18-22. In contrast, orange and red shades boxes denote the below average trend. Also, data for various sales indicators are available in volumetric terms from the source. However, data for trade, credit, tax and money supply are adjusted for price effects using appropriate deflators.

The heat maps, though provides a reasonable sense about broader direction in economic activity, they lack to state the level of growth to the policymakers. For instance, based on the color schemes, it could be observed from the table 2 that, the economic activity in FY22 mostly remained in an expansionary mode compared to both FY23 and an ongoing FY24. Similarly, relative to second half of FY23, economic activity is showing gradual recovery in the first half of FY24. However, these color boxes are unable to state the significant but different level of economic growth observed

during FY22, FY23 and expected for an ongoing FY24.¹ For policymakers – especially which are taking economic decisions at relatively higher frequency like the MPC at SBP, knowing the underlying level of growth is critical. This is because, it helps policymakers to effectively evaluate the present state of the economic activity relatively to the business cycles and make decisions accordingly.

III. Methodology to construct high-frequency economic activity indicator

A leading framework for the construction of an economic activity index from multiple time series is the so-called dynamic factor model, developed by Geweke (1977) and Sargent and Sims (1977). The dynamic factor model basically posits the existence of a small number of unobserved or latent series, called factors, which drive the co-movements of the observed economic time series. Primarily, the premise of a dynamic factor model is that a small number – i.e. in our case a single latent factor, f_t , drives the co-movements of a vector of N time-series variables, X_t . The dynamic factor model posits that the observed series are the sum of the dynamic effect of the common factor and vector of idiosyncratic disturbances, e_t , which arise from measurement error and from special features that are specific to an individual series. Specifically:

$$X_t = \lambda(L)f_t + e_t$$

where L is the lag operator. The elements of the $N \times 1$ vector of lag polynomials $\lambda(L)$ are the dynamic factor loadings, and $\lambda_i(L)f_t$ is called the common component of the ith series. The dynamic factor can be rewritten in static form by stacking f_t and its lags into single vector F_t , which has dimension up to the number of lags in $\lambda(L)$:

$$X_t = \Lambda F_t + e_t$$

where Λ is a matrix with rows being the coefficients in the lag polynomial $\lambda(L)$.

The two primary methods for estimating the unobserved factor f_t are by principal components analysis (PCA) and using state-space methods, where the factor is estimated by the Kalman filter. For measuring the real economic activity indicator (IREA) for this study, we adopted the PCA approach in order to avoid sensitivity of our empirical results to specification details required under the Kalman filter framework. Specifically, the dynamic factors derived from the PCA are linear combinations (or weighted averages) of the data, and together they explain all of the variation in the dataset. However, a small number of factors usually capture the majority of the

 $^{^1}$ Supported by monetary and fiscal stimuli, Pakistan's post-Covid economic recovery remained quite sharp as – after reported a contraction of about 1.0 percent in FY20, real GDP growth reached to 5.8 percent and 6.2 percent in FY21 and FY22, respectively. However, this V-shaped recovery created significant external sector challenges for the economy, which further hit by the devastating floods and global commodity super-cycle shock. Reflecting these pressures, the economy recorded a contraction of 0.2 percent in FY23 and – according to the SBP, is expected to show a moderate growth in the range of 2 – 3 percent in the ongoing FY24.

variation. The first principal component is the most important factor because it explains most of the variation and it represents the main indicator.

Technically, the indicator (IREA in our case), or the first principal component, is a linear combination of the variables in the dataset, where the weights are the eigenvectors associated with the largest eigenvalue obtained from the principal component analysis.² Specifically:

$$IREA_t = \lambda_1 x_{1,t} + \lambda_2 x_{2,t} \dots + \lambda_N x_{N,t}$$

where the λ 's denotes the eigenvectors derived from the PCA, x's denotes the selected variables, t denotes time, and N is the number of variables in the dataset.

It is important to note that, the IREA alone does not produce an estimate of economic growth, but it does play a useful role as a qualitative measure of the economic cycle and as a summary measure of a large amount of data. The indicator has the following interpretation: values of the indicator below zero imply below average growth while values above zero imply above average growth. By construction, the indicator has a mean of zero and standard deviation of one.

