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Nowcasting Nepal's GDP

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ABSTRACT

This paper proposes a statistical framework to nowcast Nepal's annual GDP. We identify 11 headline indicators available at monthly frequency which are regularly followed and monitored by media, economists, and market participants. Using these variables, we estimate the bridge equation and dynamic factor model to nowcast GDP. Our results show that GDP nowcasts tracks GDP realization, and are comparable to the benchmark forecast by other organizations. These simple models based on medium-size datasets can be used to nowcast Nepal's GDP and thus monitor economic activity in real-time.

Keywords: Nowcasting, Nepal, bridge equation, dynamic factor model.

JEL Codes: C22, C50, E37

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1 INTRODUCTION

Policymakers and market participants regularly monitor the state of the economy and incorporate it in their decision-making. Real gross domestic product (GDP) is the main indicator which is highly monitored and reflects the situation of an economy. Data on the Nepalese GDP are regularly published by the National Statistics Office (NSO) on an annual basis. However, there are ongoing efforts to streamline the publication of quarterly GDP regularly in time. Thus, there is a considerable delay and lags in the release of GDP data despite its importance in policy decisions such as monetary policy, fiscal policy, and macroprudential policy.

Despite the significant lag in GDP data release, there are many other headline indicators which are available with a shorter time lag, especially monthly basis. Currently, the Nepalese fiscal year begins in mid-July, and NSO provides the preliminary GDP estimate in around April/May of the year. Likewise, NSO has also been trying to publish the manufacturing production index and GDP on a quarterly basis since 2024 though there is a lag of 1-2 quarters. Highly monitored and viewed data about the state of the Nepalese economy are available in Nepal Rastra Bank's publication 'Current Macroeconomic and Financial Situation' which is produced monthly with a lag of less than a month. Thus, policymakers and market participants update their views about the state of the economy by monitoring the most relevant indicators which are available in a shorter time lag than GDP. In this context, producing up-to-date nowcast of GDP using such available headline indicators is crucial for policymakers to know about "where we are now".

This paper aims to propose a statistical framework to forecast Nepal's GDP using other headline indicators available at a higher frequency. We use the medium-scale dataset that includes 11 variables available at monthly frequency. The dataset consists publicly available headline indicators which are followed and monitored by economists, media, market participants and public officials. Our sample period for the estimation begins in 2000 because of the data unavailability for some indicators prior to this period. We propose three models for Nowcasting Nepal's GDP: simple bridge equation, dynamic factor model and bridge equation with principal components. We performed model evaluation based on in-sample forecast in which the dynamic factor model performs better. However, due to the small sample in the estimation, we propose the model averaging to nowcast GDP rather than relying on a single model. We forecast the GDP for 2023-2024 using data for 3, and 9 months to perform a benchmark comparison with the forecast of the International Monetary Fund and Asian Development Bank. This comparison shows that our forecast closely tracks the actual GDP growth and are comparable to the forecast made by these organizations.

We contributed to the nowcasting literature, especially the application for the low-income countries. This work is related to the growing nowcasting literature in economics after the seminal work by Giannone et al. (2008). There are a number of studies in GDP nowcasting such as for Japan by Bragoli (2017), for Canada by Bragoli (2017), for Turkey by Modugno et al. (2016), for Germany by Andreini et al. (2023), for Czech Republic by Rusnák (2016), for USA by Almuzara et al. (2023), and for India by Bhadury et al. (2020). Details of the literature survey regarding methods and application are available in Bańbura et al. (2013), and Cascaldi-Garcia et al. (2023). To our knowledge, no previous studies have attempted to nowcast Nepal's GDP. Thus, we add to this area of literature by nowcasting Nepal's GDP.

The next section includes data and variables. Section 3 presents nowcasting models, and the results are presented in Section 4. Finally, Section 5 concludes this policy paper.

2 DATA AND VARIABLES

In this section, we describe the variables and data sources that we use in nowcasting Nepal's GDP.

