INTERNATIONAL MONETARY FUND

IMF Country Report No. 25/318

CAMBODIA

SELECTED ISSUES

December 2025

This paper on Cambodia was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the member country. It is based on the information available at the time it was completed on November 5, 2025.

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November 5, 2025

Approved By
Asia and Pacific Department

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CONTENTS

SATELLITE DATA FOR NOWCASTING[1]

A. Motivation – Why Satellite Data

1. **Cambodia faces limited institutional capacity in the production and timely release of quality official statistics, limiting policymakers' ability to make agile and effective policy decisions.** While the country has made significant improvements on the availability and quality of national statistics, further strengthening of statistical capacity is needed. GDP data is available only at annual frequency and published with a significant lag, limiting timely analysis of comprehensive economic developments. To address this data gap, various methods can be used to estimate aggregate economic activity using high-frequency indicators that represent key sectors of the economy. However, these input indicators from traditional sources also often come with delays. These data issues are not unique to Cambodia. Many economies confront similar challenges and have been exploring options.

2. **Satellite indicators are available for nearly all countries in the world. They exist in near-real time and at granular levels capturing nuances that may otherwise go undetected.** They can serve as proxies for economic activity in various sectors of the economy. In particular, data on nighttime lights, nitrogen dioxide (NO2) emissions, and vegetation-related indices can help uncover underlying patterns and trends in sectors like manufacturing and agriculture.[2] In Cambodia, quarterly GDP growth rate (interpolated, see section on Data and Methodology) is positively correlated with changes in nighttime light (NTL), vegetation health index (VHI), and precipitation (PCP) (Figure 1). Satellite indicators can complement and fill the gaps in traditional indicators as they provide near real-time reflection of what is seen and felt on the ground and capture nuances in economic activity at high spatial and temporal granularities.

3. **Machine learning models can make the best use of satellite indicators, along with macroeconomic data to analyze their complex interactions for nowcasting GDP.** First, the dataset is split into 'train' and 'test' sets. The model learns patterns based on the train set, and its predictions are then evaluated against observed values in the test set—data that was not used during training (i.e. out-of-sample). This approach has the advantage of the model's performance to be assessed based on its ability to generalize to unseen data. In addition, in contrast to linear methods, the predicted value obtained through this approach accounts for complex, non-linear interactions that may exist between various indicators. Lastly, the nowcast can be updated monthly as up-to-date, high-frequency input data become available.

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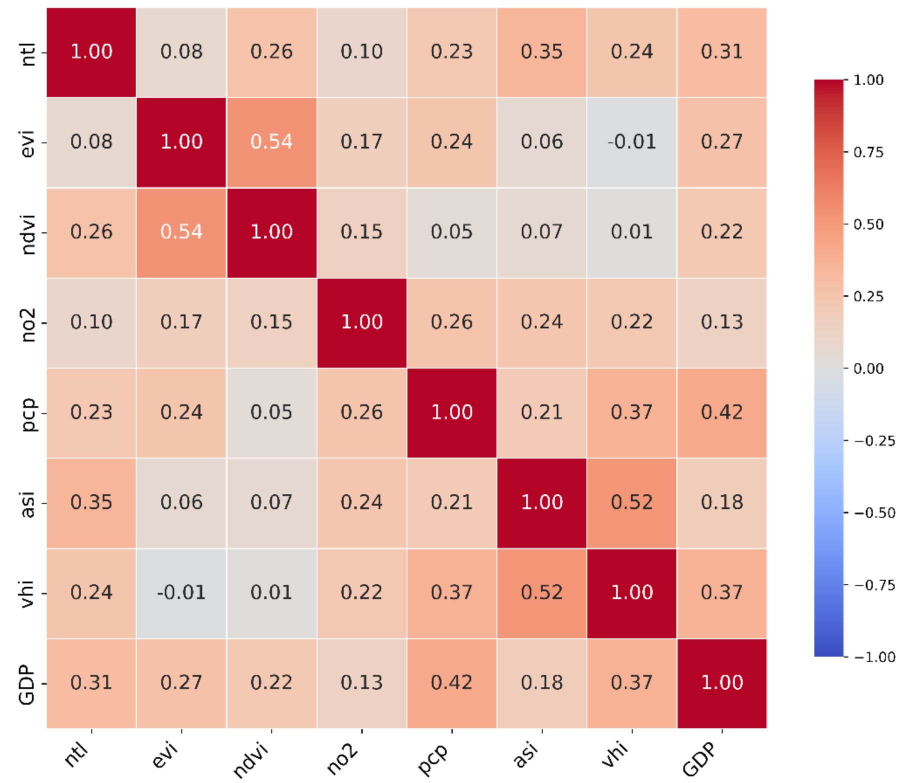
[1] Prepared by Iyke Maduako, Dharana Rijal, and Alberto Sanchez Rodelgo (all STA).

[2] See analytical examples by Gibson (2020) and McSharry and J. Mawejje (2024) for nighttime lights, Ezran, Morris, Rama, and Riera-Crichton (2023) for nitrogen dioxide (NO2) emissions, and Puttanapong, Prasertsoong, and Peechapat (2023) and Hu and Xia (2018) for vegetation-related indices.

