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Nowcasting and Near-Term Forecasting Cambodia's Economy

Dyna Heng, Fei Han, Sovanney Chey, Raksmey Uch, Dy Kuchsa, and Pholla Phork

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Prepared by Dyna Heng, Fei Han, Sovanney Chey, Raksmey Uch, Dy Kuchsa, Pholla Phork*

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ABSTRACT: Assessing the current state of the economy and forecast the economic outlook in the next few quarters are important inputs for policymakers.This paper presents a suite of models with an integrated approach to forecast Cambodia's economy in the current and next few quarters. First, we estimate historical quarterly GDP using information extracted from high-frequency indicators to construct quarterly nowcasting model. Second, we forecast current economic activities using a high-requency data such as credit, export, tourist arrival, foreign reserves, and trading partner's GDP. Third, we present inflation forecasting models for Cambodia. Fourth, the paper present a vector autoregression model to forecast Cambodia's GDP in the next few quarters using global forecasts of China's and US's economy as well as oil and rice price. This paper showcase how high-frequency data set can be utilized in assessing current economic activities in countries with limited and lagged data.

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WORKING PAPERS

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Contents

Glossary

ARMA	Auto-Regression Moving Average
ARMAX	Auto-Regression Moving Average with Exogenous Variables
CDOT	Capacity Development Office in Thailand
CPI	Consumer Price Index
DFM	Dynamic Factor Model
GDCE	General Department of Customs and Exercise
GDP	Gross Domestic Product
FPAS	Forecasting and Policy Analysis System
MEF	Ministry of Economy and Finance
MIDAS	Mixed Frequency Data Sampling
NBC	National Bank of Cambodia
NTF	Near-term forecasting
OLS	Ordinary Least Squared
U-MIDAS	Unrestricted Mixed Frequency Data Sampling
VAR	Vector Auto-Regression
VARX	Vector Auto-Regression with Exogenous Variables

Executive Summary

We present a suite of forecasting models in an integrated approach to conduct nowcasting and near-term forecasting of Cambodia's economy, specifically, GDP and inflation. Nowcasting is the forecast of the present, helping policymakers assess the current state of the economy. Near-term forecasting assesses the economic outlook in the next couple of quarters. These tools together provide inputs to the macroeconomic frameworks used to check economic and accounting consistency in macroeconomics surveillance and to the medium-term forecasting and policy analysis system at the National Bank of Cambodia.

We propose an integrated four-step approach to produce these forecasts. In the first step, due to the lack of quarterly (real) GDP, we estimate historical quarterly GDP using information extracted from important high-frequency indicators considered to be closely related to economic activities, particularly monthly data on exports, credit, foreign reserves, and broad money. The results were discussed and iterated to capture key turning points of the Cambodian economy so far. The second step nowcasts current economic activities using high-frequency data on credit, exports of garment, and tourist arrivals, as well as quarterly GDP of Cambodia's largest trading partners (US, China and EU). The third step forecasts Cambodia's headline CPI inflation for the current quarter through a bottom-up approach: specifically, each key CPI component is forecasted for the current quarter and then aggregated to produce the forecasts for the headline CPI inflation. In the last step, we present Vector Autoregression (VAR) models to forecast jointly Cambodia's GDP and inflation in the next couple of quarters which should capture some of the feedback effects between the two variables. The VAR models also include some other important macroeconomic variables, particularly credit growth and exchange rate, and take the GDP nowcasts and inflation forecasts for the current quarter from the second and the third steps as the latest available "historical" data. Key foreign variables such as global commodity prices and key trading partners' GDP growth and inflation are also included as exogenous variables in the VAR models.

The exercise illustrated in this paper showcase how high-frequency dataset can be utilized in assessing current economic activities in countries with limited and lagged data, and to broadly forecast economic outlook a couple of quarters ahead. Despite the lack of innovative and timely data such as nightlight index and emission, our work shows that developing countries like Cambodia can still take the advantage of relatively high-frequency data for a timely macroeconomic assessment.

I. Introduction

Policymakers often need to assess the current state of the economy in real-time. For instance, when major events such as global financial crisis, sharp increases in oil price, and/or Covid-19 pandemic occurred, policymakers introduced intervention measures and counter-cyclical policies to alleviate the negative impact of these shocks to economic activities. These evidence-based policy actions require timely assessment on the state of the economy. On the other hand, real-time forecasting, which present macroeconomic outlook, is also a crucial foundation for macroeconomic policies, especially the forward-looking monetary policy decision-making.

Although the rise of digitalization provides more useful information on economic activities, macroeconomic data deficiencies and publication lags in many developing countries including Cambodia remain major challenges for making timely policy decisions. The data needed for timely analysis is often unavailable because of the publication lags or the mixed/incompatible frequencies of the key economic indicators. In many developing countries, the data compilation process *per se* faces quality issues with significant publication lags.

To elude the lack of and/or lags in data for economic assessment, many central banks and government agencies use nowcasting techniques, e.g., Bridge, Mixed-Data Sampling (MIDAS), Unrestricted MIDAS (U-MIDAS) and Dynamic Factor Models (DFMs), which are econometric methods to forecast the economy "here and now". Nowcasting relies on the idea that economic activities and business cycles can be captured by a small number of key high-frequency indicators (see, e.g., Giannone, Reichlin, and Small (2008)). Key central banks such as New York Fed, Bank of England, and Reserves Bank of Australia have been using nowcasting to assess the economy in real-time as key high-frequency indicators become available. Another common issue for some of the developing particularly low-income countries is the lack of historical quarterly (real) GDP data. In fact, many of these countries only have GDP available at the annual frequency. In this context, the idea of nowcasting low-frequency variables using high-frequency indicators can also be, and in fact has long been, used to estimate historical quarterly GDP based on annual GDP data (see, e.g., Chow and Lin (1971)).

Nowcasting models are generally reduced-form representation of the economy, which are ideal for producing more timely forecasts of low-frequency variables such as quarterly GDP. As most macroeconomic frameworks are constructed in annual data, the nowcasting and near-term forecasting (NTF) of quarterly GDP can helpfully provide insights on the economic assessment, especially when the assessment takes place in the middle or at the last quarter of the year. This exercise is also important for fiscal policy and public budget preparation, especially when policymakers need an update on macroeconomic assessment during public budget preparation and negotiation processes.[1]

We present a suite of forecasting model in an integrated approach to conduct nowcasting and near-term forecasting of Cambodia's economy, specifically, real GDP and inflation. Nowcasting is the forecast of the present, helping policymakers assess the current state of the economy, and near-term forecasting provides the economic outlook for the new couple of quarters. These tools together provide inputs to the macroeconomic frameworks used for macroeconomics surveillance and to the forecasting and policy analysis system (FPAS) at

[1] In many countries, budget preparation starts in first quarter of the year, which requires macroeconomic assessment and outlook to estimate budget envelope. During the budget negotiation among line ministries in June/July, usually another macroeconomic assessment and forecast is required to check that if the macroeconomic development and outlooks substantially change; in which case the budget preparation needs to be revised before submitting to the parliament for approval.

the National Bank of Cambodia (NBC). In other words, these tools help create a narrative about where the economy is and where it is headed in the near term.

We propose an integrated four-step approach to produce the nowcasts of (real) GDP that takes into account the information contained in the high-frequency indicators as well as the near-term joint forecasts of GDP and inflation that capture some of the feedback effects between the two variables. In the first step, due to the lack of quarterly GDP, we estimate historical quarterly GDP using information extracted from important high-frequency indicators considered to be closely related to economic activities, such as monthly data on exports and foreign reserves. The second step nowcasts current economic activities using high-frequency data on credit, exports of garment, and tourist arrivals, as well as quarterly GDP of Cambodia's largest trading partners (US, China and EU). The third step forecasts Cambodia's headline CPI inflation for the current quarter through a bottom-up approach: specifically, each key CPI component is forecasted for the current quarter and then aggregated to produce the forecasts for the headline CPI inflation. In the last step, we present Vector Autoregression (VAR) models to forecast jointly Cambodia's GDP and inflation in the next couple of quarters which should capture some of the feedback effects between the two variables. The VAR models also include some other important macroeconomic variables, particularly credit growth and exchange rate, and take the GDP nowcasts and inflation forecasts for the current quarter from the second and the third steps as the latest available "historical" data. Key foreign variables such as global commodity prices and key trading partners' GDP growth and inflation are also included as exogenous variables in the VAR models (VARX models).

The exercise illustrated in this paper showcase how high-frequency dataset can be utilized in assessing current economic activities in countries with limited and lagged data, and to broadly forecast economic outlook few quarters ahead. Our work shows that despite the lack of timely innovative data such as nightlight or emission data, developing countries like Cambodia can still take more advantage of monthly and quarterly data for a timely macroeconomic assessment.

Figure 1. Process for Nowcasting and Near-Term Forecasting (NTF)

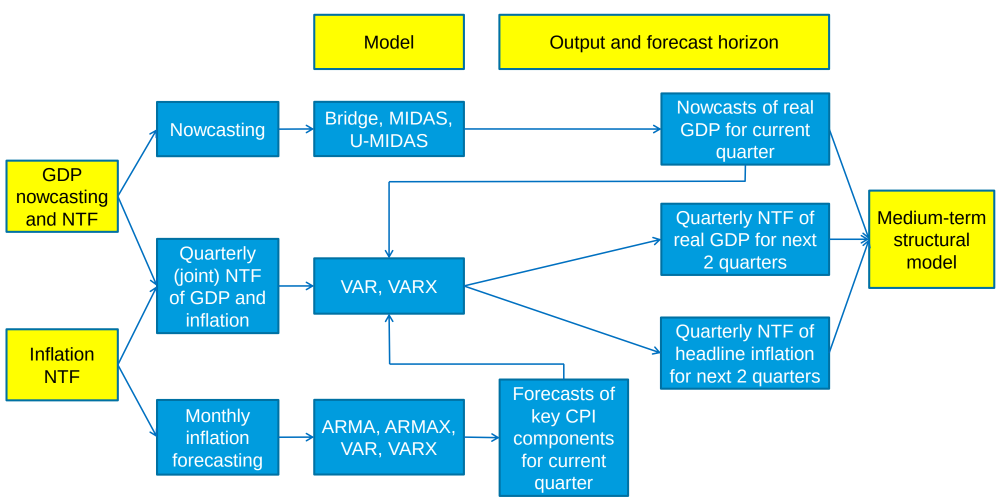


Figure 1 summarizes the process for nowcasting and near-term forecasting of Cambodia's GDP and Inflation. Nowcasting models (Bridge, MIDAS and U-MIDAS) estimate the quarterly GDP in the current quarter, while NTF models (VAR and VARX models) produce joint forecasts of GDP and inflation in the next couple of quarters (or near term).[2] Together, these tools complement each other in the assessment of the economy in the present and next two quarters ahead.

The paper contributes to the growing literature on nowcasting and empirical work in developing countries in several ways. First, we show an integrated approach of real-time nowcasting and near-term forecasting with an application to Cambodia, using a combination of models and tools to estimate key variables of interest for policymakers. Second, we showcase how developing countries can make better use of timely available high-frequency data to assess the current state of the economy in real-time as many new innovative big data such as nightlight data are not timely available for many developing countries. Third, given the importance of the high-frequency indictors in both the estimation of historical quarterly GDP (first step) and the nowcasting of current quarter's GDP (second step), we test the robustness of the by using different sets of high-frequency indicators in the two steps—assuming that these indicators are all driven by the same business cycle.

The paper is structured as follows. Section II discusses the key characteristics of Cambodia's economy, which sets the context for data and indicator selection in the subsequent sections. Section III presents the interpolation of quarterly GDP data. Section IV presents the methodology and results of nowcasting. Section V shift the focus to joint forecasting of GDP and inflation for the next two quarters. Section VI concludes and discusses potential future developments.

II. Key Features of Cambodia's Economy

As a small open economy, Cambodia's economic growth has been mainly driven by exports of garments and textiles, tourism and real estate and construction (Figure 2). Garment exports accounts for about 60 percent of total exports and about 1/3 of growth on average during 2003-2020 . Tourism and related services contribute about 15% of economic activities. Since the Covid-19 outbreak, there has been strong and robust growth in non-garment export such as travel goods, electronic components, and bicycles.

Cambodia's top export destinations are European Union (EU), the United States, and China (Figure 3). EU and US are the two largest export destinations of Cambodian products. China is a key source of foreign direct investment, input materials for production, and tourism until the Covid-19 pandemic (Figure 4). In particular, most input materials for Cambodia's garment exports are from China. China has also been a key development partner providing loans to public infrastructure projects in Cambodia. From the import perspective, Vietnam and Thailand are also important trading partners of Cambodia, particularly in terms of imported food and input materials.

On the back of capital inflows, Cambodia has sustained a stable exchange rate policy and accumulated a significant level of foreign reserves. The local currency, Riels, has been floating within a range of 4000-4200 Riels per US dollar since 2000 (Figure 5). Given the large share of imports in Cambodia's CPI basket, a movement in exchange rate can translate into higher inflation. However, given the stability of Riels, exchange rate has not been a major driver of inflation in Cambodia so far. Instead, we observe that inflation in Cambodia has been more associated with global commodity and energy prices, or inflation in two neighboring trading partners: Vietnam and Thailand (Figure 6).

[2] Near term in this paper refers to the next two quarters.