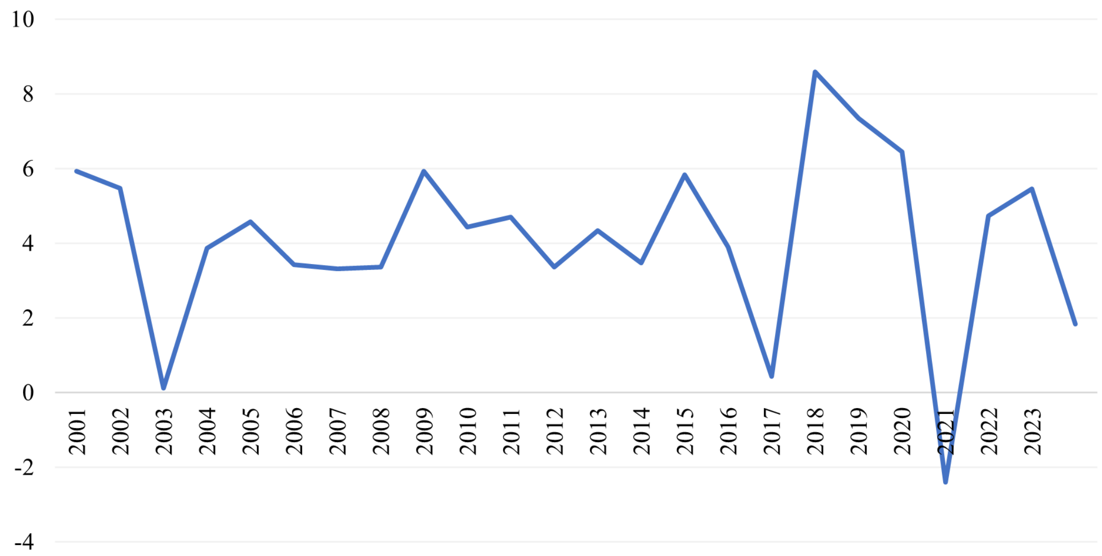
We use a relatively small-scale data set to nowcast Nepal's GDP. Following Bańbura et al. (2013) and Bragoli (2017), we mainly consider the variables that are followed and monitored by the market, newspapers, and other agencies such as central bank and national statistical office. Moreover, the literature shows a modest gain from including more variables as in Bańbura et al. (2010), and no improvement of forecast accuracy from more disaggregated information as shown in Banbura et al. (2010). Moreover, there lacks disaggreagated data on various sectors in Nepal such as indicators related to unemployment, retail sales, motor vehicle sales, and manufacturing production, among others. Thus, we take only headline variables to nowcast Nepal's GDP.

Data on Nepal's GDP are primarily available on an annual basis with a yearly lag though Nepal Statistical Office (NSO) has been trying to publish quarterly GDP regularly since 2023.

Nepal's fiscal year begins in mid-July, and annual GDP estimates are available about the end of April, resulting in 9 months lag. Even the quarterly GDP estimates are irregular with a lag of several quarters. These lags are very high compared to developed and emerging economies.

Figure 1 shows the evolution of the annual real GDP growth rates for the period 2000 to 2023. Nepal's GDP growth is highly volatile, suffering from frequent shocks. For instance, the average growth during this period was 4.10 percent, and the standard deviation is 2.33. There were large negative shocks such as the 2015 earthquake, and COVID-19 in 2020. This volatile nature of growth makes the forecasting task more difficult.

Figure 1: Evolution of Nepal's GDP Growth



Note: This figure shows the evolution of Nepal's GDP growth for the period 2001-2023.

Our target variable is real GDP growth at an annual frequency. However, this approach can be extended to the quarterly frequency. We want to predict the GDP before the publication of the NSO figure using the flow of other economic data which are released at a high frequency than GDP. Thus, our input series includes monthly data from various sectors.

Based on the structure of the Nepalese economy, we select 11 variables for nowcasting GDP. The real sector variables include the consumer price index and tourist arrivals. We include private sector credit for the financial sector which also closely proxies the private sector investment demand. Likewise, we include exports and imports, nominal exchange rates, and workers' remittance inflows for the external sector. Since 2000, worker remittances has been viewed as a major driving factor of domestic liquidity, credit, and then private demand. Government expenditure represents the fiscal sector.

Table 1: Description of variables

SN	Variables	Frequency	Aggregation	Data source
1	Consumer price index	M	L	NRB
2	Private sector credit	M	L	NRB
3	Imports of goods and services	M	S	NRB
4	Exports of goods and services	M	S	NRB
5	Nominal exchange rate	M	AV	NRB
6	Remittances inflows	M	S	NRB
7	Tourist arrivals	M	S	NRB
8	Government expenditure	M	S	NRB
9	MPI of India	M	L	MOSPI, India
10	MPI of USA	M	L	Fred at St Louis
11	Crude oil prices	M	L	World Bank
	Target variables			
12	Seasonally adjusted Real GDP	Q		NSO, Nepal
13	Real GDP	A		NSO, Nepal

Notes: This table shows the variables, data sources, frequency of availability, and aggregation. In the frequency, M stands for monthly frequency, Q for quarterly, and A for annual frequency. Aggregation stands how the variables are aggregated and used in nowcasting. L stands for the last period, S for the sum over the period, and AV for the average over the period. In data sources, NRB stands for Nepal Rastra Bank, NSO for National Statistical Office, and MOSPI for Ministry of Statistics and Program Implementation, India.

Given the interconnectedness of the Nepalese economy with India and the global economy, we also include the manufacturing production index of India and the USA. We include Indian MPI to capture the spillover from India because of high trade integration, free labor mobility, and open border with India. Likewise, we include the MPI of the USA and crude oil prices as proxies for global economic activity.