Correlation Heatmap of Growth Rates of Satellite Indicators with GDP Growth: 2010Q1-2025Q1



B. Data and Methodology

4. The machine learning method applies quarterly satellite indicators, along with the traditional variables, for training the nowcasting model. The satellite ("non-traditional") **indicators** used in this analysis include data on nighttime lights (NTL), NO2 emissions (NO2), precipitation (PCP), normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), vegetation health index (VHI), and agricultural stress index (ASI). These indicators are obtained from various sources, including Google Earth Engine and NASA (in the case of NO2) and defined as follows:

- **Nighttime Lights (NTL)** are satellite-based measurements of the intensity of light emitted at the Earth's surface, which is shown to be a good proxy for economic activities in many studies.[3]
- **Nitrogen dioxide (NO_2)** is a pollutant, primarily produced by the combustion of fossil fuels in power plants, industrial facilities, and vehicles. Because NO_2 is emitted in large quantities

[3] See, for example, Forbes (2013); Ezran et al. (2023); Gibson et al. (2021)

when economic activity is high, satellite-based observations of NO_2 can approximate the level and distribution of economic activity on the ground.

- **Normalized Difference Vegetation Index (NDVI)** and **Enhanced Vegetation Index (EVI)** are computed using the red (R) and near-infrared (NIR) bands of satellite imagery. These indices measure vegetation health and can be used to proxy agricultural output, and land use changes, as well as expansion of cropland and infrastructure development.

- **Agricultural Stress Index (ASI)** is a satellite-based indicator designed to detect areas of cropland experiencing water stress—such as drought conditions—during the growing season.

- **Vegetation Health Index (VHI)** is computed using NDVI and Land Surface Temperature (LST) as inputs. First, the vegetation condition index (VCI) is derived from NDVI to assess vegetation greenness. Then, the temperature condition index (TCI) is calculated to measure how current surface temperatures deviate from their long-term average, highlighting heat or cold stress. This is also a proxy for agricultural wellness and crop yield.

- **Precipitation indicator (PCP)** obtained from Climate Hazards Center is InfraRed-based precipitation data combined with in-situ station data (CHIRPS). This is a quasi-global rainfall dataset of CHIRPS, which covers a long history (30 plus years) and incorporates 0.05° resolution satellite imagery with in-situ station data, to create gridded rainfall time series for trend analysis and seasonal drought monitoring. This indicator is also related to agriculture and food production.

Non-traditional and Traditional Indicators Used

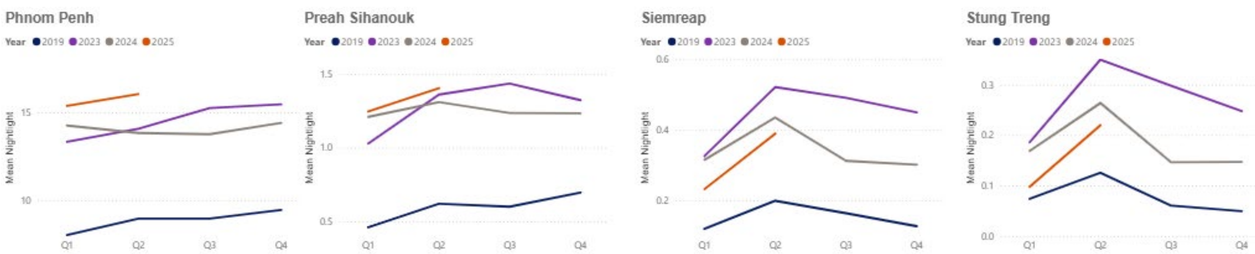
Non-traditional Indicators	**Traditional Indicators**
Nighttime Lights (NTL)	Exports and Imports
Nitrogen Dioxide (NO2)	Broad Money
Normalized Difference Vegetation Index (NDVI)	Exchange Rates
Enhanced Vegetation Index (EVI)	Consumer Price Index
Vegetation Health Index (VHI)	Lending Rate
Precipitation (PCP)	Credit
Agricultural Stress Index (ASI)	Tourist Arrivals

Box 1. Satellite Indicators to Gain Timely and Granular Insights on Macroeconomic Developments [1]

Satellite indicators can serve as proxies for economic activity in various sectors of the economy (Annex I). For example, data on nighttime lights (NTL) and vegetation-related indices can help uncover underlying patterns and trends in local economic activity in manufacturing and agriculture. They can complement traditional high-frequency indicators by providing real-time reflection of what is seen and felt on the ground. Satellite indicators can also reveal granular, regional variations in economic activity and guide policy formulation in a targeted manner.

(A) Nighttime lights (NTL):

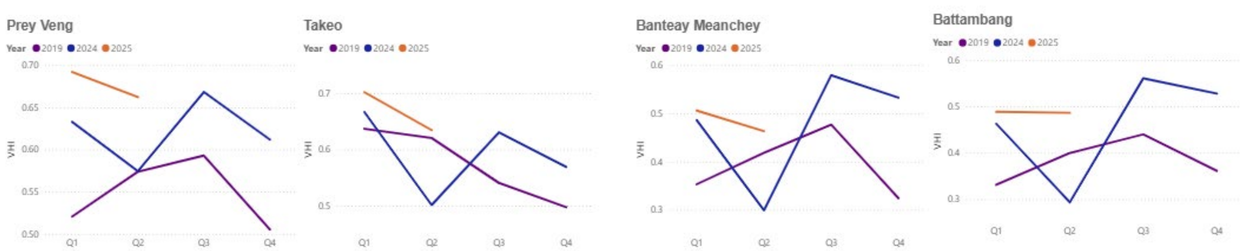
Nighttime lights, which capture the radiance or brightness of observed light can shed light on local economic activity. Compared to 2019, nighttime lights have increased across Cambodia in 2025. Urban regions, such as Phnom Penh and Preah Sihanouk, show higher nighttime lights in the first two quarters of 2025 compared to the same periods in 2023 and 2024. However, Siem Reap, a major destination for tourism, shows lower levels of nighttime lights in 2025 compared to recent years, which indicates a possible slump in the tourism sector. Other provinces in the country also show lower levels of nighttime lights in 2025, reflecting a slowdown in economic activity in the northeastern provinces such as Stung Treng, Ratanak Kiri, Mondul Kiri, and Kratie.