Figure 2: Key Drivers of Growth

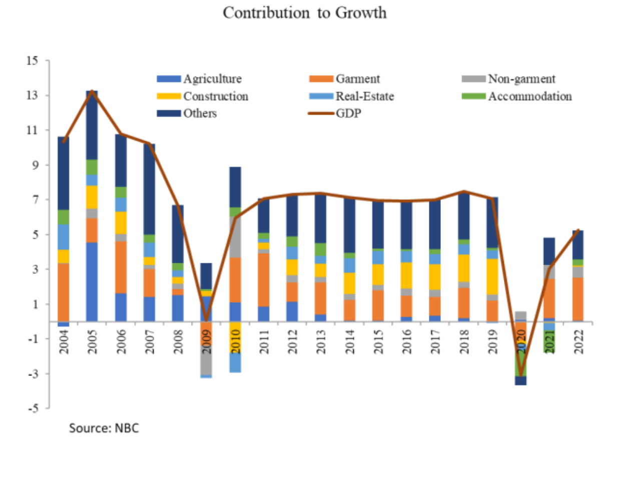


Figure 3: Key Export Destinations

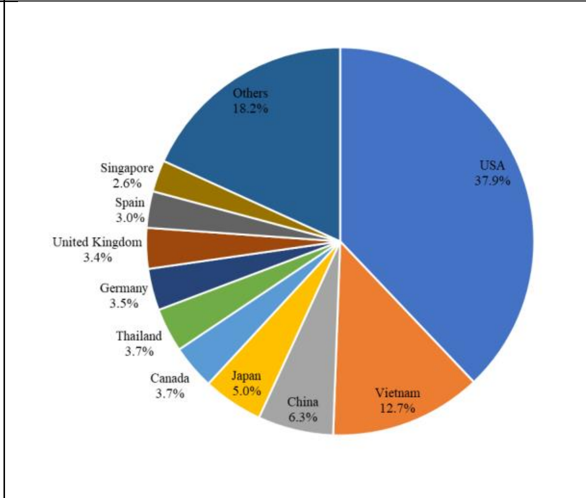


Figure 4: Key Importing Partners

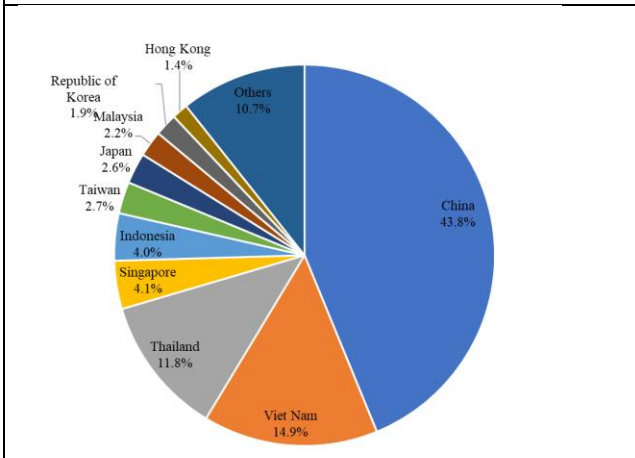


Figure 5: Exchange Rates and Reserves

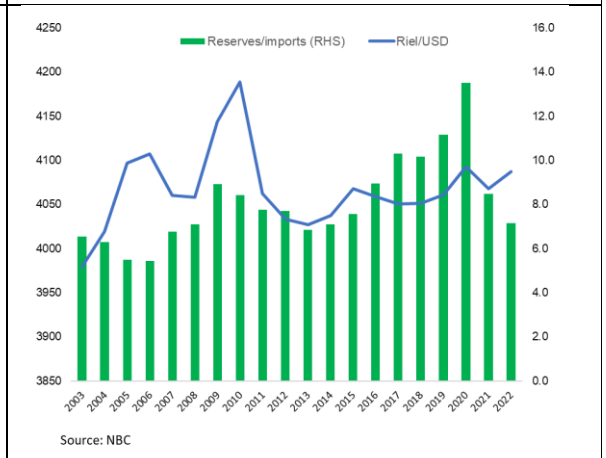


Figure 6: Inflation and Oil

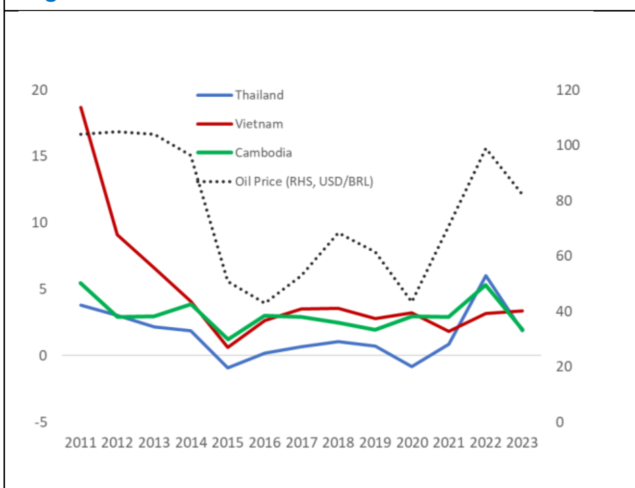
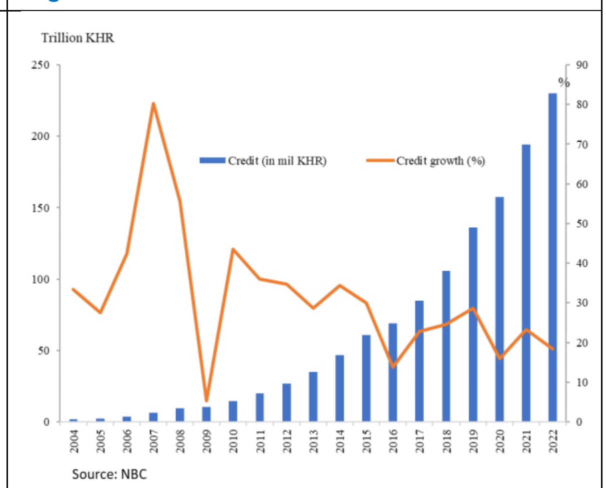


Figure 7: Private Credit and Growth



Despite nearly three decades of low inflation, Cambodia's financial system is highly dollarized. More than 80 percent of loans, deposits, and payments are denominated in US dollar. Foreign investors and tourists can use US dollar widely in economic activities and transactions along with the local currency. The high dollarization limits the scope and effectiveness of monetary policy options. The NBC can still influence credit growth and liquidity through reserve and capital requirements; nonetheless, the burden of macroeconomic management rests more on fiscal policy.

Like in many other developing countries, credit has been viewed as one of the most important monetary indicators by policymakers in Cambodia. The rapid GDP growth in Cambodia (except during Covid) has been associated with high demand for credit and fast credit growth which has been about 20 percent on average between 2000-2022, much faster than nominal GDP growth (Figure 6). In particular, credit has increased to more than 150 percent of GDP in 2023[3].

III. Estimating Cambodia's Quarterly GDP

The availability of quarterly (real) GDP data is a prerequisite for nowcasting. However, quarterly GDP data is not available yet in Cambodia. To address this issue until historical quarterly GDP data becomes officially available, we first estimate or interpolate historical quarterly GDP which is the variable of key interest in nowcasting models based on the annual GDP data.[4]

We interpolate quarterly GDP data by using information from high-frequency indicators that has strong co-movement with GDP. Intuitively, in this approach, we first examine correlation among these variables and GDP using annual data (Table 1). Then, assuming this correlation is linear, we use quarterly data of these high-frequency indicators to interpolate quarterly GDP data using annual GDP data. The sum of the four interpolated quarterly GDP in each year must be equal to the official historical annual GDP for that year. This regression-based procedure follows the Chow-Lin disaggregation method (Chow and Lin, 1971). However, we also check the robustness with the Litterman method (Litterman, 1983) which imposes different assumptions on the residuals from the regressions as the Chow-Lin method.[5] Appendix 1 provides a summary of the methods.

For this interpolation procedure, it is crucial to have a good selection of indicator series as well as proper application of the econometric models. In particular, the high-frequency indicators should reflect the quarterly movement of economic activities in Cambodia and should be available for the future periods. To test the validity of indicator selection, we include several high-frequency time series to the pool of indicator candidates and compare them in terms of their co-movement with annual GDP series. These additional candidates are imports of garment materials, exports of garments and textiles, and tourist arrival. Table 1 describes the main candidate variables considered. The selected high-frequency indicator series for quarterly GDP estimation need to be highly correlated with GDP and the correlation needs to be stable over time. Table 2 shows the correlation matrix among GDP and the key high-frequency indicators. We observe that exports of garments, foreign reserves, and private credit have high correlations with real GDP.

[3] The ratio is based on old GDP data.
[4] It should be noted that the availability of quarterly GDP data series, the assessment of current state of the economy (nowcasting) and in the near term (near-term forecasting or NTF), and satellite models for sectoral analysis are key components of a Forecasting and Policy Analysis System (FPAS) which the NBC is embarking on.
[5] The two econometric methods differ in their assumptions on the residuals of the linear relationship. The Chow-Lin method assumes that the residuals follow an AR(1) process while the Litterman method, which is a generalized method of Fernandez (1981), assumes that the residuals follow a random walk, thereby allowing the process to be non-stationary.

Table 1 High Frequency Indicator Candidates

	Frequency	Series Start Year	Source
Exports	Monthly	2002	NBC/GDCE
Imports	Monthly	2002	NBC/GDCE
Broad Money	Monthly	2002	NBC
Credit to Private Sector	Monthly	2002	NBC
Government Expenditure/Revenue	Monthly	2002	MEF
China GDP	Quarterly	2000	IMF
US GDP	Quarterly	2000	IMF
EU GDP	Quarterly	2000	IMF
Real Effective Exchange Rate	Monthly	2000	NBC

Table 2: Correlation Matrix

(Real variables in percent change, yoy)

	RGDP	M2	EXP_GMENT	EXP_RICE	IMP_GMT	IMP_OIL	CREDIT	RESERVES
RGDP	1.0							
M2	0.1	1.0						
EXP_GMENT	0.5	0.0	1.0					
EXP_RICE	-0.2	-0.2	0.1	1.0				
IMP_GMT	0.4	0.3	0.8	0.2	1.0			
IMP_OIL	0.0	0.0	0.5	0.2	0.2	1.0		
CREDIT	0.5	0.3	0.4	-0.2	0.3	0.2	1.0	
RESERVES	0.1	0.6	-0.1	-0.2	0.0	-0.1	0.3	1

Note: headline CPI is used to derive real variables. Variables are in year-on-year percent change.
Source: Authors' estimate; data from authorities

The correlation matrix points to six potential candidate variables: broad money (M2)[6], exports, imports, private credit, tourist arrival, foreign reserves, and China GDP. We also run regressions to check the robustness of the correlation (the results are in Annex 1). Although many variables are correlated with Cambodia's GDP, we may not want to include them all as underlying data for interpolation. One important concern is that variables that are used for interpolation would automatically become statistically significant in the nowcasting models by design. To alleviate this concern, we would want to minimize the number of variables without changing much the historical estimate of quarterly GDP while keeping the remaining key variables for the nowcasting model development later. Therefore, among the high-frequency variables, we use a subset for interpolation and a separate subset for developing the nowcasting models.

We first interpolate quarterly GDP series based on individual high-frequency indicators. It should be noted that the selected high-frequency variables, before being used to interpolate the GDP data, are first converted to real variables by using monthly CPI as the deflator and then seasonally adjusted using the X-13 procedure[7].

[6] Deposit and narrow money were also used to interpolate and the results are not different from the broad money.
[7] Using interpolated monthly deflator would not change the results.

The interpolated quarterly GDP series based on either one of the three variables—broad money, credit, and tourist arrival—are similar, so we can use just one variable (say, broad money) for the interpolation, instead of all the three variables (Figure 8). Meanwhile, the interpolated GDP series based on foreign reserves or imports also look similar (Figure 9). Moreover, the pattern for the interpolated series based on exports also looks similar despite exhibiting a higher volatility. Through this process, we can narrow down the high-frequency indicators to three variables, i.e., foreign reserves, broad money, and exports, which generate slightly different patterns in the interpolated real GDP (Figure 10). One approach is to use the average of the three interpolated series based on each one of these three variables (DL4RGDPM1 in Figure 11), which actually shows a similar pattern to the interpolated series based on foreign reserves alone (DL4RGDP1 in Figure 11). This may seem a bit counterintuitive but is actually reasonable, as foreign reserves are an indicator that is supposed to summarize the net effects of exports, imports, investment, and government expenditures. This exercise confirms that the interpolated series based on foreign reserves is similar to the average of the interpolated series based on the key underlying indicators (foreign reserves, broad money, and exports).

One issue in the interpolation with the selected underlying indicators above is that, if the high-frequency variables used in interpolation overlap with those used in the nowcasting models, then those variables would be statistically significant by design since such overlapping variables are used in both interpolation and nowcasting of quarterly real GDP. On the other hand, one could also argue that the variables included in the nowcasting models should also be included in the interpolation as they are important predictors of real GDP. To mitigate this issue, we also use non-overlapping variables in the interpolation and nowcasting models—which serve as a robustness check in addition to the interpolation obtained above using foreign reserves, broad money, and exports. Since the interpolation results based on some of the high-frequency variables point to very similar patterns (as shown in Figures 8-10), we narrow down the variable selection for interpolation to two key variables to avoid the overlapping issue: imports and broad money.[8] We also check the robustness of the historical quarterly GDP estimates based on the Chow-Lin approach and the Litterman approach. Table 3 shows the list of different underlying indicators and the methods used, and the results are presented in Figure 14 with the average shown in thick blue color. RGDP1 is the interpolated RGDP based on the key indicators that capture the key drivers of the Cambodian economy in the past. RGDP2 interpolation is based on a smaller set of indicators (imports and broad money) so that the variables used for interpolation do not overlap with variables used in the nowcasting model in the next section (Table 3). The pattern of the two interpolated RGDP series are quite similar (Figure 14), except a 2021Q2 and 2021Q3. This small difference is largely driven by the tourist recovery.

Once the initial quarterly GDP data is interpolated, we examine the GDP growth and output gap[9] with the NBC sectoral experts to make sure that the interpolated GDP data captures important historical events and key turning points. We reiterate the process with additional variables and check the robustness of the estimates. It should be emphasized here that the final selection of the indicators and estimation methods should be based on sectoral experts' assessment at the NBC, Ministry of Economy and Finance (MEF), and National Institute of Statistics (NIS) to ensure consistency with historical economic events. For instance, the interpolated historical GDP data seems to have captured well the impact of the global financial crisis on Cambodia, as well as the impact of the Covid-19 pandemic based on the lockdowns inside and outside the country.

[8] It is worth noting here that, as explained below, private credit, exports, tourist arrival, and foreign reserves are used as the high-frequency indicators in the nowcasting models.

[9] Output gap was estimated using Hodrick-Prescott (HP) filter with a lamda of 1600. To address end-point bias we include forecasting period into the sample.