To construct the IREA for Pakistan, first we have selected 22 monthly economic indicators, of which 19 are also part of the heat map analysis discussed above.³ We added 3 more monthly indicators - namely water availability, export of ICT services and mining and quarrying, having important linkages with the changes in economic growth in Pakistan. In the second step, we constructed our IREA using the GDP based accounting method. In this method, those indicators where only nominal values are available, excluded from the final analysis.⁴ Our sample period for the PCA analysis in this study starts from July 2015 till December 2023. This coincides with the availability of recently released quarterly real GDP data, which is our target variable. However, the selection of such sample period forced us to drop otherwise an important three business survey related indicators that are part of the existing heat map analysis.⁵

IV. Results and discussion

Based on two methods discussed above, **Figure 1** presents the loading factors of our six selected IREA from the first principal component using different specification of selected indicators. It could be observed that, most of indicators from the industry and services sectors carries higher weights in our specifications than those indicators that tends to reflect the activities in the agriculture sector. Specifically, in the first specification where we have selected all 22 indicators, POL sales, large-scale manufacturing, trade and financial indicators carries higher weights. These

² Eigenvalues and eigenvectors are measures computed from the covariance matrix of the dataset. The eigenvalues are used to rank the factors from first to last. The eigenvectors are the weights attributed to each variable in every factor. For details, see Crawly (2013).

³ These indicators are chosen from more than 29 potential indicators.

 $^{^{\}rm 4}$ Specifically, we excluded credit, financial and tax related indicators.

⁵ This included business confidence indices for industry and services, and purchasers' manager index (PMI) for industry.

indicators, apart from financial indicators, also carries a higher weight in our second specification in which we broadly selected indicators having volume data from the source.

Indicator_1 Indicator_2 Indicator_3 Indicator_4 Indicator_5 Indicator_6 Mining & quarrying ICT services Water availability KSE-100, Index RSE-100, Index
Uncertainty.
Money supply (M2)
Tax collection
Bank deposits
Credit for Imports of. Manufacturing. Textile exports Fertilizer off-take Electricity Credit for fixed Machinery imports Consumer Consumer credit POL sales Domestic cement. Auto sales 0 0.25 0.5 0 0.25 0.5 0 0.25 0.5 0 0.25 0 0.25 0.5 0.5 0.5 0.25

Figure 1: Factor Loadings of Indicators

Source: Authors' calculations

Note: Indicators 1, 2 and 3 and Indicators 4, 5 and 6 belongs to first and second specifications, respectively. Also, Indicator_1 and Indicator_4 are having variables adjusted for both price and seasonality; Variables in Indicator_2 and Indicator_5 are only adjusted for price effect; and variables in Indicator_3 and Indicator_6 are unadjusted for both price and seasonality.

Based on the factor loadings of each variable presented above, on average, the first principal component on average explains around 54 percent of total variation in the selected six monthly IREA versions. Using these factor loadings (weights), **Figure 2** exhibit the normalized six versions of monthly IREA constructed for Pakistan in both level and 12-mothh change basis.

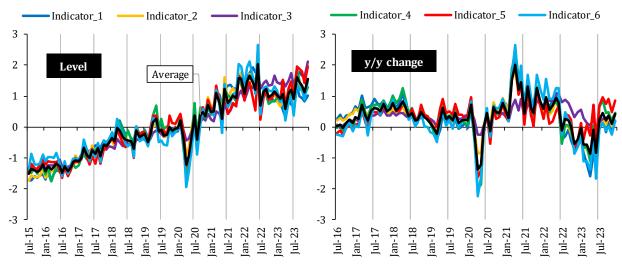


Figure 2: Monthly Indicator of Real Economic Activity (IREA) for Pakistan, Normalized

Source: Authors' calculations

Note: Based on variables mentioned in Figure 1, Indicator_1 and Indicator_4 are having variables adjusted for both price and seasonality; Variables in Indicator_2 and Indicator_5 are only adjusted for price effect; and variables in Indicator_3 and Indicator_6 are unadjusted for both price and seasonality. Black line denotes the simple average of six IREA versions.