Sources: National Aeronautics and Space Administration (NASA/VIIRS/002/VNP46A2) and IMF Staff Calculations

(B) Vegetation-related indices:

Vegetation-related indices are calculated based on the amount of light reflected by plants and serve as proxies for vegetation health. Among these indices, the Vegetation Health Index (VHI) takes into account both vegetation greenness and data on surface temperatures, thereby serving as a proxy for agricultural wellness. In Cambodia, average VHI in the provinces with higher shares of cropland indicate healthier vegetation in the first two quarters of 2025 as compared to the same periods in 2019 and 2024.



Sources: FAO - Agricultural Stress Index System (ASIS), http://www.fao.org/giews/earthobservation/, [Date accessed: 09-23-2025] and IMF Staff Calculations.

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[1] This box was prepared by Dharana Rijal (STA).

5. The machine learning model applies interpolated series when some data points are missing in the traditional high-frequency macroeconomic indicators. The model takes key macro variables (Table 1), most of which are available starting 2010q1. In case some observations are missing, we impute data based on some historical patterns as needed. For GDP, Cambodia has annual data only. We have applied the quarterly GDP series (year-on-year growth rates) of Cambodia's major trading partners,[4] aggregated with respective export weights, for producing Cambodia's quarterly GDP series. This interpolation methodology is applied since export growth in Cambodia drives its business cycles and navigates economic growth over time.

6. The nowcasting model uses the random forest machine-learning algorithm to predict year-on-year quarterly GDP growth rate. Random forest (Breiman, 2001) is a collection of decision trees, with each built on various subsamples of data drawn with replacement (i.e., bootstrapping). For each tree, a random subset of predictors is selected at each split. At each node of the decision tree, the algorithm chooses the feature and split point that minimizes the root mean squared error (RMSE). This process continues recursively until a stopping criterion is met, such as minimum node size, or if additional splits no longer reduce the RMSE. The final prediction is obtained by averaging the predictions from all trees, a process known as bootstrap aggregation or bagging. The final prediction can be represented as:

$$\mathrm{y(x)}= \frac{1}{M}\sum_{\mathrm{m=1}}^{\mathrm{M}} T^{m}(x)$$

where y(x) is the predicted value; x is the vector of input variables we use to make a prediction; m is the index of each individual Decision Tree in the Random Forest, ranging from 1 to M, where M is the total number of Trees; and $T^m(x)$ is the prediction made by the m^{th} decision tree for input x. The Random Forest prediction is obtained by averaging the outputs of all individual trees in the ensemble.

7. The machine learning algorithm analyzes the underlying relationships among key variables by splitting the dataset into two groups ("training" and "test" datasets). This is the key feature of the algorithm which exploits the "training" dataset to learn the relationships in the past, uses the statistical relationships to predict values based on the "test" dataset, and evaluates goodness of the fit based on the difference between the model-based predicted values and the actual values in the "test" dataset. We implement cross-validation in a chronological order where 85 percent of the historical data is treated as the "training" dataset representing the "past", and the remining 15 percent of the historical data is treated as the "test" dataset (or "holdout sets") representing the "future".

[4] Major trading partners include Canada, China, Germany, Japan, Korea, Malaysia, Singapore, Thailand, United States, and Vietnam.

C. Results and Interpretation

8. `The random forest machine-learning technique demonstrates a strong fit, pointing to a nowcasting result of 5.7 and 6.7 percent GDP growth year-on-year in 2025q1 and 2025q2, respectively with the underlying stories. The alignment between the actual and nowcast regression lines can be measured by root mean square error (RMSE) of 0.9 (Figure 2). Shapley decomposition shows contributions of the variables to the predictive power of the model. (Figure 3). It is important to note that shapely contributions are not linked to causality, but contributions of the variables to the ability of the model to accurately predict the GDP growth rate. The addition of satellite variables to the list of indicators used to train the model improved the model accuracy by over 20 percent. This percentage might not seem substantial because of the weight of the traditional indicators, which is significantly higher. However, in situations where these traditional indicators are scarce or not collected on time, satellite indicators can fill the gap and contribute more to the accuracy of models.

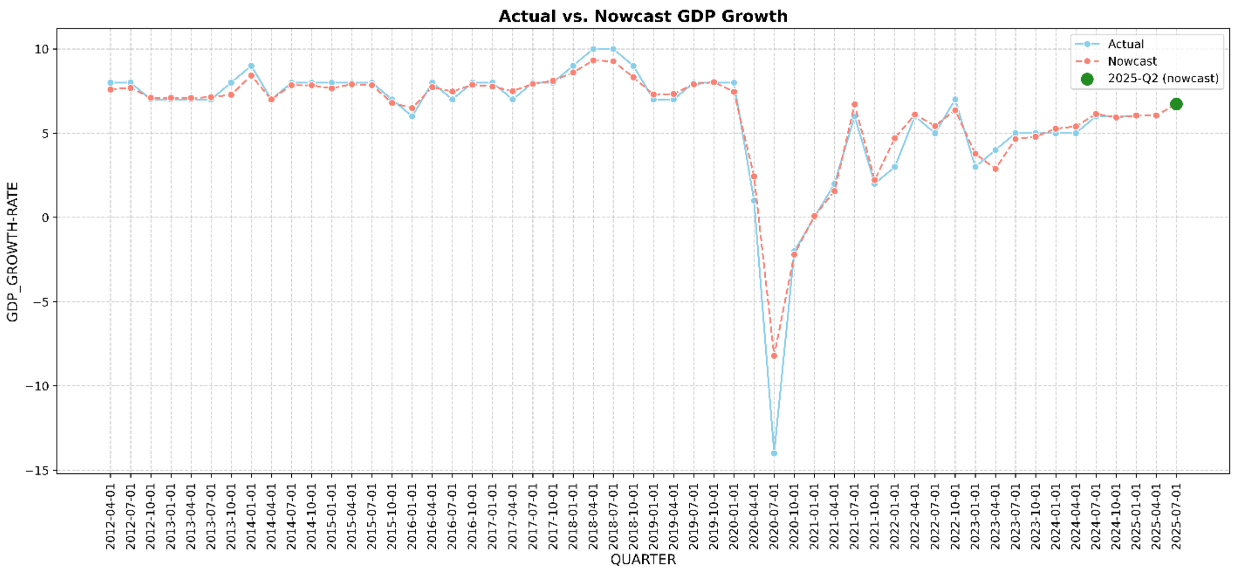
- Amongst satellite indicators, Nightlight and NO2 seem to be the most influential variable across time. Looking over the period of 2012-2025, we find that NO_2 emission seems to have the largest influence on model predictions among satellite indicators. This suggests NO_2 emission levels (as a proxy for industrial activity) are highly predictive of GDP dynamics in Cambodia.