Figure 8: Interpolation with Broad Money, Credit, or Tourist Arrival	Figure 9: Interpolation with Foreign Reserves, or Imports

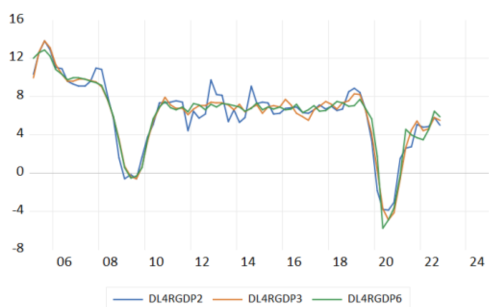
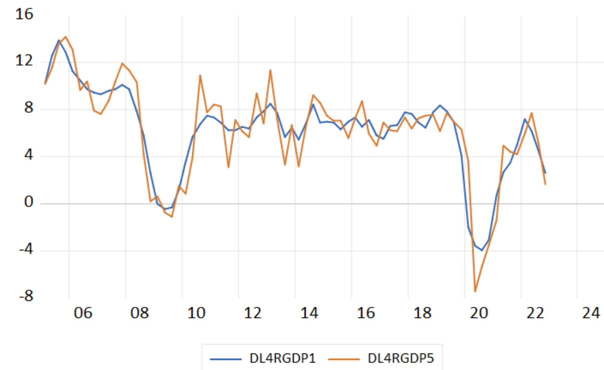

	

Figure 10: Interpolation with Foreign Reserves, Broad Money, or Exports	**Figure 11: Interpolation with Average of Foreign Reserves, Broad Money, or Exports**

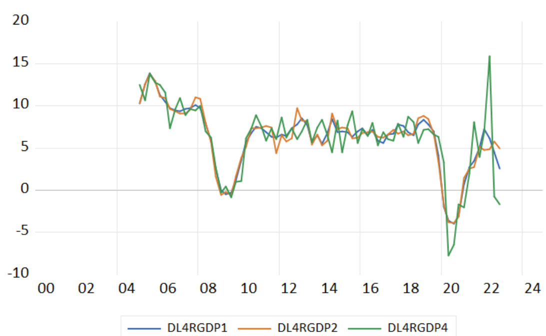
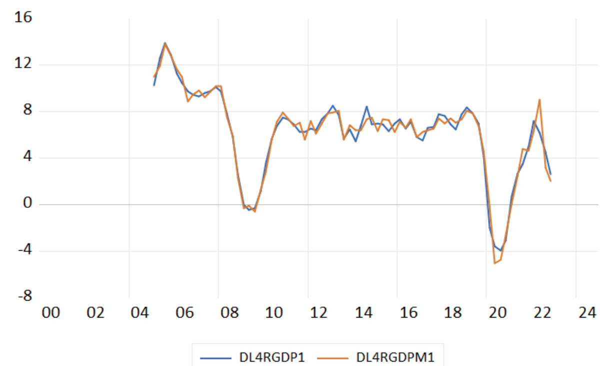
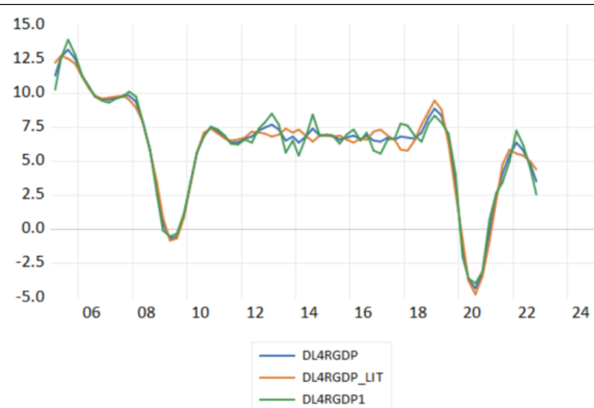
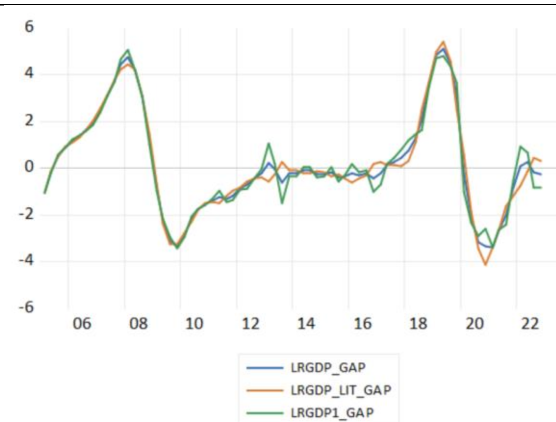

	

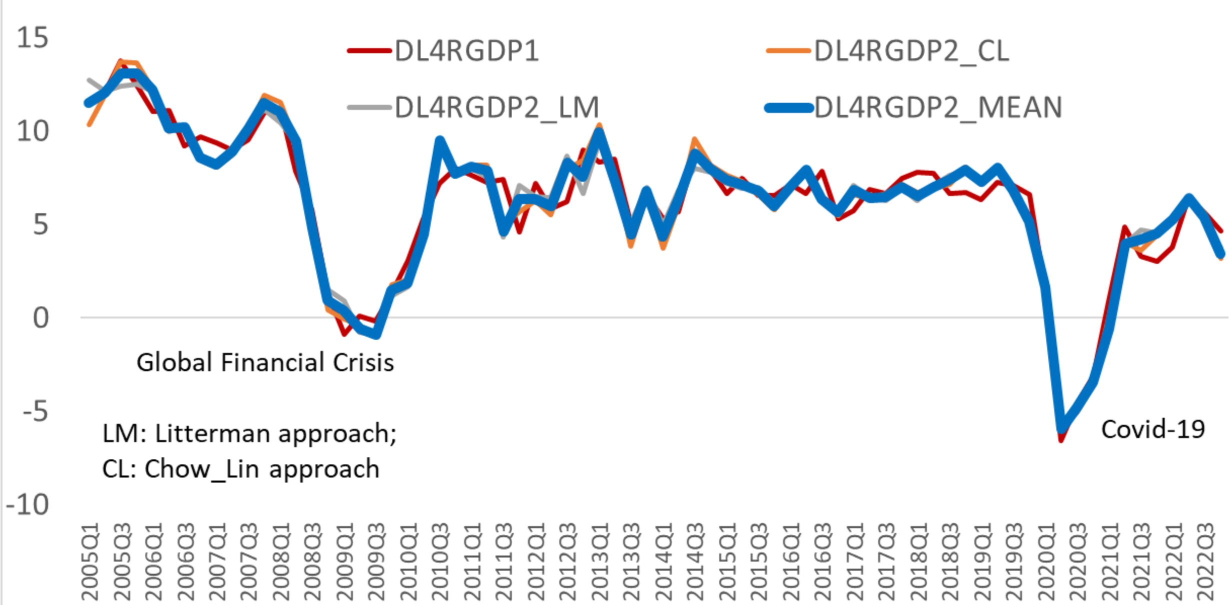
Figure 12: Quarterly GDP Growth	**Figure 13: Output Gap**
	

Finally, in this paper, after consulting with the authorities, we opt to use quarterly RGDP1 (interpolation with foreign reserves, broad money, and exports) as the baseline interpolated real GDP for two main reasons: i) the key drivers of the economy in the past should be included in the interpolation, and ii) the results are more consistent with the authorities' real sector insights.

Table 3: Robustness Check in Interpolation

Interpolated GDP	Underlying High-Frequency Indicators	Independent Variables for Nowcasting Models in next section
RGDP1	Foreign Reserves, Private Credit, Tourist Arrival	First lag of RGDP, key trading partner's RGDP, Private Credit, Exports, Tourist Arrival, and Foreign Reserves.
RGDP2	Imports and Broad Money	

Figure 14: Historical Quarterly GDP Estimates



Source: Authors

It should be noted that at the time of finalizing this paper, the NIS of Cambodia just published the newly rebased annual GDP data for 2000-2022, which is overall about one-third higher than the old GDP data used in the previous interpolations. That said, in terms of growth rate, the new GDP data is not much different from the old one. We discuss the new GDP data and its effect on the interpolation, nowcasting models and GDP nowcasts in Annex V.

IV. Nowcasting GDP

Several approaches have been used to nowcast Cambodia's (real) GDP. These include Bridge equation (e.g. Rünstler et al., 2009), MIDAS (Clements and Glvao, 2007), Mixed frequency Factor Models (e.g. Giannone, Reichlin and Small, 2008), and machine learning models (e.g. Baroumi et al. 2010). Overall, the nowcasting models can be classified into univariate (e.g., Bridge, MIDAS, and U-MIDAS) and multivariate models (e.g., mixed-frequency VAR and DFMs).

For example, the Federal Reserve Bank of St-Louis uses forecasting approach with mixed frequencies to nowcast quarterly GDP growth of the US. The Federal Reserve Bank of Atlanta developed "GDPNow", a nowcasting model for the U.S. GDP growth that uses the Bridge equation approach. The New York Fed also produces nowcasts of quarterly GDP growth using a wide range of macroeconomic data as they become available through a DFM approach. These approaches all read the real-time flow of information and evaluate its effects on current economic conditions. The Bank of English (BOE) nowcasts global GDP growth employing a suite of models (MIDAS, DFM, Bayesian VAR) with a wide range of high-frequency data and uses the key outputs of these nowcasting models into the Monetary Policy Committee's assessment of the UK economy. The BOE's data include soft data (surveys of economic conditions such as purchasing manager indices), hard data (e.g., trade and retail sales), and market data (e.g., interest rates, exchange rates, and commodity prices).

For econometric techniques, this paper uses relatively simpler univariate methods given the current technical capacity at the NBC: the Bridge equation, MIDAS and U-MIDAS. The Bridge model (see, for example, Baffigi et al., 2004) relies on linear regressions that link ("bridge") high-frequency explanatory variables (e.g., monthly data on exports) with the low-frequency target variable (e.g., quarterly GDP). Because of its simplicity and transparency, numerous policy institutions have used bridge equations to guide policy decisions (e.g., the Federal Reserve Bank of Atlanta (GDPNow), Federal Reserve Bank of San Francisco (Ingenito and Trehan, 1996), Euro Area (Baffigia, Golinellib and Parigia, 2004), and Norges Bank (Foroni and Marcellino, 2013)).

The MIDAS model (see, for example, Clements and Galvao, 2008) is a reduced-form regression in which data are available at different frequencies (Ghysels, Sinko and Valkanov, 2007). To prevent the parameter proliferation issue arising from the different frequencies (see below), the MIDAS model uses the so-called distributed lag polynomials that depend on a smaller number of parameters. The MIDAS approach is often used in the case of large frequency mismatches, for example, when using daily indicators to nowcast a quarterly variable. In the case of relatively small frequency mismatches (e.g., using monthly indicators to nowcast a quarterly variable), the Unrestricted-MIDAS (U-MIDAS) model tends to perform better than MIDAS (see, for example, Foroni, Marcellino and Schumacher, 2012)).

In other words, the Bridge model basically produces a forecast by initially converting all the high-frequency indicators, e.g., by summing or averaging, to the target (low) frequency or the frequency of the target variable such as GDP. Some dynamics of the high-frequency variables might be lost due to this conversion (Baffigi et al., 2004; Foroni and Marcellino, 2013). Under MIDAS and U-MIDAS, the high-frequency variables are converted to the target frequency using the "skip" or "split" sampling rather than averaging or summing. These converted variables (and their lags) are added to the model, allowing them to have different parameters unlike the case of summing or averaging. However, this creates the so-called "parameter proliferation" problem with too many parameters to estimate.

Under MIDAS, the parameters of the split/skip-sampled variables are assumed to follow a specific functional form (e.g., a polynomial function) that depends on fewer parameters, thereby reducing the overall number of parameters to estimate. The drawback is that ordinary least squares (OLS) cannot be applied due to the nonlinear functional form of parameters and that the assumption of the functional form could be wrong (Ghysels et al., 2004; Clements and Galvão, 2009). On the other hand, in U-MIDAS models, these variables are added to the base forecasting model directly without any restrictions on the shape of their associated parameters. Thus, OLS can be applied to estimate U-MIDAS models. However, the drawback of U-MIDAS models is that there are too many parameters to be estimated and hence the frequency mismatch between the target variable and the high-frequency indicators cannot be too large (Foroni et al., 2015). Other approaches such as Bayesian approaches (Akbal et al. 2023, Cimadomo et al. 2022) has also been used to mitigate the effect of reduced predictive weight of high-frequency indicators relatively to the interpolated historical quarterly GDP growth. The Bayesian approaches address the issue that nowcast estimates could be "overly" aligned with the GDP trend, in particular when high-frequency indicators signal sudden cyclical shifts that are weakly correlated with the historical trend.

To nowcast Cambodia's quarterly GDP, the monthly indicators are converted to quarterly data, using the sum or average of the observations in the quarter based on their stock or flow nature. The Bridge model is then estimated using OLS. If the monthly indicators have publication lags, we use an auxiliary regression to forecast the high-frequency indicators so that each quarter has a complete set of high-frequency values.

As explained in the following section, developing the nowcasting model involves (i) selecting predictors based on the key economic variables that are meaningful and useful to forecast GDP, (ii) model evaluation and selection based on the econometric techniques, and (iii) nowcasting exercise to test the validity of the model over time. The process is regularly repeated to finetune the nowcasting models.

A. Selecting Predictors

To choose the appropriate regressors, we first examine the correlation among real quarterly GDP (the dependent variable) with the potential candidate indicators such as: Exports, tourist arrival, private credit, and foreign reserves. The insights on the key drivers of the Cambodia's economy and on the data quality and availability discussed in Section II help identify the potential regressors.

The inclusion of the right-side variables or indicators in the Bridge model is not based on causal relations (as compared to a structural model), but on a pre-assessment or prior that they contain timely updated information on the future direction of the dependent variable (e.g., real GDP). The inclusion of specific explanatory indicators is not based on causal relations alone, but also on the statistical fact that they contain timely updated information. Dropping or keeping variables involve the process of running the regression and compare the models based on a number of selection criteria: Root Mean Squared Error (RMSE), Akaike Information Criteria, and R Squared.

We examine the data for unit roots, conduct seasonal adjustment, and convert monthly to quarterly data. First, key variables are transformed to growth rate (quarter on quarter). Moreover, to ensure the stationarity of the variables in the OLS regression, we apply the Augmented Dicky-Fuller unit root test to each variable. All variables in growth rate are stationary (i.e., the test rejects the null hypothesis of a unit root).

Second, when observed a seasonal pattern, we conduct seasonal adjustment on the variables using the X-13 seasonal adjustment procedure (U.S. Census Bureau, 2022) as required to seasonally adjust the series. Third, all the selected RHS variables have monthly frequency. As the target variable is quarterly GDP, we convert the high-frequency indicators from monthly to the quarterly frequency. For the Bridge model, we use the aggregation approach by summing or averaging the monthly data based on the nature of the indicators, i.e. "sum observation" for "flow" variables and "average observation" for "stock/index" variables.

B. Evaluating and Selecting the Models

This section lays out the specification, evaluation, and selection of the models. As mentioned above, we use relatively simpler approaches: The Bridge equation, MIDAS, and U-MIDAS models. The Bridge model is specified as:

$$y_{t_q} = \alpha + \sum_{i=1}^{j} \beta_i(L) x_{it_q} + u_{t_q}$$

y here is the seasonally adjusted quarter-on-quarter GDP growth. x are the high-frequency indicators such as private credit and exports, which are aggregated to quarterly according to their stock/flow nature. t_q indicates time in quarter. $\beta_i(L)$ are polynomials in the lag operator *L*. u_{t_q} *is an i.i.d. error term. j* is the number of high-frequency indicators. The lag length of $\beta_i(L)$ is often set to zero, so that $\beta_i(L) = \beta_{0i}$, which implies that the model is static and helps with the economic interpretation of the results. In this paper, lag length is chosen based on the Akaike information criterion. As the Bridge equation is linear, OLS estimation is optimal, and the optimal nowcasts/forecasts can be obtained by replacing the unknown parameters with the OLS estimates.