It could be observed from figure 2 that, the IREA(s) are broadly reflecting a reasonable picture of underlying pattern of economic activity experienced in Pakistan during 2016-2023 period. For instance, during FY15 and FY17, the IREA from all six versions are showing a positive growth momentum. This growth was driven primarily by increased infrastructure development and investments under the China-Pakistan Economic Corridor (CPEC) initiative. Moreover, in the same period, favorable global terms-of-trade shock also supported growth through lower domestic inflation, which declined from around 10 percent in early 2014 to historical lows of about 2 percent by the end of 2015. This led the SBP to cumulatively reduce its policy rate by 375 basis points; from 10 percent in October 2014 to 6.25 percent in May 2016.6

However, as depicted in IREA trend in figure 2, the economy experienced lower growth momentum from 2018 till early 2020 period. This slowdown reflected the impact of policy measures that were introduced to counter the excessive external imbalances that emerged in late 2017 and 2018 period. In particular, PKR experienced significant declined in its value that help relieved the otherwise growing pressures on the already lower level of foreign reserves. To counter the spillovers from currency decline and its ensuing pressures on domestic prices, SBP started to raise the policy rate with large magnitude. Cumulatively, SBP increased the policy rate by about 750 basis points during 2018-19 period. Furthermore, to address the external payment pressures, the country entered into the IMF program in July 2019 and for the first time implemented market-based flexible exchange rate mechanism.

The IREA prominently reflects the impact of lockdowns due to COVID-19 pandemic on economic activity in Pakistan, particularly in Q2-2020. The impact can be observed in both level and on y/y basis. However, the ensuing V-shaped recovery in economic activity is also quite visible from figure 2. This recovery was further supported by significant expansion in monetary and fiscal stimuli, estimated to be of around 8 percent of GDP. Besides introduction of targeted refinance schemes to support employment and households, SBP sharply reduced its policy rate from 13.25 percent before the pandemic hit to 7 percent in the subsequent six months. It is important to note here that, in the absence of official national accounts data- which was available only on annual basis during the COVID shock, tracking economic activity through monthly IREA becomes quite important. This is because, as observed from figure 2, the subsequent economic recovery after FY20 remained quite sharp as annual real GDP growth averaged around 6 percent in FY21 and FY22. This strong growth, together with significant positive output gap, fueled inflation and external imbalances, and created notable policy challenges in subsequent years.

In FY23, the economy, which was already facing external challenges due to higher import growth amid adverse terms-of-trade shock after Russia-Ukraine war, also hit hard by the unprecedented floods. The resultant supply chain disruptions further fueled inflationary pressures and constrained economic activity. The later impact is as also depicted in monthly IREA in figure 2. To counter these pressures, SBP introduced several restrictive measures in addition to continue with monetary tightening, where the policy rate reached to historic high of 22 percent from 7

⁶ Since SBP target policy rate was introduced in May 2015, we use the difference in ceiling rate of SBP's interest rate corridor, which previously served as the policy signalling rate.

percent observed in September 2021. PKR also reported significant depreciation, especially in second half of FY23. In aggregate these measures weighed heavily on economic conditions as real GDP declined by 0.2 percent in FY23; the third contraction reported in country's economic history. However, in the ongoing FY24, figure 2 shows some gradual increase in monthly IREA, especially after withdrawal of earlier restrictive measures to curtail imports. However, unlike COVID, the pace of recovery remained gradual in the presence of tight monetary as well fiscal policy stance.

Nowcasting real GDP growth

Provided that the constructed monthly IREA indicates the underlying trend and turning points in the economic activity quite reasonably, in this section we will attempt to explore its qualities for nowcasting country's quarterly real GDP growth. For this, we first converted the monthly IREA to quarterly indicator using simple averages in order to compare it with trend in real GDP. We then normalized both the IREA and real GDP to scale both the variables in the same units. As depicted in **Figure 3**, the IREA is tracking the trend in real GDP quite closely in both levels and on y/y change basis.