- In the recent period of 2021-2025, the nighttime light (NTL) shows stronger influence on the model, indicating its growing alignment with economic activities visible from space at night. Factors, such as urbanization, tourism, household electricity access and consumption, might explain the growing influence.

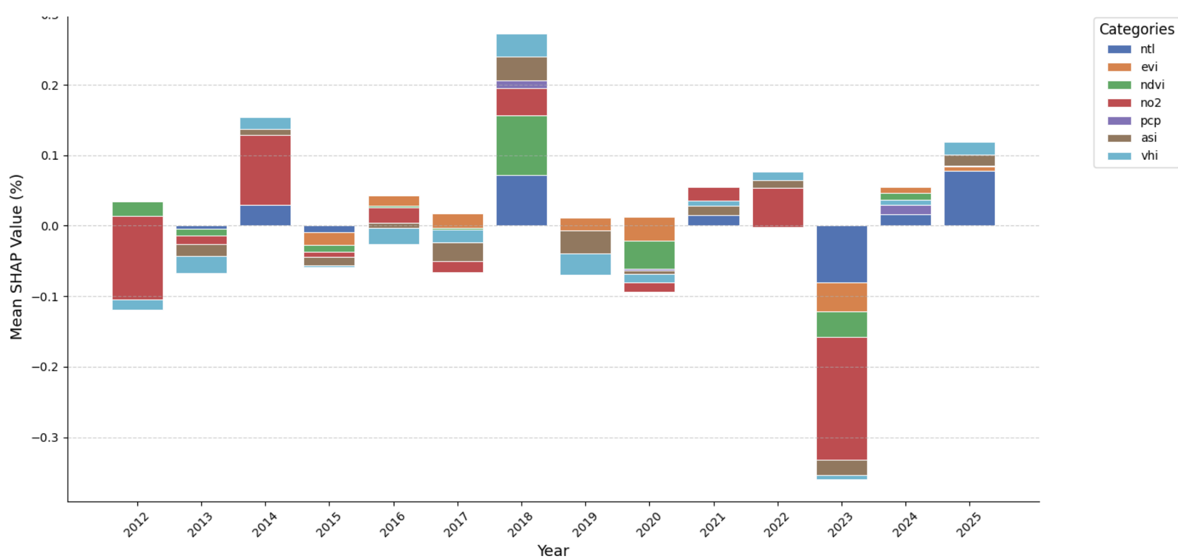
- The vegetation indices show modest but consistent contributions to economic activities over the years, with spikes in 2017 and the first quarter of 2025. This reflects important roles of agriculture in Cambodia's economy when it faces volatility in production potentially under the influence of climate change.

- The nowcast for the first quarter of 2025 indicates a year-over-year growth rate of 5.68 percent. Our analysis shows that non-traditional indicators complement traditional ones and serve as good alternatives when traditional indicators are scarce. Including non-traditional indicators in the nowcasting model improved RMSE and MAE metrics by over 20 percent, reducing RMSE from 1.2 to 0.9 and MAE from 1.0 to 0.8.

Quarterly GDP Versus Nowcast



Shapley Contribution of The Satellite Indicators Over Time



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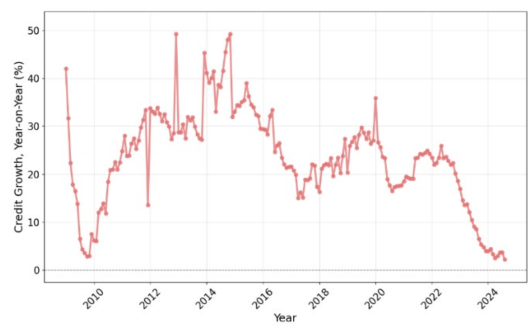
EXTERNAL DRIVERS OF CREDIT CYCLES IN CAMBODIA[1]

Cambodia's credit cycles exhibit significant sensitivity to global financial conditions, with common global and regional factors explaining around 60 percent of the country's credit growth variance—among the highest in Asia. Our analysis shows that Cambodia's response to external shocks, including US monetary policy, Chinese growth, and global risk sentiment, operates almost entirely through a common global credit channel rather than direct bilateral transmission. This high-beta exposure to the global financial cycle is an important driver of Cambodia's domestic credit swings.