The MIDAS/U-MIDAS model is specified as following:

$$y_{t_m} = \alpha + \sum_{i=1}^{j} \beta_i x_{it_m} + \sum_{i=1}^{j} \beta_i x_{it_{m-1}} + \sum_{i=1}^{j} \beta_i x_{it_{m-2}} + u_{t_m}$$

x_{it_m} is the first skip-sampled quarterly high-frequency variable, and $x_{it_{m-1}}$ and $x_{it_{m-2}}$ are the second and third skip-sampled variables. "skip-sampling" refers to selecting a specific sequence of months to create the right hand side x variables. In other words, for monthly to quarterly data conversion, instead of averaging or summing up the monthly variables into quarter, the model use value of the variable for each month as a value for that quarter. For instance, we would take the following observations in the monthly data: 1, 4, 7, 10,… (thereby skipping 2 and 3, 5 and 6, etc.)

It should be noted that while the MIDAS approach is often suitable as it uses distributed lag polynomials that depend on a smaller number of parameters (to address parameter proliferation issues). By contrast, the unrestricted MIDAS model (U-MIDAS) is often used when the frequency mismatch is small. U-MIDAS generally performs better than MIDAS when mixing quarterly and monthly data, which is the frequency used in this paper.

Unlike MIDAS, U-MIDAS does not use functional distributed lags. We convert the higher frequency indicators to quarterly frequency using split-sampling.

Table 4: Robustness Check, Bridge Regression Results

(QoQ, Growth rate)

VARIABLES	(1) RGDP1	(2) RGDP2_CL	(3) RGDP2_LM	(4) RGDP2_MEAN
One Lag	0.148*	0.241***	0.201*	0.199*
	(0.083)	(0.069)	(0.114)	(0.116)
GDP_China	0.002***	0.001**	0.001*	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
GDP_US	0.001	0.002	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Private Credit	0.051	0.013	0.009	0.009
	(0.036)	(0.050)	(0.047)	(0.048)
Reserves	0.096***	0.082**	0.033*	0.058**
	(0.023)	(0.031)	(0.029)	(0.029)
Exports	0.081***	0.043*	0.042*	0.042*
	(0.017)	(0.023)	(0.022)	(0.022)
Tourist	0.015***	0.011**	0.007*	0.009*
	(0.004)	(0.005)	(0.005)	(0.005)
Crisis	-0.006	-0.006	-0.007	-0.006
	(0.005)	(0.006)	(0.006)	(0.006)
Constant	0.001	0.006	0.008**	0.007*
	(0.003)	(0.004)	(0.004)	(0.004)
Observations	74	74	74	74
R-squared	0.701	0.464	0.452	0.470

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 summarizes the key conclusions in the model estimate. Using the data from 2004Q1 till 2022Q2 for estimation period, we observe that the coefficients of exports, tourist arrival, private credit, foreign reserves, and China real GDP are positive and statistically significant in all the regressions: Bridge, MIDAS, and U-MIDAS. This is intuitive as these variables are the key drivers of the economy. The coefficients of the US or EU GDP growth are positive but not statistically significant. This is also in line with expectation since the US and EU are key export destination of Cambodia's product, and thus are highly correlated with the export variable. Dropping exports from the regression, the US or EU GDP growth would become statistically significant. For the model selection, we keep the exports variable as it is the indicator that can be obtained on a monthly basis from the General Department of Custom and Exercise. These models look reasonable as they capture the key drivers of the economy, and the right-hand side variables can be obtained or estimated timely as the NBC and MEF staff have access to these data on a monthly basis. The model estimates are summarized in Table 5.

Table 5: Summary of Nowcasting Models

	Dependent Variable: DLOG(RGDP)		
	BRIDGE	MIDAS	U-MIDAS
One Period Lag	(+)*	(-)***	(+)
DLOG(RGDP_China)	(+)***	(+)***	(+)*
DLOG(RGDP_US)	(+)	(+)***	(+)
DLOG(Credit)	(+)	(+)	(+)
DLOG(Exports)	(+)***	(+)**	(+)***
DLOG(Reserves)	(+)***	(+)**	(+)***
DLOG(Tourist)	(+)***	(+)***	(+)***
Crisis	(-)	(-)**	(-)**
R Squared	0.701	0.73	0.68
Akaike Information Criteria	(6.36)	(6.70)	(6.38)
Durbin-Watson Statistics	2.19	2.03	2.14

Source: Authors' estimates

* indicates 10 percent, ** 5 percet, and *** 1 percent, respectively.

Figure 15A: Forecast Comparison

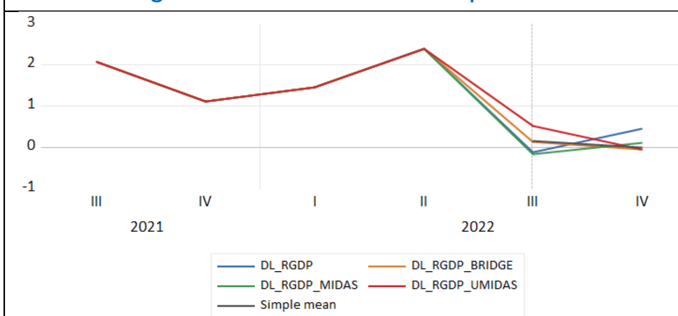


Table 15B: Year on Year Comparison

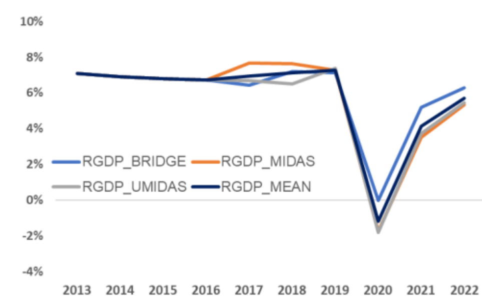


Figure 16A: Nowcast the Turning Point (Covid-19, QoQ)

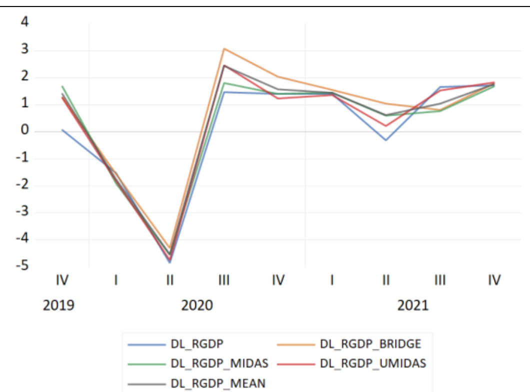
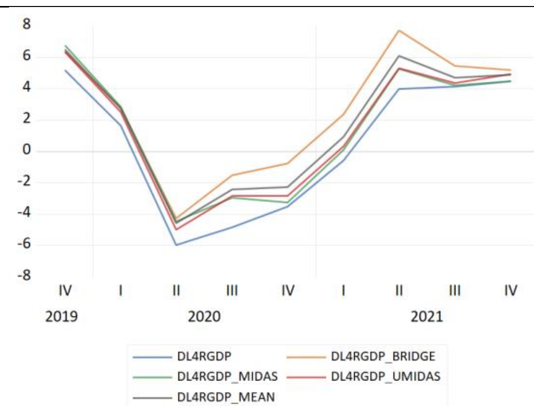


Figure 16B: Nowcast the Turning Point (Covid-19, YoY)



To test the validity of the models, we conduct pseudo out-of-sample forecast evaluation (Figure 15A) for the period 2022Q3-Q4 and check the performance of each model. Since the interpolated quarterly real GDP is also an estimate of the actual underlying data, we also conduct forecast evaluation by converting the quarterly nowcasts to annual nowcasts and comparing them with the actual annual real GDP data (Figure 15B). To obtain meaningful statistics, we extend the annual evaluation period to 2017-2022. Overall, we observe that the nowcasts perform broadly fine, with U-MIDAS having the best statistics in terms of RMSE. We also run the in-sample forecast to check if the model captures the key turning point. As shown in (Figure 16A and 16B), our model can capture well the turning point during the Covid-19 pandemic due to a significant drop in tourist arrival and exports. It should be noted here that the models need to be evaluated and finetuned regularly when new datasets become available.

C. Nowcasting Cambodia's GDP

Based on the model selection in the previous section, we shift focus to nowcast Cambodia's GDP for 2023Q1 and 2023Q2 as an illustration. After model evaluation and selection based on the sub-sample until 2022Q2, we re-estimate the model with full sample (until 2022Q4), taking advantage of the full dataset. The nowcast estimates of real GDP for 2023Q1 suggest a softening in economic activity, but the growth momentum is slightly picking up in Q2. On a year-on-year basis, the real GDP growth is estimated to slightly decelerate to 4.3 percent in 2023Q1 and is projected to rise slightly in Q2 (4.6 percent). For 2023Q2, the growth was mostly driven by a rebound in tourist arrival and exports despite the slowdown of China's growth.

Figure 17: Growth Forecast (QoQ)

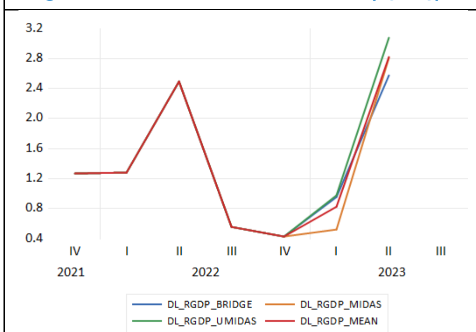


Figure 18: Growth Forecast (YoY)

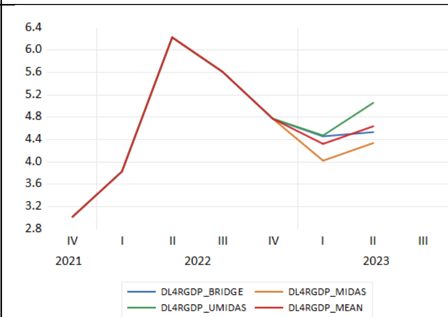
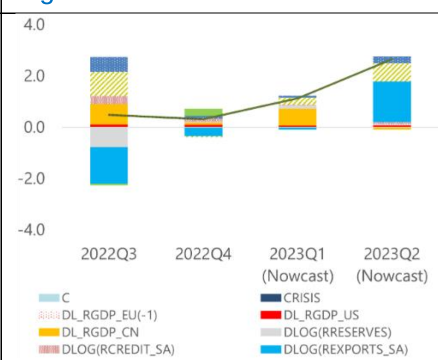


Figure 19: Growth Forecast[10]

Figure 20: Growth Contribution



[10] Note: The different green shades represent the 30th-, 60th-, and 90th-percentiles. The blue line denotes the median (50th-percentile) forecast.

V. Near-Term Joint Forecasting of GDP and Inflation

This section discusses the approach to produce the *joint* forecasts of (real) GDP and inflation—the key variables of interest to the NBC—for the next two quarters (near term). Compared to the GDP nowcasting, joint forecasting of both GDP and inflation takes into account important feedback effects between the two variables. We take a two-step approach in doing so: the first step forecasts the monthly inflation for the remaining months of the current quarter and the second step takes the inflation forecast and GDP nowcast for the current quarter as initial conditions to jointly forecast GDP and inflation for the next two quarters. The first step can be skipped if the actual inflation data are already available for the current quarter.[11]

A. Monthly Inflation Forecasting

This section lays out the suite of models for forecasting monthly headline CPI inflation in Cambodia for the current quarter, i.e., the first step. Once the monthly inflation forecasts are obtained for the current quarter, they are then converted to quarterly forecast for the current quarter to prepare for the joint forecasting of near-term GDP and inflation. For the specific exercise, since we already have inflation data until June 2023, we will skip the first step and use the GDP nowcasts for 2023Q1 and Q2 obtained in the previous section and the actual inflation data until 2023Q2 to jointly forecast GDP and inflation for 2023Q3 and Q4.

For the forecasting of headline CPI inflation in Cambodia, we use a bottom-up or disaggregate approach where headline CPI is broken down into three components, i.e., food CPI, oil-related CPI, and core CPI. Each of these three CPI components is likely to be driven by different factors. For example, the food CPI is likely to be affected more by the global food prices, particularly rice prices in the case of Cambodia, while the oil-related CPI is more driven by global oil prices. Therefore, we model and forecast each of these three components separately using selected exogenous variables that appear to be key drivers of the corresponding CPI component in Cambodia. The most important foreign variables included are changes in the global food (or rice), energy (or oil), and fertilizer prices, as well as inflation in Cambodia's key trading partners, i.e., China, Thailand, the U.S. and Vietnam. Table 7 shows the correlation matrix between the three CPI components and these foreign variables, where the historical global commodity price data are mainly obtained from the IMF's Primary Commodity Price System (PCPS)[12] and the trading partners' inflation data from respective country authorities' websites. Clearly, food CPI inflation is highly correlated with Vietnam CPI inflation, oil-related CPI inflation is highly correlated with global rice and oil prices, as well as inflation in key trading partners, while core CPI inflation is highly correlated with global energy prices and Vietnam CPI inflation. In addition, it is also worth noticing that the food CPI inflation is also highly correlated with core CPI inflation, likely suggesting a high pass-through from food prices to core prices.

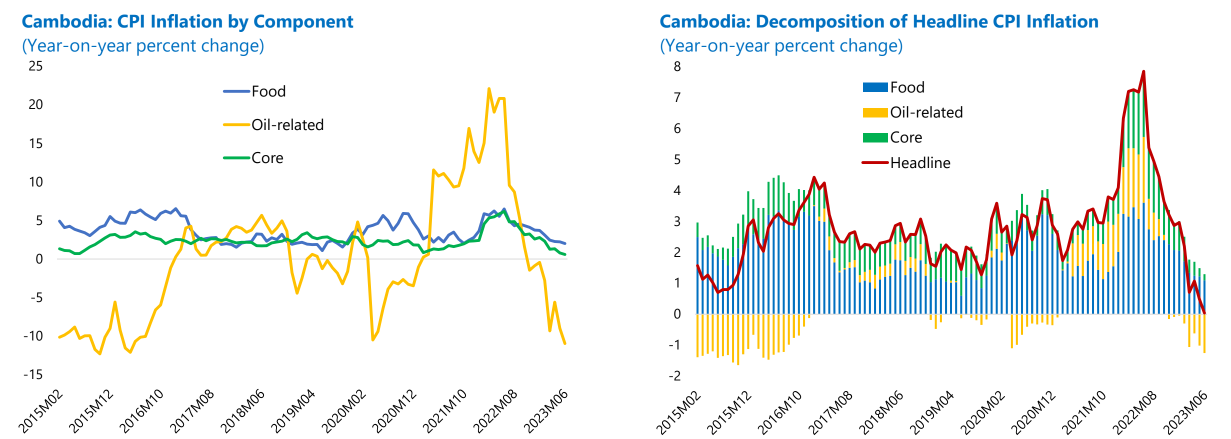
[11] For example, say we are in July, and have historical inflation data until June and have produced GDP nowcasts for Q2, then we can skip the first step and forecast jointly GDP and inflation for Q3 and Q4. But if we are in September and have actual inflation data until August and have produced GDP nowcast for Q3, then we will need to forecast the monthly inflation for September in the first step and then jointly forecast GDP and inflation for Q4 and Q1 next year in the second step.
[12] With the exception of global fertilizer prices which are obtained from the World Bank's Commodity Markets Outlook (CMO) database as it also provides forecasts for such prices.