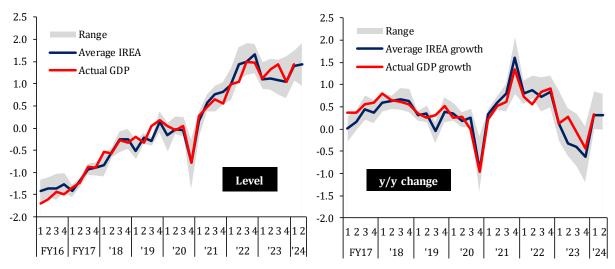


Figure 3: Indicator(s) of Real Economic Activity (IREA) and Trend in Real GDP, Normalized

Source: Authors' calculations

Note: Range reflects the six IREA versions estimated on monthly basis.

In particular, it could be visible from figure 2 that the IREA's tracking of real activity was quite significant up to FY22. From FY23 onwards, however, some deviations emerged between the IREA and in real GDP. In particular, unlike the trend in actual GDP, the IREA suggests significant impact of floods and other restrictive measures in slowing down the underlying economic activity during FY23. Apart from missing variables, one possible reason that may explain this deviation between the IREA and actual real GDP in FY23, is because of the way the latter calculated. Specifically, PBS calculates GDP using the accounting approach according to the international standards. However, due to data limitations, around 10 percent of GDP in Pakistan is having fixed growth on both quarterly and on annual basis. To some extent, this treatment shadows the

underlying trend in real activity and doesn't fully reflect the economic conditions, which otherwise depicted in monthly indicators. For the ongoing FY24, provided the ease in restrictive measures and post-floods improvement in agriculture sector, the IREA closely tracks the gradual uptick in the economic activity in Q1-FY24 and suggests moderation in real GDP growth during the second quarter.

For the nowcasting purposes, since the IREA is measured at monthly frequency and underlying real GDP is measured at quarterly frequency, we use the mix of empirical models. Specifically, we use the bridge and mixed-data sampling models, where the later branch of models is commonly referred as MIDAS. In the bridge models, we run the linear regressions that link high-frequency data to low-frequency data. The link is created by aggregating the high-frequency data. A simple bridge equation linking the monthly activity indicator to economic output is written as:

$$GDP_t = \alpha + \beta IREA_t^Q + \varepsilon_t$$

where IREA_t^Q represents the our monthly indicator aggregated to quarterly frequency, GDP_t denotes real GDP, α is a constant, β is the coefficient on the indicator, and ε_t is an error term. The aggregation scheme is usually a simple average of the monthly values within the corresponding quarter. In particular, bridge models are not standard macroeconometric models, since they do not specify a causal relationship; rather, they are justified by the statistical fact that the indicator contains timely updated information. For this reason, the bridge model technique allows early estimates of the low-frequency variable.

Unlike bridge models, the MIDAS is considering as a modern modelling approach, which directly relates high-frequency data to low-frequency data using frequency alignment rather than aggregation (Ghysels et al., 2004). Frequency alignment is an advantage of the MIDAS approach because aggregating high-frequency data can throw away potentially relevant information. Specifically, a simple MIDAS model can be written a:

$$GDP_t = \alpha + \sum_{i=1}^{q} \beta IREA_{t-i}^{M} + \varepsilon_t$$

where $IREA_t^M$ represents the monthly indicator appropriately aligned to quarterly frequency. As detailed by Foroni et al. (2015), the MIDAS model can be freely estimated or a polynomial, step or beta lag structure can be imposed. However, the later specifications are more suitable when modelling daily and weekly data.⁷

Based on the above classification of models, **Table 3** presents forecast evaluation statistics for the sample period of Q1-2023 till Q3-2023. It could be observed that, in case of bridge equation

⁷ For more details on MIDAS modelling, see Armesto et a. (2010)

models, IREA-6 performed relatively better than other versions of the activity indicator. Similarly, MIDAS modelling also indicate IREA-6 as a better predictor of economic activity than others.