A. Introduction

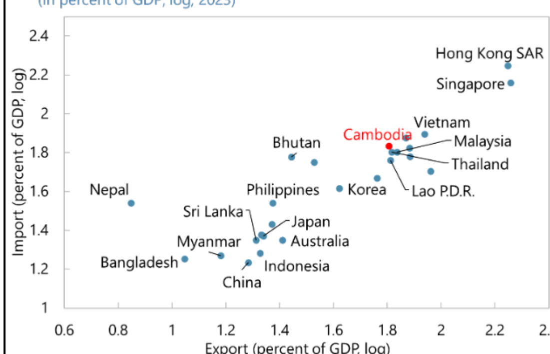
1. **Cambodia's credit growth has experienced extraordinary volatility over the past decades.** Private credit growth surged to over 25 percent annually for nearly two decades and sharply fell to a log single-digit growth in 2024. The cycles coincide remarkably with global events: the 2008-09 global financial crisis brought sharp contraction, followed by a sustained boom from 2010-2019 that ranked among the highest credit growth rates globally. The COVID-19 period brought a brief slowdown, followed by renewed rapid expansion through 2022, before the abrupt deceleration in 2023-24.

Credit Growth over Time



Sources: IFS; and IMF staff calculations.

Trade Openness of Asian Economies
(In percent of GDP, log, 2023)



Sources: IMF.

2. **Various explanations have been proposed for the recent volatility**, such as the unwinding of leveraged positions and changes in Chinese capital inflows. But given the complexity of these dynamics and the limited availability of high-frequency domestic data, quantifying the impact of various channels is a challenging task for policy makers.

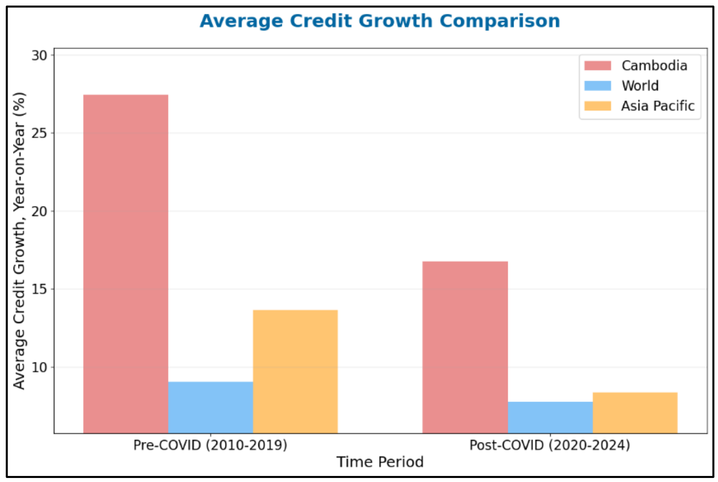
3. **Cambodia's economy remains highly dollarized, and its openness—with trade exceeding 120 percent of GDP—creates multiple channels through which global financial conditions can transmit easily to domestic credit markets**. This structural characteristic creates a landscape where banks can easily borrow from abroad and build up leverage in boom years. Subsequently, banks' loan to deposit ratio reached nearly 130 percent at the peak of 2021. These developments suggest that external factors may play a significant role in Cambodia's credit dynamics.

[1] Prepared by Natasha Che (APD).

4. **This annex aims to quantify the influence of external factors on Cambodia's credit cycles.** Using a dynamic factor model applied to credit data from over 100 countries, we extract global and regional credit factors and measure Cambodia's sensitivity to these common dynamics. We then investigate whether external shocks—including changes in US and Chinese economic conditions, global risk sentiment, and US monetary policy surprises—affect Cambodia uniquely or primarily through their impact on the global common factor.

B. Data and Methodology

5. **Our analysis draws on monthly credit-to-private-sector data for over 100 countries from 2000 to 2024**. The global dataset enables the extraction of common credit factors. Cambodia's credit growth substantially exceeds both regional and global averages, highlighting its position as an outlier in terms of credit expansion. This extreme growth profile may signal an amplified response to external factors.



6. **Cambodia's high credit growth stems from a confluence of drivers.** For much of the past two decades, the country has been a frontier economy undergoing rapid transformation, characterized by elevated GDP growth and a notable reduction in poverty. This created strong underlying demand for capital. The supply side of the credit equation was equally robust, fueled by several unique factors. High dollarization of the economy reduced currency risk, making it an attractive destination for foreign funding. A substantial portion of this credit boom was associated with the real estate and construction boom, which both drove and was driven by the nation's rapid economic development.

7. **For individual external drivers, we compile monthly indicators covering key transmission channels**:

- **Real economy indicators**: US and China Purchasing Managers' Indices (PMI) from the Institute for Supply Management and China's National Bureau of Statistics
- **Financial stress and risk sentiment**: US high-yield corporate credit spreads from FRED
- **Monetary policy shocks**: Orthogonalized US monetary policy surprises from the Federal Reserve Bank of San Francisco, capturing unexpected FOMC policy changes

Private credit and all external variables are transformed to year-over-year changes to ensure stationarity, except for monetary policy surprises which are inherently stationary.

8. Following Miranda-Agrippino and Rey (2020), we employ a state-space dynamic factor model to extract common components from credit growth across countries. Miranda-Agrippino and Rey demonstrate that a single global financial cycle factor explains over 20 percent of the variance in international risky asset prices, reflecting aggregate risk aversion and global financial conditions. Their work provides a well-established framework for identifying common dynamics in international financial variables, showing how US monetary policy and global risk sentiment drive synchronization across countries. Credit cycles around the world have similar underlining drivers as risk asset prices. We thus adapt a similar methodology to credit markets, where global credit factors may reflect common underlying forces affecting credit conditions worldwide.

9. The model decomposes each country's credit growth into common factors and idiosyncratic components:

$$y_{i,t} = \Lambda_i F_t + \epsilon_{i,t}$$

where $y_{i,t}$ is the standardized year-over-year credit growth for country i at time t, F_t is a vector of common factors, Λ_i are the factor loadings for country i, and $\epsilon_{i,t}$ is the idiosyncratic error term. The factors follow an autoregressive process:

$$F_t = \Phi F_{t-1} + \eta_t$$

where Φ is the transition matrix and $\eta_t \sim N(0, Q)$ is the factor innovation.