Figure 21 shows the historical CPI inflation components and the headline inflation decomposition by components (y/y). We observe that i) the oil-related inflation has been much more volatile than food or core inflation, while all three components of CPI have declined (in y/y terms) since mid-2022; ii) the recent high inflation episode in the first half of 2022 was mostly drive by the increase in food and core inflation; and iii) the faster decline in core inflation than food inflation since mid-2022 seems to be in line with the slowdown in economic activities. As mentioned earlier, since the GDP nowcasts are only available until 2023Q2, there is no need to forecast inflation in this exercise.

Table 7: Correlation in Percent Change in Prices

	CPI_FOOD	CPI_OIL	CPI_CORE
CPI_FOOD	1.0	0.3	0.7
CPI_OIL	0.3	1.0	0.2
CPI_CORE	0.7	0.2	1.0
P_FOOD	0.2	0.4	0.1
P_ENERGY	0.5	0.1	0.5
P_RICE	0.2	0.6	0.2
P_OIL	0.2	0.6	0.1
P_FERT	0.2	0.2	0.2
CPI_CN	0.1	0.4	0.0
CPI_TH	0.2	0.5	0.2
CPI_US	0.2	0.6	0.1
CPI_VN	0.5	0.4	0.4

Figure 21. Cambodia: Inflation Developments



That said, there is still merits in discussing the forecasting models for inflation if there is a need to forecast inflation for the current quarter.[13] The set of the NBC's inflation forecasting models encompasses single-equation autoregressive moving-average (ARMA) models and ARMAX models (i.e., ARMA models augmented with exogenous variables) for each of the three CPI components using monthly data. The ARMA models are specified as follows:

[13] For example, if we were in September 2023 with GDP nowcasts available until 2023Q3 and inflation data available until August 2023, we would need to forecast inflation for September 2023.

$$\Delta\log(CPI_t^S) = \alpha + \sum_{i=1}^{p} \beta_i \Delta\log(CPI_{t-i}^S) + \varepsilon_t^S + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j}^S$$

where S = food, or oil-related, or core. The ARMAX models extend the ARMA models by including the foreign variables specified above as exogenous drivers of Cambodia's inflation:

$$\Delta\log(CPI_t^S) = \alpha + \sum_{i=1}^{p} \beta_i \Delta\log(CPI_{t-i}^S) + \varepsilon_t^S + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j}^S + \sum_{k=0}^{K} \delta_k^S X_{t-k}^S$$

where X denotes a vector of the foreign exogenous variables. Since the three CPI components are correlated and could affect each other, we also use a reduced-form vector autoregressive (VAR) model with the three CPI components as endogenous variables, as well as a VARX model (i.e., VAR model augmented with exogenous variables), to model and forecast them jointly.[14] Similar foreign variables as those used in the ARMAX models are used as exogenous variables in the VARX model. Both the VAR and VARX models are estimated using monthly data. More specifically, the VAR model is specified as follows:

$$\begin{bmatrix} \Delta\log(CPI_t^{food}) \\ \Delta\log(CPI_t^{oil}) \\ \Delta\log(CPI_t^{core}) \end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix} \Delta\log(CPI_{t-i}^{food}) \\ \Delta\log(CPI_{t-i}^{oil}) \\ \Delta\log(CPI_{t-i}^{core}) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{food} \\ \varepsilon_t^{oil} \\ \varepsilon_t^{core} \end{bmatrix}$$

Similarly, the VARX model is specified as:

$$\begin{bmatrix} \Delta\log(CPI_t^{food}) \\ \Delta\log(CPI_t^{oil}) \\ \Delta\log(CPI_t^{core}) \end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix} \Delta\log(CPI_{t-i}^{food}) \\ \Delta\log(CPI_{t-i}^{oil}) \\ \Delta\log(CPI_{t-i}^{core}) \end{bmatrix} + \sum_{k=0}^{K} C_k X_{t-k} + \begin{bmatrix} \varepsilon_t^{food} \\ \varepsilon_t^{oil} \\ \varepsilon_t^{core} \end{bmatrix}$$

The four models are estimated using monthly data. The number of lags of the dependent variable is determined by the optimal lag length based on the Akaike information criterion. The specific set of foreign exogenous variables to be included in the models above consist of global food (or rice) prices, global energy (or oil) prices, global fertilizer prices, and the headline inflation of Cambodia's key trading partners (i.e., China, Thailand, the U.S., and Vietnam). In determining the specifications of the models, including the specific foreign variables and their lags to be included in the ARMAX and VARX models, we consider these variables' statistical significance as well as the models' information criteria (particularly the Akaike information criterion), residual properties, coefficient stability, in-sample fit, and pseudo out-of-sample forecasting performance using standard statistical measures such as the root mean squared error (RMSE). Other domestic factor such as economic activities and exchange rate could also affect inflation while at the same time be affected by inflation as well. Therefore, we will also consider these other domestic factors in the quarterly joint forecasting of GDP and inflation in the near term (next few quarters).

Once the foreign exogenous variables are determined for the ARMAX and VARX models, all the models (including ARMA and VAR models) are estimated using all the data available to produce out-of-sample inflation forecasts for each of the three CPI components for the remaining months of the current quarter. The simple

[14] It is worth noting that reduced-form VAR models are sufficient for forecasting purposes, while structural VAR models, although spanning the same estimation space as reduced-form VAR models, are mostly for policy analysis instead of forecasting.

average of the forecasts from the four different models is then obtained as the forecast for each of the three CPI components, given that the simple average of forecasts tends to outperform the more sophisticated combination methods in empirical applications (Stock and Watson, 2004). The forecasts of the three CPI components are then aggregated using their respective weights in the CPI basket to obtain the headline CPI inflation forecasts.

As mentioned earlier, since the GDP nowcasts are only available until 2023Q2, there is no need to forecast inflation in this exercise. Therefore, we only estimate the four models specified above without generating any forecast. Table 8 summarizes the key results of the model estimates. For brief, we exclude the results from ARMA and VAR. Details are provided in Annex III. We observe that, in line with expectation, global rice and oil prices are important drivers of Cambodia's food and oil-related inflation, respectively. Meanwhile, after controlling the global prices, the key trading partners' inflation continues to have significant effects on the food and oil-related inflation in Cambodia. There is some evidence that global prices could also affect the core inflation in Cambodia, but the results are not robust across the models. These findings are largely consistent with the literature on small open economies that import food and oil from the global market or foreign countries.

Table 8: Summary of Inflation Forecasting Models

Foreign Variables 1/	**Food**		**Oil-Related**		**Core**	
	ARMAX	VARX	ARMAX	VARX	ARMAX	VARX
DL_CPI_CN	(+)***	(+)***	(+)***	(+)***		
DL_CPI_TH	(+)***		(+)***	(+)***	(+)***	
DL_CPI_US	(+)***	(+)*	(+)***	(+)***		
DL_CPI_VN	(+)***					
DL_P_RICE	(+)***	(+)**			(+)***	
DL_P_OIL			(+)***	(+)***		
DL_P_ENERGY					(+)*	
DL_P_FERTILIZER					(+)***	(-)**
Adjusted R-squared	0.49	0.37	0.59	0.58	0.44	0.21
Akaike info criterion	2.53	1.68	3.47	3.51	1.41	0.65
Durbin-Watson stat	1.99		2.01		1.82	

Source: Authors' estimates.
* indicates 10 percent, ** 5 percet, and *** 1 percent, respectively.
1/ Either contemporaneous or lagged values are included.
Note: Results from ARMA and VAR models are not listed as they do not include foreign exogenous variables.

That said, if needed, we can use the four models specified above to forecast inflation for the current quarter. This is straightforward with ARMA and VAR models, but to do this with the ARMAX and VARX models, we would also need forecasts of the foreign exogenous variables, i.e., global prices and inflation in key trading partners. The forecasts of global commodity prices (except fertilizer prices) and trading partners' inflation can be obtained from the IMF's latest World Economic Outlook (WEO) database, while the forecasts of global fertilizer prices can be obtained from the World Bank's CMO database.

B. Joint Near-Term Forecasting of GDP and Inflation

So far, we have produced GDP nowcasts and, if needed, inflation forecasts for the current quarter. Such nowcasts or forecasts have not taken into account the interactions or feedback effects between the two variables as well as with other variables, such as money or credit growth and exchange rate. As we are interested in the forecasts of GDP and inflation for the near term (next two quarters), such feedback effects could be important. This would require modeling the two variables in a system, e.g., a VAR model, which treats both variables as endogenous variables and can capture the feedback effects.

Model Specifications

To capture the feedback effects, two different VAR models are used differing by the endogenous variables. The simple VAR model has only real GDP growth and inflation as endogenous variables while the extended VAR model includes two additional endogenous variables, real credit growth and real exchange rate depreciation, to capture the macrofinancial and external linkages. The choice of variables in the extended model reflects the theoretical setup of a New-Keynesian small open economy model (see, e.g., Bjørnland, 2008; Clarida and others, 2001), except that credit growth is used in lieu of interest rate due to the weak interest rate transmission in Cambodia. More specifically, the following two VAR models are estimated using quarterly data:

VAR 1:

$$\begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\end{bmatrix} + \begin{bmatrix}\varepsilon_t^{GDP}\\ \varepsilon_t^{CPI}\end{bmatrix}$$

VAR 2:

$$\begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\\ \Delta\log(Credit_t)\\ \Delta\log(EXR_t)\end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\\ \Delta\log(Credit_t)\\ \Delta\log(EXR_t)\end{bmatrix} + \begin{bmatrix}\varepsilon_t^{GDP}\\ \varepsilon_t^{CPI}\\ \varepsilon_t^{Credit}\\ \varepsilon_t^{EXR}\end{bmatrix}$$

Moreover, as a small open economy, these domestic variables would also be affected by foreign exogenous variables. For example, global commodity prices and inflation in the key trading partners could affect Cambodia's inflation, while real GDP growth of the key trading partners could also affect Cambodia's real GDP growth. One approach is to model the feedback effects through a well-specified structural or semi-structural model. Instead, as a starting point, we use a statistical approach in this paper by augmenting the VAR models above with foreign exogenous variables, i.e., VARX models, to capture such effects, which should be less subject to mis-specification issues:

VARX 1:

$$\begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix}\Delta\log(GDP_t)\\ \Delta\log(CPI_t)\end{bmatrix} + \sum_{k=0}^{K} C_k X_{t-k} + \begin{bmatrix}\varepsilon_t^{GDP}\\ \varepsilon_t^{CPI}\end{bmatrix}$$

VARX 2:

$$\begin{bmatrix} \Delta\log(GDP_t) \\ \Delta\log(CPI_t) \\ \Delta\log(Credit_t) \\ \Delta\log(EXR_t) \end{bmatrix} = A + \sum_{i=1}^{p} B_i \begin{bmatrix} \Delta\log(GDP_t) \\ \Delta\log(CPI_t) \\ \Delta\log(Credit_t) \\ \Delta\log(EXR_t) \end{bmatrix} + \sum_{k=0}^{K} C_k X_{t-k} + \begin{bmatrix} \varepsilon_t^{GDP} \\ \varepsilon_t^{CPI} \\ \varepsilon_t^{Credit} \\ \varepsilon_t^{EXR} \end{bmatrix}$$

Joint NTF of GDP and Inflation

The four models are estimated using quarterly data between 2004Q4 and 2023Q2. Inflation, credit, and exchange rate data are all available until 2023Q2. While the interpolated quarterly GDP data are only available until 2022Q4, the GDP nowcasts for 2023Q1-Q2 are also treated as historical data in the estimation. The number of lags of the dependent variable is determined by the optimal lag length based on the Akaike information criterion. Specifically, two lags are selected for all the models.

The specific set of foreign exogenous variables to be included in the VARX models consist of the real GDP growth of the U.S., China, and EU (following the insights from the nowcasting models), global commodity prices, and the headline inflation of Cambodia's key trading partners. In determining the specifications of the models, including the specific foreign variables and their lags to be included in the ARMAX and VARX models, we consider these variables' statistical significance as well as the models' information criteria (particularly the Akaike information criterion), residual properties, coefficient stability, and in-sample fit.

Table 9 summarizes the key results from the model estimates. For brief, we exclude the results from the two VAR models. Details are provided in Annex III. We observe that, in line with expectation and the nowcasting results, the real GDP growth of China and the U.S. have significantly positive impact on Cambodia's real GDP growth. Meanwhile, global rice prices and some of the key trading partners' inflation, e.g., Vietnam's inflation, are also important in driving Cambodia's inflation. Although the lagged real GDP growth of EU also has some positive impact on Cambodia's growth, the impact is not statistically significant. Interestingly, the global energy prices have a negative impact on Cambodia's real GDP growth (albeit insignificant at the 95-percent confidence level), likely capturing global cost-pushing or supply shocks. While the inflation of some of Cambodia's key trading partners seem to have some positive effects on Cambodia's real GDP growth, the effects are relatively marginal.[15] These findings are also largely consistent with the literature on small open economies that import food and oil from the global market or foreign countries.

[15] For robustness, we also estimate restricted VARX models where the coefficients of global commodity prices and trading partners' inflation are restricted to be zero for the real GDP equation while the coefficients of trading partners' real GDP growth are restricted to be zero for the inflation equation. The estimated coefficients remain largely unchanged.

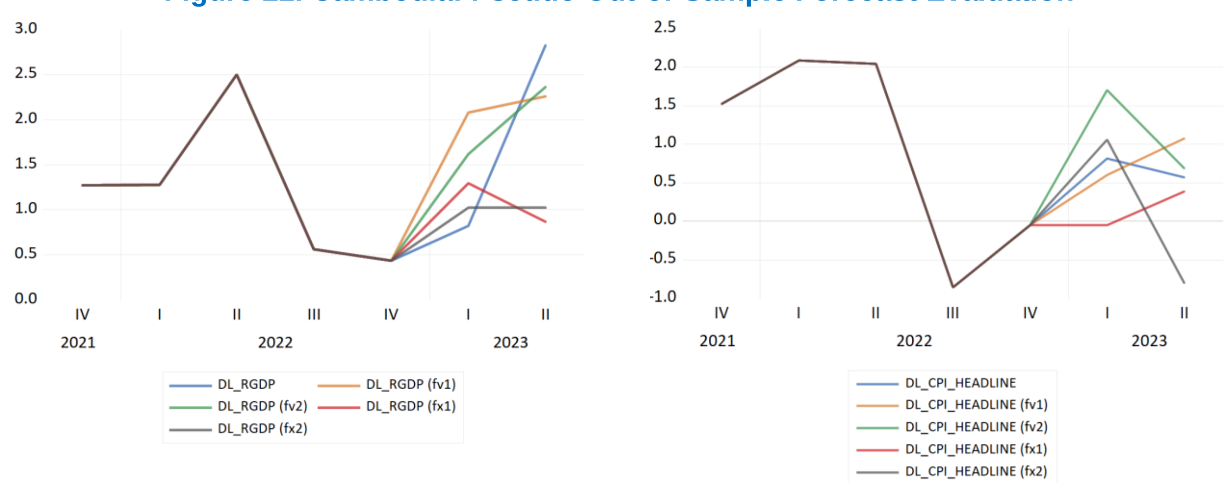
Table 9: Summary of NTF Models for GDP and Inflation

Foreign Variables	GDP		Inflation	
	VARX 1	VARX 2	VARX 1	VARX 2
DL_RGDP_CN	(+)***	(+)***		
DL_RGDP_US	(+)***	(+)***		
DL_RGDP_EU(-1)	(+)	(+)		
DL_P_RICE			(+)**	(+)***
DL_P_ENERGY	(-)*	(-)		
DL_CPI_CN	(+)*	(+)		
DL_CPI_TH	(+)*	(+)*		
DL_CPI_VN			(+)***	(+)**
Adjusted R-squared	0.40	0.37	0.58	0.72
Akaike info criterion	3.21	3.23	3.41	3.04

Source: Authors' estimates.
* indicates 10 percent, ** 5 percet, and *** 1 percent, respectively.
Note: Results from VAR 1 and VAR 2 models are not listed as they do not include foreign exogenous variables.