Table 3: Forecast Evaluation Statistics and GDP Nowcast for Q2-FY24

	Indicator_1	Indicator_2	Indicator_3	Indicator_4	Indicator_5	Indicator_6
Bridge equation	•		•	•		•
MAPE	1.460	1.748	1.645	2.919	2.582	0.834
Theil U1	0.007	0.009	0.010	0.017	0.014	0.005
Theil U2	0.520	0.682	0.765	1.365	1.186	0.313
Nowcast, Q2-FY24						
q/q, %	-0.38	0.79	1.50	-1.27	1.17	0.45
y/y, %	0.52	1.70	2.42	-0.37	2.08	1.37
Weighted, q/q	0.41					
Weighted, y/y	1.32					
MIDAS method						
MAPE	0.071	0.087	0.107	0.143	0.161	0.087
Theil U1	0.004	0.005	0.007	0.008	0.009	0.005
Theil U2	0.457	0.586	0.883	1.119	1.253	0.562
Nowcast, Q2-FY24						
q/q, %	1.64	-1.01	-0.21	-2.53	-0.30	-0.08
y/y, %	0.75	0.12	0.69	1.65	0.60	0.82
Weighted, q/q	-0.18					
Weighted, y/y	0.73					
Memorandum item:						
Actual real GDP growth, ((2-FY24 (PBS data)					
q/q, %	0.01					
y/y, %	1.00					

Source: Authors' calculations, PBS

Note: Weights are calculated from inverse of Theil U1 statistics. MAPE is a mean absolute percentage error, also known as mean absolute percentage deviation. Theil U1 and U2 are measures of forecast accuracy, where lower values indicate better forecasting powers. Also, Indicator_1 and Indicator_4 are having variables adjusted for both price and seasonality; Variables in Indicator_5 are only adjusted for price effect; and variables in Indicator_3 and Indicator_6 are unadjusted for both price and seasonality.

Using the evaluation statistics for each IREA, the above **Table 3** also exhibit the nowcasts from both bridge and MIDAS models for the second quarter of the ongoing FY24. These nowcasts are then weighted according to the model performance discussed earlier. For instance, weighted q/q real GDP growth for Q2-FY24 is estimated at 0.4 percent according to bridge models and negative 0.18 percent as per MIDAS methods. The simple average of these two methods suggest a q/q growth of 0.12 percent. For the same period, PBS data shows a flat growth on quarterly basis. Similarly, the simple average of weighted y/y real GDP growth according to both nowcasting models stands at 1.1 percent, which is quite close to PBS calculated real GDP growth of 1.0 percent for Q2-FY24.

Overall, the nowcasting exercise cements the usefulness of high-frequency indicators to predict near-term growth in case of Pakistan with relatively higher precision. This will further improve the quality of policy input provided by the Bank staff for regular monetary policy

decisions. In particular, given the frequency of shocks have increase in recent years and on top off that climate change is also effecting the economic activity at various levels, such high-frequency measures provide timely information to policymakers for effective decisions.

V. Conclusion and way forward

In this article, we constructed a monthly high-frequency indicator of economic activity for Pakistan, IREA. For this, we use the most recent information from a range of monthly data releases to help decipher changes in economic activity. The monthly data on which the indicator is based are carefully selected to ensure they contain relevant and meaningful information on economic conditions in Pakistan. In this way, the constructed monthly activity indicators help provide timely information on state of the current business cycle and fill the gap associated with large lags involve in release of other official economic activity and national accounts data.

In addition, provided our monthly indicators closely track the development in real GDP, we also test their usefulness in nowcasting GDP growth for the reference quarter. Using the mix sample modelling approaches, ur results indicate a reasonable power of such indicators in predicting near-term growth. This will serve as an important input for the regular monetary policy decisions taken by the MPC at the SBP.

Going forward, this study provides the basic framework for the construction of much more disaggregated indicators to track sectoral developments. For example, in the next step, monthly activity indicators for key sectors like agriculture, manufacturing and services can be developed that will further enrich the policy input for the conduct of monetary policy. Moreover, learning from emerging literature, new data sets like payment system can also be integrated into such frameworks as research elsewhere shows that they also carry significant predictable qualities for the underlying economic activity.

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