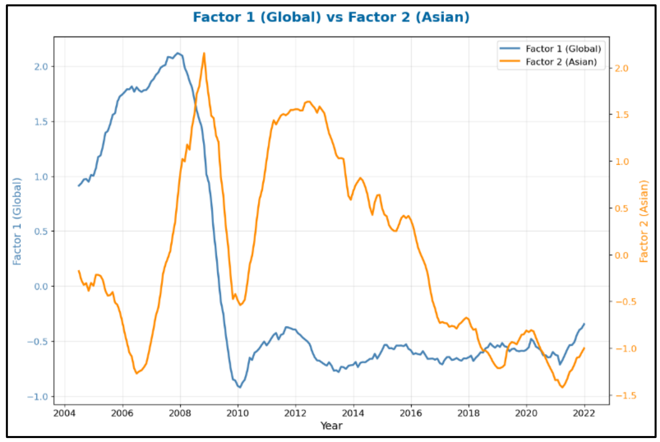
10. We jointly estimate both global and regional (Asian) factors using constrained maximum likelihood estimation. The global factor loads on all countries, while the regional factor loads only on Asian economies[2]. Cambodia is excluded from factor estimation to avoid mechanical correlation with the extracted factors, then its loading coefficients are calculated by regressing Cambodia's credit growth on the estimated factors.

11. We then test whether external shocks affect Cambodia primarily through the global factor or through idiosyncratic bilateral channels. Building on Miranda-Agrippino and Rey's finding that US monetary policy drives the global financial cycle through common transmission channels, this approach allows us to distinguish between country-specific exposure and participation in broader global cycles.

12. To this end, we estimate two competing VAR models. The first model includes individual external shock variables, including US monetary policy surprises, US corporate credit spreads, US and Chinese PMI, and Cambodia's credit growth. The second model adds the extracted global credit factor to this system. By comparing impulse responses and Granger causality tests across both specifications, we can assess whether apparent relationships between external variables and Cambodia's credit growth actually operate through common global channels.

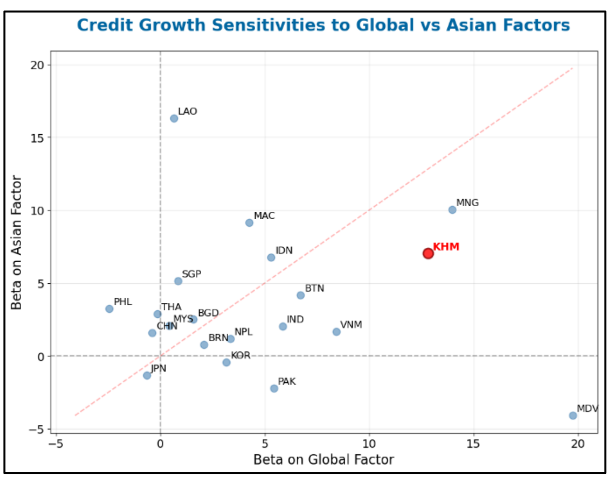
[2] Asian economies included in regional factor estimation: China, Japan, Korea, Indonesia, India, Laos, Malaysia, Philippines, Singapore, Thailand, Vietnam, Bangladesh, Bhutan, Nepal, Pakistan, Maldives, Brunei, Macao SAR, and Mongolia (19 countries excluding Cambodia which is omitted from factor estimation).

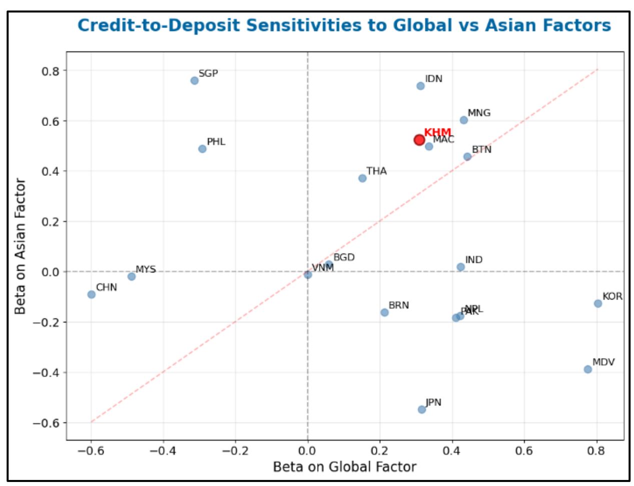
C. Results



13. The extracted global and Asian factors reveal both periods of synchronization and divergence[3]. During certain episodes, the global and regional factors move together, most notably during the post-2008 financial crisis period (2009-2010) and the 2020 downturn and subsequent recovery, suggesting common external shocks affecting both global and regional credit conditions simultaneously. On the other hand, the factors also exhibit substantial periods of divergence, with the regional Asian factor showing greater volatility and often moving independently of global trends. These divergent periods suggest the presence of Asia-specific credit dynamics that operate beyond the influence of global common financial conditions. The higher volatility of the regional factor should be interpreted with caution, however, as it is estimated from a much smaller sample of countries than the global factor, which may contribute to weaker identification and amplified volatility.