We also evaluate the models by examining the models' pseudo out-of-sample forecasting performance. This is conducted by first estimating the models using a sub-sample until 2022Q4 and then generating the forecasts of Cambodia's real GDP growth and inflation for 2023Q1-Q2. Finally, we compare the forecasts with the GDP nowcasts and actual inflation data for 2023Q1-Q2 using the standard statistical measures such as RMSE. The evaluation results suggest that the forecasts from the VAR 2 model have the lowest RMSE, suggesting that the VAR 2 model outperforms the other models in this particular exercise. It is worth noting that this does not necessarily mean that the VAR 2 model always outperforms the other models; instead, the finding very much depends on the estimation and evaluation periods. Therefore, we will continue to take the model averaging approach to generate the mean forecasts. The pseudo out-of-sample forecasts from all four models are shown in Figure 22.

Figure 22. Cambodia: Pseudo Out-of-Sample Forecast Evaluation

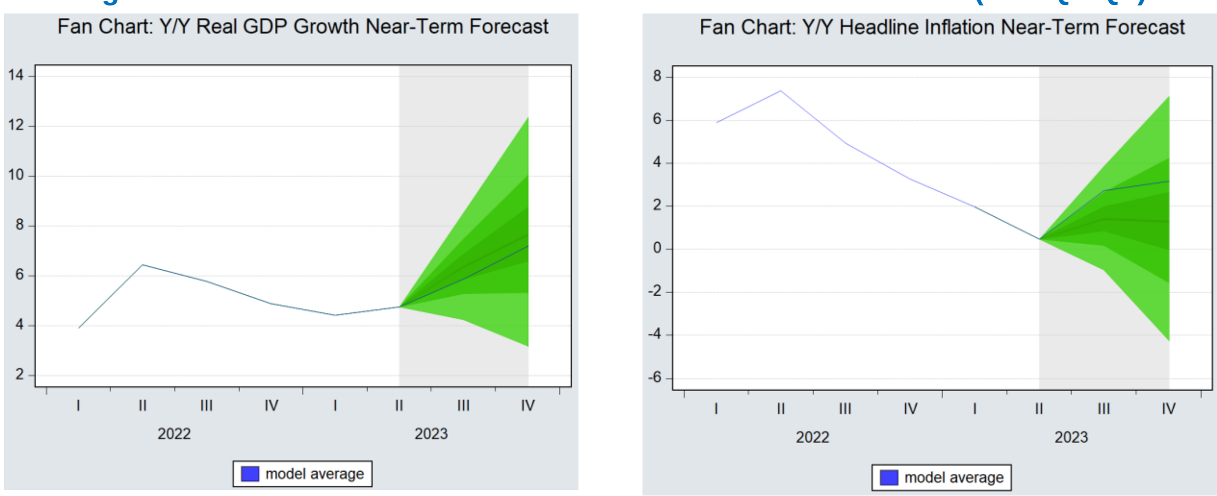


Once the foreign exogenous variables are determined for the VARX models, all the models are estimated again using all the data available (until 2023Q2) to produce forecasts of Cambodia's real GDP growth and inflation for

2023Q3-Q4. As in the nowcasting exercise, the average of the forecasts from the four models is our baseline (model average) forecast. We also use the "best" model identified according to the pseudo out-of-sample forecast evaluation, i.e., VAR 2 model, to generate the fan charts for Cambodia's y/y real GDP growth and inflation, respectively. Figure 23 shows the model average forecasts for y/y real GDP growth and inflation, together with the fan charts that present the 30^{th}-, 50^{th}- (median, in blue line), 60^{th}- , and 90^{th}-percentiles of the forecasts from VAR 2 model.

The baseline near-term forecasts imply some recovery in both real GDP growth and inflation in Cambodia for the second half of 2023. More specifically, y/y growth in the second half of 2023 would have rebounded to about 6.5 percent, compared to 4.6 percent in the first half of 2023, while y/y inflation would have also recovered somewhat to 2.9 percent in the second half of 2023, compared to 1.2 percent in the first half. For the whole year of 2023, real GDP would have grown by about 5½ percent, suggesting a slight recovery compared to 2022 (5.2 percent), while inflation would have fallen significantly in 2023 to about 2¼ percent, well below the 2022 level of over 5 percent. These baseline forecasts are broadly in line with the latest forecasts in the IMF's 2023 Article IV Staff Report for Cambodia (IMF, 2024).

Figure 23. Cambodia: Near-Term Forecasts of GDP and Inflation (2023Q3-Q4)



Note: The different green shades represent the 30th-, 60th-, and 90th-percentiles. The blue line denotes the median (50th-percentile) forecast.

VI. Conclusion

This paper presents a suite of models in an integrated four-step approach to conduct nowcasting and near-term forecasting of Cambodia's economy. Nowcasting forecasts the present, helping policymakers assess the current state of the economy, while near-term forecasting provides the economic outlook in the next couple of quarters. These tools together provide inputs to the macroeconomic frameworks used to check economic and accounting consistency in macroeconomics surveillance and to the forecasting and policy analysis system at the NBC.

More specifically, we propose a four-step approach to produce these forecasts. In the first step, due to the lack of quarterly (real) GDP, we estimate historical quarterly GDP using information extracted from important high-frequency indicators considered to be closely related to economic activities, particularly monthly data on exports, credit, foreign reserves, and broad money. The second step nowcasts current economic activities using high-frequency data on credit, export of garment, and tourist arrivals, as well as quarterly GDP of Cambodia's largest trading partners (US, China and EU). The third step forecasts Cambodia's headline CPI inflation for the current quarter through a bottom-up approach: specifically, each key CPI component is forecasted for the current quarter and then aggregated to produce the forecasts for the headline CPI inflation. The last step involves estimating VAR models to forecast jointly Cambodia's GDP and inflation in the next couple of quarters, which should capture some of the feedback effects between the two variables. The VAR models also include some other important macroeconomic variables, particularly credit growth and exchange rate, and take the GDP nowcasts and inflation forecasts for the current quarter from the second and the third steps as the latest available "historical" data. Key foreign variables such as global commodity prices and key trading partners' GDP growth and inflation are also included as exogenous variables in the VAR models.

The exercise illustrated in this paper showcase how high-frequency dataset can be utilized in assessing current economic activities in countries with limited and lagged data, and to broadly forecast economic outlook a couple of quarters ahead. Despite the lack of innovative and timely data such as nightlight index and emission, our work shows that developing countries like Cambodia can still take the advantage of relatively high-frequency data for a timely macroeconomic assessment.

It should be noted that the models may need further fine tuning as new high-frequency indicators and new data become available. The model operating staff should adjust the models when needed and constantly assess and finetune the models. After all, forecasting is never a mechanical construct from a model. Moreover, staff at the NBC also need to incorporate best judgments about developments in the Cambodian economy and the policy transmission mechanism. A suite of models and judgements need to be employed to inform "official forecast".

Going forward, the nowcasting and NTF exercise could be further enhanced by: i) improving data availability and adding potentially important information such as measures of PMI, business sentiment index, retail sales, etc.; and ii) extending the analysis to alternative more efficient (but more computationally demanding) approaches, including principal component analysis and more complicated multivariate models (e.g., mixed-frequency VAR, DFMs). Moreover, the nowcasts and near-term forecasts should be regularly updated to inform policymakers the real-time assessment of the economy, which would have important implications for monetary and financial policies as well as fiscal policies in budget preparation processes.

Annex I. Correlation and Interpolation Method

For a robustness check, We also run a regression of GDP growth in the annual series on the proposed explanatory variables in annual series. We observe that all key variables have expected signs and are statistically significant (except the foreign reserves).

Dependent Variable: DLOG(RGDP)
Method: Least Squares
Sample (adjusted): 2004 2022
Included observations: 19 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(CREDIT)	0.105	0.061	1.720	0.106
DLOG(EXPORTS)	0.166	0.073	2.280	0.038
DLOG(TOURIST)	0.016	0.007	2.179	0.046
DLOG(RESERVES)	0.077	0.063	1.236	0.236

R-squared	0.542581	Mean dependent var	0.064038
Adjusted R-squared	0.451097	S.D. dependent var	0.03503
S.E. of regression	0.025953	Akaike info criterion	-4.280407
Sum squared resid	0.010103	Schwarz criterion	-4.081578
Log likelihood	44.66386	Hannan-Quinn criter.	-4.246757

Interpolation Method

The paper derives Cambodia's Quarterly GDP data from annual GDP Data using a quarterly data of export, credit, and foreign reserves, all of which have strong correlation with GDP. The method make use of a statistical relation between low frequency data and high frequency indicator variable through regressions. These methods are developed by Chow-Lin (1971), and Fernandez (19xx), and Litterman with different assumption on the residual. All these three methods can be implemented with build-in interpolation functions in EViews 12/13. We briefly discuss the approach here.

The Chow-Lin (1971) procedure assume linear relationship between high frequency variable (not causation):

$$y_{hf} = X\beta + u$$

y_{hf} here is the high frequency data (e.g. quarterly GDP) and X are selected indicators (such as quarterly export data). Then the method makes use of a statistical relationship between low frequency data and high frequency data through a regression equation

$$Y = Cy = C(X\beta + u) = CX\beta + Cu, \quad E(uu') = V$$

Where C (sum) is $n\,X\,4n$ matrix converts *4n* quarterly observations into *n* annual observations. The method assume that residual (u) follow a first-order auto-regression.

$$u_t = \rho\, u_{t-1} + \varepsilon_t$$

$\hat{\beta}$ and $\hat{y}$ can be estimated with generalized least squared (GLS). The EViews built-in function estimate β and ρ with maximum likelihood and the Kalman Filter.

Fernandez (1981) method has similar solution process to the Chow-Lin procedure but assume that the residuals follow a random walk (non-stationary process): $u_t = u_{t-1} + \varepsilon_t$. Litterman (1983) Method further correct for serial correlation in the residual by assuming that $\boldsymbol{\varepsilon_t}$ is a white noise process.

ANNEX II: Nowcasting Model

The following tables shows the details of the results. Table A1 is the estimate model for nowcasting.

Table A: Bridge Model

Dependent Variable: DLOG(RGDP)
Method: Least Squares
Sample (adjusted): 2007Q2 2022Q4
Included observations: 63 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(RGDP(-1))	0.121361	0.063597	1.908276	0.0617
DL_RGDP_CN	0.001965	0.000404	4.858763	0
DL_RGDP_US	0.000503	0.000711	0.707803	0.4821
DLOG(RCREDIT_SA)	0.07529	0.027363	2.751548	0.0081
DLOG(RRESERVES)	0.110278	0.016576	6.652746	0
DLOG(REXPORTS_SA)	0.087028	0.011891	7.318612	0
DLOG(TOURIST_SA)	0.015638	0.002473	6.322615	0
CRISIS	-0.006163	0.00319	-1.932103	0.0586
C	-0.000235	0.002194	-0.106989	0.9152

R-squared	0.856333	Mean dependent var	0.013441
Adjusted R-squared	0.835049	S.D. dependent var	0.014416
S.E. of regression	0.005855	Akaike info criterion	-7.311545
Sum squared resid	0.001851	Schwarz criterion	-7.005383
Log likelihood	239.3137	Hannan-Quinn criter.	-7.19113
F-statistic	40.23365	Durbin-Watson stat	2.278641
Prob(F-statistic)	0		

Table B: MIDAS model

Dependent Variable: DLOG(RGDP)
Method: MIDAS
Sample (adjusted): 2008Q1 2022Q4
Included observations: 60 after adjustments
Method: PDL/Almon (polynomial degree: 3)
Automatic lag selection, max lags: 12
Chosen selection: 4 9 7 11

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(RGDP(-1))	-0.449177	0.106602	-4.213606	0.0001
DL_RGDP_CN	0.001454	0.0004	3.635845	0.0007
DL_RGDP_US	0.00323	0.000603	5.358813	0
CRISIS	-0.006967	0.003517	-1.980674	0.054
C	-0.000677	0.002371	-0.285686	0.7765
Page: MONTHLY Series: DLOG(RCREDIT_SA_F) Lags: 4				
PDL01	0.330274	0.184241	1.792622	0.0801
PDL02	-0.230123	0.168822	-1.363111	0.1799
PDL03	0.050752	0.032749	1.549715	0.1285
Page: MONTHLY Series: DLOG(RRESERVES_F) Lags: 9				
PDL01	0.05599	0.037538	1.491543	0.1431
PDL02	0.024383	0.017524	1.391423	0.1713
PDL03	-0.003705	0.001663	-2.227508	0.0312
Page: MONTHLY Series: DLOG(REXPORTS_SA_F) Lags: 7				
PDL01	-0.001553	0.016659	-0.093222	0.9262
PDL02	0.038934	0.012675	3.071776	0.0037
PDL03	-0.00511	0.001565	-3.265907	0.0021
Page: MONTHLY Series: DLOG(TOURIST_SA) Lags: 11				
PDL01	-0.001674	0.005843	-0.286455	0.7759
PDL02	0.006032	0.002092	2.882881	0.0061
PDL03	-0.000608	0.000155	-3.908913	0.0003

R-squared	0.895561	Mean dependent var	0.012719
Adjusted R-squared	0.856701	S.D. dependent var	0.014345
S.E. of regression	0.00543	Akaike info criterion	-7.360096
Sum squared resid	0.001268	Schwarz criterion	-6.766698
Log likelihood	237.8029	Hannan-Quinn criter.	-7.127985
Durbin-Watson stat	2.066978		

Table C: UMIDAS Model

Dependent Variable: DLOG(RGDP)
Method: MIDAS
Sample (adjusted): 2007Q2 2022Q4
Included observations: 63 after adjustments
Method: U-MIDAS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLOG(RGDP(-1)	0.071122	0.083443	0.852341	0.3989
DL_RGDP_CN	0.001454	0.000491	2.960269	0.005
DL_RGDP_US	0.000841	0.000983	0.855123	0.3973
CRISIS	-0.007426	0.003742	-1.984686	0.0537
C	-0.001904	0.002732	-0.696987	0.4897
Page: MONTHLY Series: DLOG(RCREDIT_SA_F) Lags: 4				
LAG1	0.17757	0.067417	2.633916	0.0118
LAG2	0.023192	0.044714	0.518672	0.6067
LAG3	0.031905	0.066343	0.48091	0.6331
LAG4	0.12979	0.069403	1.870085	0.0685
Page: MONTHLY Series: DLOG(RRESERVES_F) Lags: 4				
LAG1	0.087021	0.031607	2.753177	0.0087
LAG2	0.143646	0.047701	3.011407	0.0044
LAG3	0.132438	0.032056	4.131412	0.0002
LAG4	0.063027	0.032609	1.93282	0.06
Page: MONTHLY Series: DLOG(REXPORTS_SA_F) Lags: 4				
LAG1	0.042818	0.012773	3.352281	0.0017
LAG2	0.073251	0.015284	4.792633	0
LAG3	0.079121	0.013562	5.834252	0
LAG4	0.037937	0.010303	3.682198	0.0007
Page: MONTHLY Series: DLOG(TOURIST_SA) Lags: 4				
LAG1	-0.000447	0.007961	-0.056167	0.9555
LAG2	0.019264	0.009234	2.086316	0.0431
LAG3	0.014207	0.003474	4.089023	0.0002
LAG4	0.027844	0.007749	3.593047	0.0009

R-squared	0.8909	Mean dependent var	0.013441
Adjusted R-squar	0.838947	S.D. dependent var	0.014416
S.E. of regressio	0.005785	Akaike info criterion	-7.205825
Sum squared res	0.001406	Schwarz criterion	-6.491447
Log likelihood	247.9835	Hannan-Quinn criter.	-6.924857
Durbin-Watson st	2.617919		

Annex III: Near-Term Forecasting Models

Tables: Inflation forecasting models

Dependent Variable: DL_CPI_FOOD
Method: ARMA Maximum Likelihood (BFGS)
Sample: 2004M01 2023M12
Included observations: 240
Convergence achieved after 58 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.063532	0.119024	0.533779	0.594
DL_P_RICE	0.047184	0.009122	5.17223	0
DL_P_RICE(-2)	0.016742	0.010722	1.561469	0.1198
DL_CPI_CN(-3)	0.435791	0.1292	3.372997	0.0009
DL_CPI_TH(-1)	0.224733	0.075208	2.98815	0.0031
DL_CPI_US(-2)	0.39921	0.146197	2.730638	0.0068
DL_CPI_VN	0.414333	0.091607	4.522927	0
AR(1)	0.363838	0.064393	5.650282	0
AR(2)	-0.599126	0.062696	-9.556042	0
MA(1)	-0.213372	4.519188	-0.047215	0.9624
MA(2)	0.999996	42.35619	0.023609	0.9812
SIGMASQ	0.648921	13.65669	0.047517	0.9621

R-squared	0.499999	Mean dependent var	0.513418
Adjusted R-squarec	0.475876	S.D. dependent var	1.141608
S.E. of regression	0.826483	Akaike info criterion	2.535946
Sum squared resid	155.7409	Schwarz criterion	2.709978
Log likelihood	-292.3135	Hannan-Quinn criter.	2.606068
F-statistic	20.72715	Durbin-Watson stat	1.981879
Prob(F-statistic)	0		

Dependent Variable: DL_CPI_OIL
Method: ARMA Maximum Likelihood (BFGS)
Sample: 2008M02 2023M12
Included observations: 191
Convergence achieved after 66 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.55607	0.064408	-8.633543	0
DL_P_OIL	0.105267	0.010594	9.936543	0
DL_CPI_CN	0.712707	0.362716	1.964919	0.0509
DL_CPI_CN(-1)	0.959104	0.261349	3.669826	0.0003
DL_CPI_TH	0.852486	0.251126	3.394656	0.0008
DL_CPI_US(-1)	1.155094	0.141333	8.172849	0
AR(1)	0.851471	0.067272	12.6572	0
MA(1)	-1	135.8265	-0.007362	0.9941
SIGMASQ	1.66764	5.542627	0.300875	0.7639

R-squared	0.607035	Mean dependent var	0.073511
Adjusted R-squared	0.589762	S.D. dependent var	2.065448
S.E. of regression	1.322916	Akaike info criterion	3.458148
Sum squared resid	318.5193	Schwarz criterion	3.611396
Log likelihood	-321.2531	Hannan-Quinn criter.	3.520221
F-statistic	35.14321	Durbin-Watson stat	2.006132
Prob(F-statistic)	0		

Dependent Variable: DL_CPI_CORE
Method: ARMA Maximum Likelihood (BFGS)
Sample: 2008M02 2023M12
Included observations: 191
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.241478	0.056669	4.26119	0
DL_P_ENERGY	0.00656	0.005583	1.17495	0.2416
DL_P_ENERGY(-1)	0.005432	0.006152	0.882922	0.3785
DL_P_RICE	0.058646	0.005513	10.6375	0
DL_P_RICE(-1)	0.015006	0.007274	2.063057	0.0406
DL_P_RICE(-3)	0.013447	0.005761	2.33415	0.0207
DL_P_FERT	-0.018	0.003939	-4.569914	0
DL_P_FERT(-4)	0.014727	0.006053	2.432964	0.016
DL_CPI_TH(-3)	0.033506	0.081826	0.409475	0.6827
AR(1)	-0.793009	0.10319	-7.684903	0
AR(2)	0.04372	0.131592	0.332237	0.7401
AR(3)	0.31265	0.098316	3.180037	0.0017
MA(1)	0.789252	0.108645	7.264481	0
SIGMASQ	0.21947	0.017854	12.29267	0

R-squared	0.416112	Mean dependent var	0.25198
Adjusted R-squared	0.373228	S.D. dependent var	0.6147
S.E. of regression	0.486651	Akaike info criterion	1.471552
Sum squared resid	41.91885	Schwarz criterion	1.709938
Log likelihood	-126.5332	Hannan-Quinn criter.	1.568109
F-statistic	9.703116	Durbin-Watson stat	1.836127
Prob(F-statistic)	0		

Tables. VAR and VARX models for joint NTF of GDP and inflation

Vector Autoregression Estimates
Date: 02/23/24 Time: 18:21
Sample (adjusted): 2004Q4 2022Q4
Included observations: 73 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DL_RGDP	DL_CPI_HEADLINE
DL_RGDP(-1)	0.1659726...	0.2031417253437525
	0.1122904...	0.1518112502461106
	[1.47807]	[1.33812]
DL_RGDP(-2)	-0.1443570...	0.1318971124081541
	0.1068898...	0.1445098638384028
	[-1.35052]	[0.91272]
DL_CPI_HEADLINE(-1)	0.0511164...	0.6084828098116739
	0.0835705...	0.1129833142861125
	[0.61166]	[5.38560]
DL_CPI_HEADLINE(-2)	-0.1822725...	-0.302858092963061
	0.0854016...	0.1154589263559664
	[-2.13430]	[-2.62308]
C	1.9375159...	0.2128617447762995
	0.2977533...	0.4025481280232813
	[6.50712]	[0.52879]
CRISIS	-2.7987940...	0.3032948132714753
	0.5562891...	0.7520760574894319
	[-5.03119]	[0.40328]
R-squared	0.3767853...	0.3577028030683607
Adj. R-squared	0.3302767...	0.3097701764316711
Sum sq. resids	93.855805...	171.5471185744925
S.E. equation	1.1835678...	1.600126480889299
F-statistic	8.1014200...	7.462616346473302
Log likelihood	-112.75496...	-134.7680593272319
Akaike AIC	3.2535608...	3.85665915965019
Schwarz SC	3.4418177...	4.044916100018551
Mean dependent	1.5395495...	1.11510372631447
S.D. dependent	1.4462570...	1.926005186547964
Determinant resid covariance (dof adj.)		3.584088489563218
Determinant resid covariance		3.019135528175883
Log likelihood		-247.4964506112213
Akaike information criterion		7.109491797567706
Schwarz criterion		7.486005678304429
Number of coefficients		12

Vector Autoregression Estimates
Date: 02/23/24 Time: 18:21
Sample (adjusted): 2004Q4 2022Q4
Included observations: 73 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DL_RGDP	DL_CPI_H...	DL_RCREDIT	DL_REXR
DL_RGDP(-1)	0.2633865...	0.0173937...	0.4876691...	0.0753885...
	0.1231055...	0.1435846...	0.2931062...	0.1406853...
	[2.13952]	[0.12114]	[1.66380]	[0.53587]
DL_RGDP(-2)	-0.1211806...	-0.0959765...	-0.3256471...	0.2167360...
	0.1230739...	0.1435478...	0.2930311...	0.1406493...
	[-0.98462]	[-0.66860]	[-1.11131]	[1.54097]
DL_CPI_HEADLINE(-1)	-0.5029765...	1.3881208...	-0.1885388...	-1.4146189...
	0.2300226...	0.2682878...	0.5476689...	0.2628705...
	[-2.18664]	[5.17400]	[-0.34426]	[-5.38143]
DL_CPI_HEADLINE(-2)	-0.0891541...	-0.7375286...	0.2895753...	0.5668810...
	0.2485560...	0.2899043...	0.5917957...	0.2840505...
	[-0.35869]	[-2.54404]	[0.48932]	[1.99570]
DL_RCREDIT(-1)	-0.0437712...	0.0973199...	0.1093849...	-0.1007186...
	0.0522711...	0.0609667...	0.1244543...	0.0597356...
	[-0.83739]	[1.59628]	[0.87892]	[-1.68607]
DL_RCREDIT(-2)	0.0299136...	0.2021736...	0.3035045...	-0.2166607...
	0.0487857...	0.0569014...	0.1161557...	0.0557525...
	[0.61316]	[3.55305]	[2.61291]	[-3.88612]
DL_REXR(-1)	-0.5990644...	0.8620531...	-0.6307151...	-1.0215986...
	0.2402573...	0.2802251...	0.5720371...	0.2745668...
	[-2.49343]	[3.07629]	[-1.10258]	[-3.72077]
DL_REXR(-2)	0.0500264...	-0.3188821...	0.5210621...	0.1756670...
	0.2601318...	0.3034057...	0.6193569...	0.2972793...
	[0.19231]	[-1.05101]	[0.84130]	[0.59092]
C	2.0476889...	-0.8906870...	3.1463395...	1.3121405...
	0.4131100...	0.4818325...	0.9835881...	0.4721033...
	[4.95676]	[-1.84854]	[3.19884]	[2.77935]
CRISIS	-2.5951330...	0.0340934...	-3.3415228...	0.4455545...
	0.5554859...	0.6478932...	1.3225759...	0.6348109...
	[-4.67182]	[0.05262]	[-2.52653]	[0.70187]
R-squared	0.4391881...	0.5698161...	0.3963041...	0.5292967...
Adj. R-squared	0.3590721...	0.5083613...	0.3100618...	0.4620534...
Sum sq. resids	84.457978...	114.89509...	478.77975...	110.30200...
S.E. equation	1.1578440...	1.3504561...	2.7567514...	1.3231876...
F-statistic	5.4819042...	9.2721126...	4.5952428...	7.8713646...
Log likelihood	-108.90401...	-120.13745...	-172.23102...	-118.64834...
Akaike AIC	3.2576443...	3.5654097...	4.9926309...	3.5246123...
Schwarz SC	3.5714059...	3.8791713...	5.3063924...	3.8383738...
Mean dependent	1.5395495...	1.1151037...	5.5624572...	-0.4819939...
S.D. dependent	1.4462570...	1.9260051...	3.3188876...	1.8040635...
Determinant resid covariance (dof adj.)		6.026352908334924		
Determinant resid covariance		3.342914877623465		
Log likelihood		-458.3798264606391		
Akaike information criterion		13.65424182083943		
Schwarz criterion		14.90928808996183		
Number of coefficients		40		

Vector Autoregression Estimates
Date: 02/23/24 Time: 18:21
Sample (adjusted): 2004Q4 2022Q4
Included observations: 73 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DL_RGDP	DL_CPI_HEADLINE
DL_RGDP(-1)	0.2175477...	0.04464457171094634
	0.1344494...	0.1518966447548676
	[1.61806]	[0.29391]
DL_RGDP(-2)	-0.0050440...	0.007888022932552169
	0.1098819...	0.1241410763034861
	[-0.04590]	[0.06354]
DL_CPI_HEADLINE(-1)	0.0164843...	0.2661328680954479
	0.0922422...	0.1042123189599807
	[0.17871]	[2.55376]
DL_CPI_HEADLINE(-2)	0.0530053...	-0.1814018219298151
	0.0917818...	0.1036921291690133
	[0.57751]	[-1.74943]
C	0.0654075...	0.08406032188628902
	0.3080659...	0.3480428840092899
	[0.21232]	[0.24152]
DL_RGDP_CN	0.2318630...	-0.03397282435874401
	0.0772537...	0.08727882269825804
	[3.00132]	[-0.38924]
DL_RGDP_US	0.5515297...	0.0378544009629213
	0.1088052...	0.1229246586346405
	[5.06896]	[0.30795]
DL_RGDP_EU(-1)	0.1098292...	-0.000843371688744731
	0.0930320...	0.1051045862187667
	[1.18055]	[-0.00802]
DL_P_RICE	-0.0118527...	0.04373960741504197
	0.0168406...	0.01902598730077915
	[-0.70382]	[2.29894]
DL_P_ENERGY	-0.0230364...	0.007885178505243878
	0.0127470...	0.01440119741840365
	[-1.80720]	[0.54754]
DL_CPI_CN	0.4923988...	-0.01823159403990475
	0.2943330...	0.3325278664635866
	[1.67293]	[-0.05483]
DL_CPI_TH	0.4423556...	0.1406213213233222
	0.2218862...	0.250679851688847
	[1.99361]	[0.56096]
DL_CPI_VN	-0.1116364...	0.5003074149192761
	0.1347824...	0.1522727871696827
	[-0.82827]	[3.28560]
R-squared	0.5158763...	0.651574035481352
Adj. R-squared	0.4190516...	0.5818888425776222
Sum sq. resids	72.908773...	93.05889942420845
S.E. equation	1.1023367...	1.245384140363985
F-statistic	5.3279399...	9.350250868667382
Log likelihood	-103.53687...	-112.4437339457572
Akaike AIC	3.1927909...	3.436814628650883
Schwarz SC	3.6006810...	3.844704666115665
Mean dependent	1.5395495...	1.11510372631447
S.D. dependent	1.4462570...	1.926005186547964