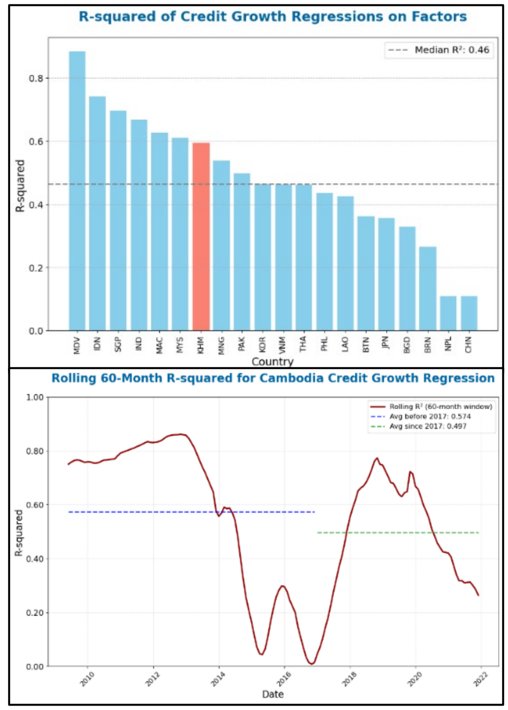
14. Cambodia exhibits among the highest loadings on both global and regional factors for credit growth. The scatter plot reveals Cambodia's position in the upper-right quadrant, indicating strong sensitivity to both global conditions (β = 12.82) and regional dynamics (β = 7.02). This suggests Cambodia experiences amplified responses to both worldwide and regional credit cycles. The significant synchronization with global and Asian financial cycles likely reflect trade linkages and cross-border capital flows within the region.



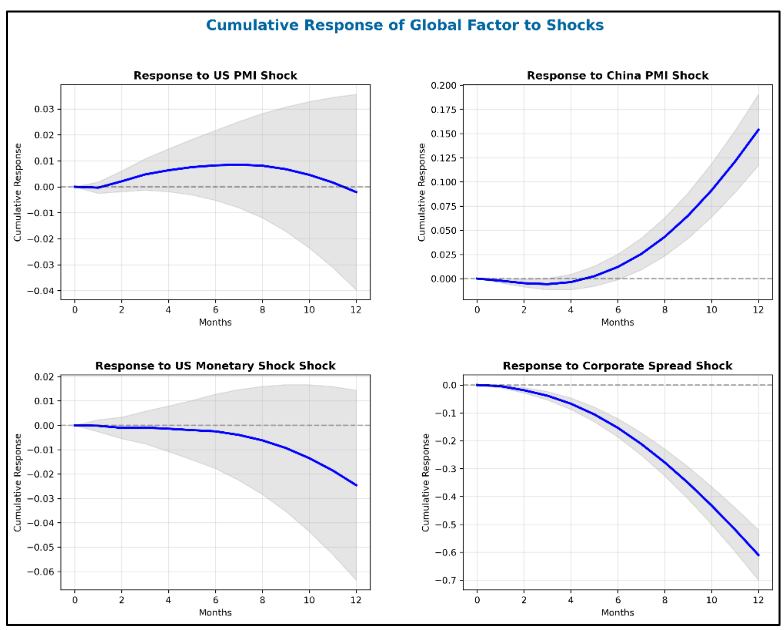


[3] The orthogonalization process ensures these factors capture independent sources of variation, with the regional factor representing Asian-specific credit dynamics after controlling for global trends. This decomposition allows us to separately identify Cambodia's sensitivity to worldwide versus region-specific credit conditions.

15. The credit-to-deposit ratio (CDR) loadings reveal a contrasting pattern in factor transmission channels. Cambodia’s CDR shows moderate sensitivity to the global factor (β = 0.31) but exhibits a higher response to the regional Asian factor (β = 0.52). This pattern suggests that compared to the global factor, regional factors may have a relatively stronger impact on bank balance sheet composition. This differentiation may reflect distinct transmission channels: while global factors primarily drive overall credit expansion through broad economic and financial conditions, regional factors appear more influential for banking sector leverage and funding structures. This could indicate that regional economic integration and intra-Asian capital flows play a particularly important role in shaping how Cambodian banks manage their lending.



16. The factor model demonstrates strong but time-varying explanatory power across Asian economies. The full-sample regression of Cambodia's credit growth on both factors shows a high model fit, yielding an R^2 of 60 percent, indicating that global and regional factors together explain more than three-fifths of Cambodia's credit growth variation. This high explanatory power underscores the importance of external factors in driving Cambodia's credit cycles. However, a rolling window analysis reveals important temporal variation in this relationship, with an average R^2 of 0.57 for the sample before 2017 and 0.5 for the sample since. This variation suggests that while external factors have historically been dominant drivers of Cambodia's credit cycles, their influence may be episodic, with domestic factors potentially playing a larger role during certain periods, particularly in the recent post-pandemic environment.

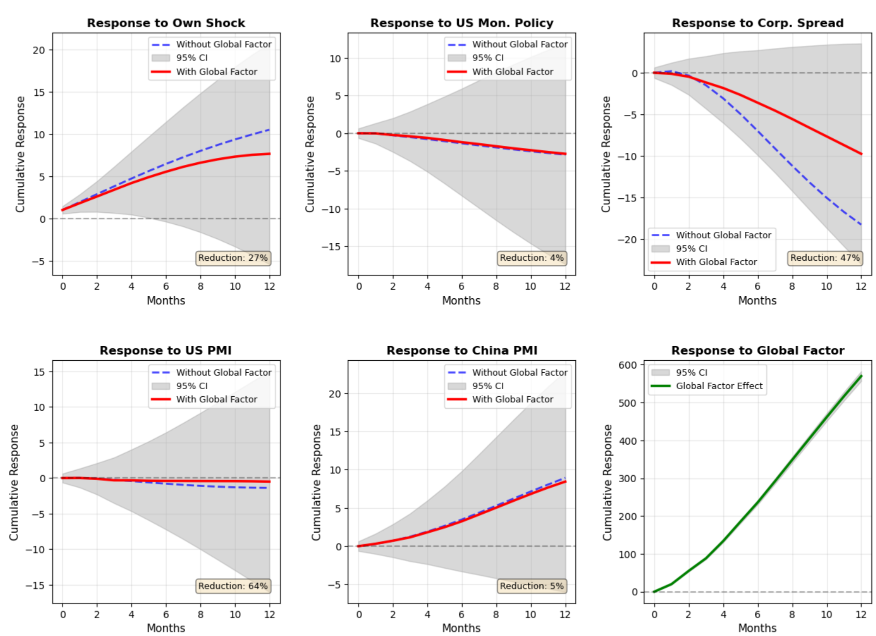


17. To understand the economic interpretation of the global factor, we examine its reaction to various external shocks through impulse response analysis. The global factor exhibits distinct patterns of response to different types of external disturbances, validating its role as a conduit for international credit cycle transmission. Specifically, the factor shows a strong and persistent positive response to improvements in Chinese economic activity, as measured by China PMI shocks. This finding underscores China's growing importance as a driver of global business cycles. Conversely, the global factor responds negatively to US monetary policy tightening and corporate spread widening. The negative response to corporate spreads is particularly significant, indicating that global risk sentiment and credit market conditions are key drivers of the global factor. The response to US PMI shocks is more muted, with the global factor showing only modest positive responses that fade after 12 months. This suggests that while US manufacturing performance matters for global credit conditions, the transmission of US economic shocks may be more complex and mediated through other channels such as consumer demand monetary policy.

18. To distinguish between direct bilateral transmission and common global channels, we employ two VAR specifications. The critical question is whether external shocks affect Cambodia directly through unique bilateral exposures, or primarily through their impact on the global credit cycle. For instance, does Cambodia respond to China's growth because of specific trade linkages (direct channel), or because China drives global credit conditions that affect all countries, with Cambodia being particularly sensitive (global channel)? By comparing VARs with and without the global factor, we can identify which mechanism dominates.

19. The results from this comparison are revealing. The key finding is that when the global factor is included in the VAR specification, most external variables lose their apparent direct influence on Cambodia's credit growth, as evidenced by the wide confidence intervals around zero in the impulse response functions when the global factor is included in the estimation. In contrast, the global factor itself shows a highly significant and persistent effect even after 12 months.

Credit Growth: Response to Shocks (With vs Without Global Factor)



Sources: IFS; and IMF staff calculations.

20. The Granger causality results provide statistical confirmation of this pattern. Two variables—corporate spread and China PMI-- that initially appeared to Granger-cause Cambodia's credit growth lose their significance when the global factor is controlled for. The corresponding cumulative impulse responses show reductions of 47 percent and 5 percent respectively when the global factor is included.

P-Values from Granger Causality Tests

Variable	P value without Global Factor	P value with Global Factor
Monetary Policy	0.35	0.84
Corporate spread	0.02**	0.98
US PMI	0.41	0.57
China PMI	0.07*	0.12
Global Factor	NA	0.00***

*** p<0.01, ** p<0.05, * p<0.1. P-values below these thresholds indicate that the underlining variable has statistically significant predictive power for Cambodia's credit growth (rejecting the null hypothesis of no Granger causality). P-values above these thresholds suggest no significant relationship.

21. These results provide important context for understanding Cambodia's credit volatility, though the time-varying nature of the relationships warrants careful interpretation.. The comparison between the two VAR specifications demonstrates that Cambodia exhibits little idiosyncratic sensitivity to external shocks beyond what would be expected from common global financial conditions. Rather than representing unique bilateral transmission channels, Cambodia's credit dynamics reflect a high-beta exposure to common global credit cycles that affect all economies. These results suggest that Cambodia's high credit volatility emerges from its position as a high-sensitivity economy within the global financial system. On the other hand, the declining explanatory power of the global factors in recent years indicates that domestic factors may periodically become more prominent. The recent credit deceleration, for instance, may reflect a combination of global financial conditions and country-specific factors such as real estate market adjustments and changes in capital inflows that are not fully captured by the global factors.

D. Conclusion

22. Our analysis reveals that common global and regional factors explain over 60 percent of Cambodia's credit variance, with the country exhibiting among the highest sensitivities to global credit cycles in our regional sample. However, rolling window analysis indicates this relationship shows significant time variation. Interestingly, when we control for the global credit factor in our VAR analysis, individual external shocks lose their statistical significance in driving Cambodia's credit growth. This suggests that external influences on Cambodia's credit cycles work primarily through common global financial cycle dynamics rather than through unique exposure to specific countries or shocks.

23. These findings provide important insight for policymakers. Macroprudential policies are likely to be more effective than traditional monetary policy tools for managing credit cycle, as much of the domestic credit growth volatility is in fact outsized responses to common global shocks. In a dollarized economy with limited monetary autonomy, instruments such as loan-to-value ratios, capital requirements, and lending standards can be adjusted to dampen domestic amplification of global shocks without resorting to control over exchange rates or interest rates.

24. Enhanced monitoring of global financial conditions becomes particularly valuable given Cambodia's high sensitivity to global cycles. Our analysis shows that variables such as corporate spreads provide important signals about global credit conditions that ultimately affect Cambodia. This suggests that early warning systems should incorporate a suite of global financial market indicators to anticipate potential pressures before they fully transmit to the domestic economy.

25. These findings should be interpreted with appropriate caveats. The declining explanatory power of global factors in recent years suggests that the transmission mechanisms may be evolving or that recent credit dynamics reflect a greater role for domestic factors not captured in our framework. Future research could explore whether structural changes in Cambodia's financial system or shifts in the composition of capital flows could have altered the sensitivity to global cycles.

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