Determinant resid covariance (dof adj.)	1.833380143694655
Determinant resid covariance	1.238537909044991
Log likelihood	-214.973528456421
Akaike information criterion	6.602014478258111
Schwarz criterion	7.417794553187674
Number of coefficients	26

Vector Autoregression Estimates
Date: 02/23/24 Time: 18:21
Sample (adjusted): 2004Q4 2022Q4
Included observations: 73 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DL_RGDP	DL_CPI_H...	DL_RCREDIT	DL_REXR
DL_RGDP(-1)	0.2477918...	-0.1506304...	0.6033740...	0.1209183...
	0.1499346...	0.1358286...	0.3773290...	0.1615945...
	[1.65267]	[-1.10897]	[1.59907]	[0.74828]
DL_RGDP(-2)	0.0285413...	-0.0840250...	-0.1793595...	0.1998613...
	0.1238422...	0.1121910...	0.3116644...	0.1334730...
	[0.23047]	[-0.74895]	[-0.57549]	[1.49739]
DL_CPI_HEADLINE(-1)	-0.3493286...	1.2958360...	-0.0769450...	-1.2417737...
	0.2312044...	0.2094525...	0.5818547...	0.2491844...
	[-1.51091]	[6.18678]	[-0.13224]	[-4.98335]
DL_CPI_HEADLINE(-2)	-0.1049345...	-0.4341301...	0.1549908...	0.3006495...
	0.2786887...	0.2524694...	0.7013548...	0.3003614...
	[-0.37653]	[-1.71954]	[0.22099]	[1.00096]
DL_RCREDIT(-1)	-0.0199316...	0.0469006...	0.0448904...	-0.0591598...
	0.0530611...	0.0480690...	0.1335349...	0.0571875...
	[-0.37564]	[0.97569]	[0.33617]	[-1.03449]
DL_RCREDIT(-2)	0.0178983...	0.1307494...	0.2412238...	-0.1492773...
	0.0507307...	0.0459579...	0.1276701...	0.0546758...
	[0.35281]	[2.84498]	[1.88943]	[-2.73022]
DL_REXR(-1)	-0.4376736...	1.0826878...	-0.6937378...	-1.1180375...
	0.2354894...	0.2133344...	0.5926384...	0.2538027...
	[-1.85857]	[5.07507]	[-1.17059]	[-4.40514]
DL_REXR(-2)	-0.1845490...	-0.2337387...	0.1955869...	0.0150139...
	0.2891122...	0.2619123...	0.7275867...	0.3115955...
	[-0.63833]	[-0.89243]	[0.26882]	[0.04818]
C	0.3496826...	-0.9403582...	1.6533499...	1.5197568...
	0.4328764...	0.3921510...	1.0893871...	0.4665397...
	[0.80781]	[-2.39795]	[1.51769]	[3.25751]
DL_RGDP_CN	0.2108635...	0.0315666...	0.2206693...	-0.0997133...
	0.0793159...	0.0718538...	0.1996084...	0.0854840...
	[2.65853]	[0.43932]	[1.10551]	[-1.16646]
DL_RGDP_US	0.5008677...	0.1341396...	0.1685320...	-0.1309778...
	0.1129801...	0.1023508...	0.2843284...	0.1217662...
	[4.43324]	[1.31059]	[0.59274]	[-1.07565]
DL_RGDP_EU(-1)	0.1031978...	0.0481336...	0.0349828...	-0.0734592...
	0.0936250...	0.0848166...	0.2356189...	0.1009059...
	[1.10225]	[0.56750]	[0.14847]	[-0.72800]
DL_P_RICE	-0.0165953...	0.0434869...	-0.0241298...	-0.0340836...
	0.0172063...	0.0155875...	0.0433019...	0.0185444...
	[-0.96449]	[2.78984]	[-0.55725]	[-1.83794]
DL_P_ENERGY	-0.0231754...	0.0012057...	-0.0469258...	0.0042578...
	0.0140882...	0.0127627...	0.0354547...	0.0151838...
	[-1.64503]	[0.09447]	[-1.32354]	[0.28042]
DL_CPI_CN	0.4718579...	0.1487129...	2.0729637...	0.2644517...
	0.3033011...	0.2747663...	0.7632949...	0.3268878...
	[1.55574]	[0.54123]	[2.71581]	[0.80900]
DL_CPI_TH	0.4778701...	0.4287684...	-0.2355259...	-0.1062062...
	0.2524040...	0.2286576...	0.6352061...	0.2720326...
	[1.89327]	[1.87515]	[-0.37079]	[-0.39042]
DL_CPI_VN	-0.1306758...	0.2490820...	-0.1635760...	-0.4035766...
	0.1512953...	0.1370613...	0.3807535...	0.1630611...
	[-0.86371]	[1.81730]	[-0.42961]	[-2.47500]
R-squared	0.5469838...	0.7903626...	0.4551760...	0.6618180...
Adj. R-squared	0.4175507...	0.7304663...	0.2995120...	0.5651946...
Sum sq. resids	68.223992...	55.990711...	432.08957...	79.247681...
S.E. equation	1.1037597...	0.9999170...	2.7777482...	1.1895953...
F-statistic	4.2259946...	13.195501...	2.9240934...	6.8494593...
Log likelihood	-101.11280...	-93.900025...	-168.48584...	-106.57984...
Akaike AIC	3.2359673...	3.0383568...	5.0818039...	3.3857492...
Schwarz SC	3.7693620...	3.5717515...	5.6151986...	3.9191438...
Mean dependent	1.5395495...	1.1151037...	5.5624572...	-0.4819939...
S.D. dependent	1.4462570...	1.9260051...	3.3188876...	1.8040635...

Determinant resid covariance (dof adj.)	1.967011271821402
Determinant resid covariance	0.6811888273179484
Log likelihood	-400.3171274850966
Akaike information criterion	12.8306062324684
Schwarz criterion	14.96418488997649
Number of coefficients	68

Annex IV: Newly Rebased GDP and Nowcasting Models

This Annex discuss briefly the new rebased GDP and its implication on the Quarterly GDP interpolation and nowcasting model. The New GDP data would be about 1/3 bigger than the existing one. Industry and Service sector each contributes about half of the difference. Agriculture remains largely unchanged overall although there are changes in the sub-sectors. The rebased data for industry is driven by food/beverage/tobacco, textile, and manufacture of metallic products. The service sector data is driven by wholesale and trade, financial activities, and public administration.

In term of overall growth rate, the numbers are not much different, as shown in the figure below. The new growth rates are slightly higher between 2008 and 2019, but are exactly the same between 2020-2022. With this change, the coefficients of the models are expected to change too. The results in Table A1 shows the model with new GDP data. Therefore, the forecast results also slightly change as in Figure A3 and Figure A4.

Figure A1: New and Current GDP Growth

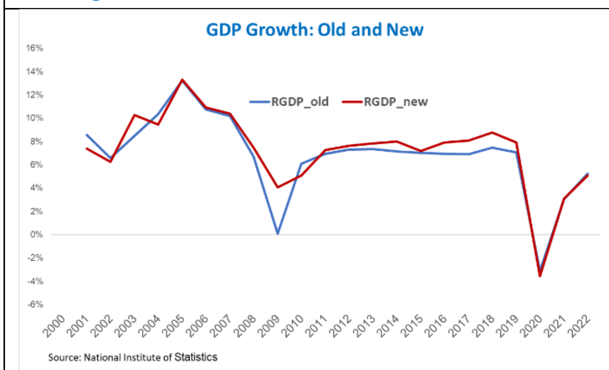


Figure A2: Interpolated GDP

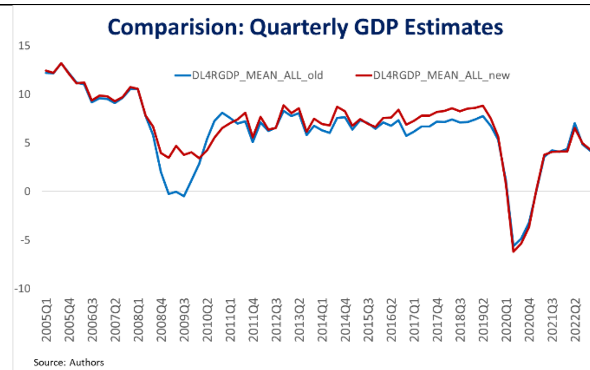


Figure A3: New and Current GDP Growth

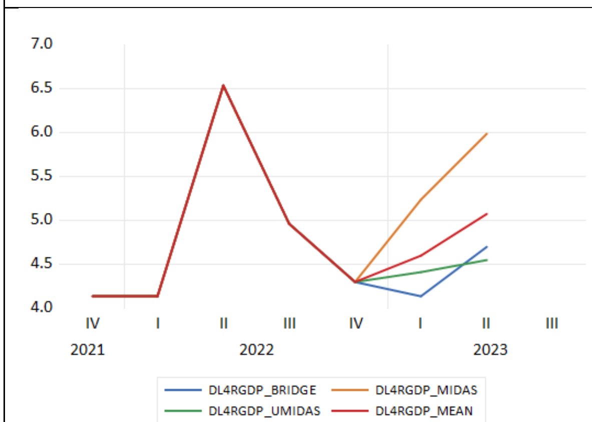
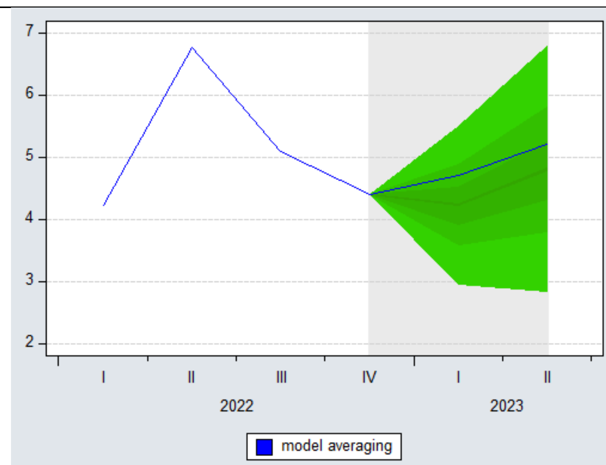


Figure A4: New and Current GDP Growth



Note: The different green shades represent the 30th-, 60th-, and 90th-percentiles. The blue line denotes the median (50th-percentile) forecast.

Table A1: Model Comparison between Old and New GDP

	RGDP1		RGDP2		RGDP_Mean_CL		RGDP_Mean_Lm		RGDP_Mean_All	
VARIABLES	Old	New	Old	New	Old	New	Old	New	Old	New
One Lag	0.065	0.051	-0.039	-0.043	0.035	0.020	0.271**	0.196*	0.134	0.093
	(0.079)	(0.085)	(0.096)	(0.095)	(0.085)	(0.087)	(0.109)	(0.109)	(0.097)	(0.098)
GDP_China	0.002***	0.003***	0.002***	0.003***	0.002***	0.002***	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
GDP_US	0.001	0.000	0.001	-0.000	-0.000	-0.001	0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GDP_EU (-1)	0.001	0.000	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Private Credit	0.085***	0.063*	0.086**	0.065	0.085***	0.066*	0.074**	0.064*	0.080***	0.065*
	(0.028)	(0.035)	(0.037)	(0.042)	(0.030)	(0.034)	(0.030)	(0.033)	(0.029)	(0.033)
Reserves	0.109***	0.134***	0.119***	0.143***	0.108***	0.135***	0.041**	0.053**	0.075***	0.095***
	(0.017)	(0.021)	(0.021)	(0.025)	(0.018)	(0.020)	(0.017)	(0.020)	(0.017)	(0.020)
Exports	0.080***	0.047***	0.078***	0.045**	0.111***	0.093***	0.062***	0.057***	0.087***	0.075***
	(0.012)	(0.016)	(0.016)	(0.018)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)
Tourist	0.016***	0.021***	0.017***	0.022***	0.013***	0.018***	0.010***	0.014***	0.012***	0.016***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Crisis	-0.005	-0.004	-0.005	-0.004	-0.003	-0.002	-0.002	-0.002	-0.003	-0.002
	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
Constant	-0.000	0.002	0.001	0.003	0.000	0.002	0.001	0.004	0.001	0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Observations	63	63	63	63	63	63	63	63	63	63
R-squared	0.858	0.789	0.781	0.724	0.831	0.786	0.751	0.675	0.798	0.738

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Annex V: Data

The data used in the nowcasting and near-term forecasting include both Cambodia's domestic high-frequency indicators and foreign and global variables such as real GDP and inflation of key trading partners and global commodity prices. These data are combined into an NBC database which consists of quarterly, monthly, and annual data. The following table summarize the data and sources. Overall, Domestic high-frequency indicators include credit, broad money, foreign reserves, tourist arrival, exports, exports of garment, consumer price index. The data on these domestic variables are largely collected and updated from the NBC, MEF, and NIS. Foreign and global variables include Fed rates, US GDP, China GDP, EU GDP, Oil price, food price, Thai CPI, Vietnamese CPI, and US CPI. Data on commodities and global environment such as commodity prices or international interest rates from the World Bank (Pink sheet), IMF, and Fed.

Monthly Data		
Variable	Source	Link
Foreign Reserves	NBC	
Tourist Arrival	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
Broad Money (M2)	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
CPI_headline	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
CPI_food	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
CPI_core	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
Exchange Rate	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
CPI in Thailand	Haver, Bank of Thailand	Bank of Thailand (bot.or.th)
CPI in Vietnam	Haver,	
CPI in China	Haver, PBOC	
Oil price	World Bank, IMF	Commodity Markets (worldbank.org)
Food Price	World Bank, IMF	Commodity Markets (worldbank.org)
Private Credit	NBC	Monetary and Financial Statistics Data (nbc.gov.kh)
Exports	NBC, MEF	Monetary and Financial Statistics Data (nbc.gov.kh)
Imports	NBC, MEF	Monetary and Financial Statistics Data (nbc.gov.kh)

Quarterly Data		
Variable	Source	Link
GDP_US	Haver, WEO	IMF World Economic Outlook Database, latest version
GDP_China	Haver, WEO	World Economic Outlook Databases (imf.org)
GDP_EU	Haver, WEO	World Economic Outlook Databases (imf.org)
Oil_forecast	Projected oil price in the future	*https://www.worldbank.org/en/research/commodity-markets* . Click on "commodity prices" link to obtain the data.
CPI_US_Forecast	Projected CPI in US	IMF World Economic Outlook Database, latest version

Annual Data		
Variable	Source	Link
GDP_US	WEO	World Economic Outlook Databases (imf.org)
GDP_KH	MEF, NBC, NIS.	KHM Macroframework or IMF World Economic Outlook Database, latest version
Oil_forecast	Projected oil price in the future	*https://www.worldbank.org/en/research/commodity-markets* . Click on "commodity prices" link to obtain the data.
Food_forecast	Projected Food price in the future	*https://www.worldbank.org/en/research/commodity-markets* . Click on "commodity prices" link to obtain the data.
CPI_US_Forecast	Projected CPI in US	IMF World Economic Outlook Database, latest version

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