Our sample begins since August 2000. This is because of two reasons. First, migration of Nepali workers and inflows of remittances emerged as a major factor driving domestic demand and imports only after 2000. Moreover, Nepal Rastra Bank also changed the balance of payments compilation in 2000, resulting in the break in workers' remittances data. Second, Nepal also experienced structural reforms in the 1990s, and the financial sector reform in the 2000s, resulting the changes in the structure of the economy. Third, only reliable data series of selected variables are available only after 2000 such as remittances. Table 1 presents the description, data sources, and publication lag. We do a log transformation of all the variables, and adjust for seasonality. We also ensure that all variables entered in the estimation are stationary. As shown in Table A.1 in the Appendix, Augmented-Dickey Fuller test results show that all variables used in the study are stationary in the first difference. Likewise, we present the correlation matrix of the variables used in the Table A.2 in Appendix.

3 NOWCASTING MODEL

In this section, we present the econometric framework or nowcasting models for Nepal's GDP. Since we use a medium scale dataset, we employ three models: bridge equation, bridge equation with principal components, and dynamic factor models. We also compare the forecasting performance of these models.

We first begin with the Bridge Equation, the simplest method of nowcasting. This method has been in wide use in many central banks such as European Central Bank (Bańbura and Saiz, 2020), Federal Reserve Bank of Atlanta (Higgins, 2014), Deutsche Bundesbank (Bundesbank, 2013), and Sveriges Riksbank (Andersson and Reijer, 2015). The bridge equation method simply forecasts low-frequency variables by leveraging the available or forecasted value of high-frequency variables. One of the challenges in implementing this method is the ragged edge problem which can be solved by applying univariate models such as ARIMA to forecast high-frequency indicators and produce their quarterly or annual aggregates, as proposed by Bańbura and Saiz (2020) and Higgins (2014).

We present the nowcasting model for annual GDP growth, which can be applied to quarterly GDP following the same procedure. We mainly focus on annual GDP because quarterly GDP releases by NSO are still irregular. Let y_t^A be annual GDP growth, and X_t is the vector of k monthly indicators which are aggregated to annual frequency. Then, the annual variable x_t^A is given by $x_t^A = \frac{1}{12}(x_t + x_{t-1} + ... + x_{t-11})$ or $x_t^A = x_t$ depending on the nature of the variable. In the first step, we produce annual aggregates, x_t^A by forecasting x_t using ARIMA based on monthly data. The ARIMA model can be written as:

$$X_t = \alpha + \sum_{j=1}^{p} \phi_j X_{t-j} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{1}$$

By constructing annual aggregates x_{it}^A based on the equation 1 for the variable $i = 1, 2, ..., k$, we use the following equation to nowcast the GDP:

$$y_t^A = \alpha^A + \sum_{i=1}^{k} \theta_i(L) x_{it}^A + u_t^A \tag{2}$$

Next, instead of using all the variables, we use a few principal components in the Bridge equation. Though the procedure is same to nowcast GDP, this approach uses a few numbers of regressors, generating a parsimonious model (Gálvez-Soriano, 2020). This approach is used in the studies by Gálvez-Soriano (2020) and Kuiper and Pijpers (2020). This method basically departs from the conventional bridge equation about the number of regressors. It uses the aggregates of a set of principal components, Z_{it}^A, rather than incorporating the indicators, x_{it}^A, themselves. These aggregated principal components, Z_{it}^A, serve as the regressors in equation 3 to generate GDP forecast. Therefore, incorporating only a few principal components makes it parsimonious compared to the conventional bridge equation. Kuiper and Pijpers (2020) obtain the annual principal component by estimating the 12-month average.

$$y_t^A = \gamma^A + \sum_{i=1}^{k} \lambda_i(L) Z_{it}^A + v_t^A \tag{3}$$

Finally, we use the dynamic factor model (DFM) to nowcast GDP. DFM is a widely used method in GDP nowcasting for its wide applicability in the dimensionality reduction of time series data. It leverages the common dynamics of multiple time series to extract a smaller number of latent factors that drive the co-movements of measurable indicators.

A DFM expresses a $N \times 1$ vector X_t of observed time series variables as a function of a smaller number of unobserved (or latent) factors f_t and a mean zero idiosyncratic component ϵ_t. DFM can be expressed in state space form as:

$$X_t = \lambda(L) f_t + \epsilon_t \tag{4}$$

$$f_t = \theta(L) f_{t-1} + \eta_t \tag{5}$$

Where $\lambda(L)$ and $\theta(L)$ are the matrix of lag polynomials. $\lambda(L)$ is the factor loading matrix, which determines how the factors, f_t, influence the observed variables. $\theta(L)$ is the autoregressive function, which determines how the factors evolve over time. $\theta(L)$ follows the AR (1) process. Equation 4 is a measurement or observation equation, which constitutes the relationship between the observed time-series, X_t, and the state variables, f_t. Equation 5 shows the evolution of the state variables.

We use these three methods to nowcast Nepal's GDP. Then, we also produce a nowcast using model averaging based on root mean square error because of the relatively short-time period due to annual observations.

4 RESULTS

This section presents the results of model evaluation and benchmark nowcasts.

4.1 Model evaluation

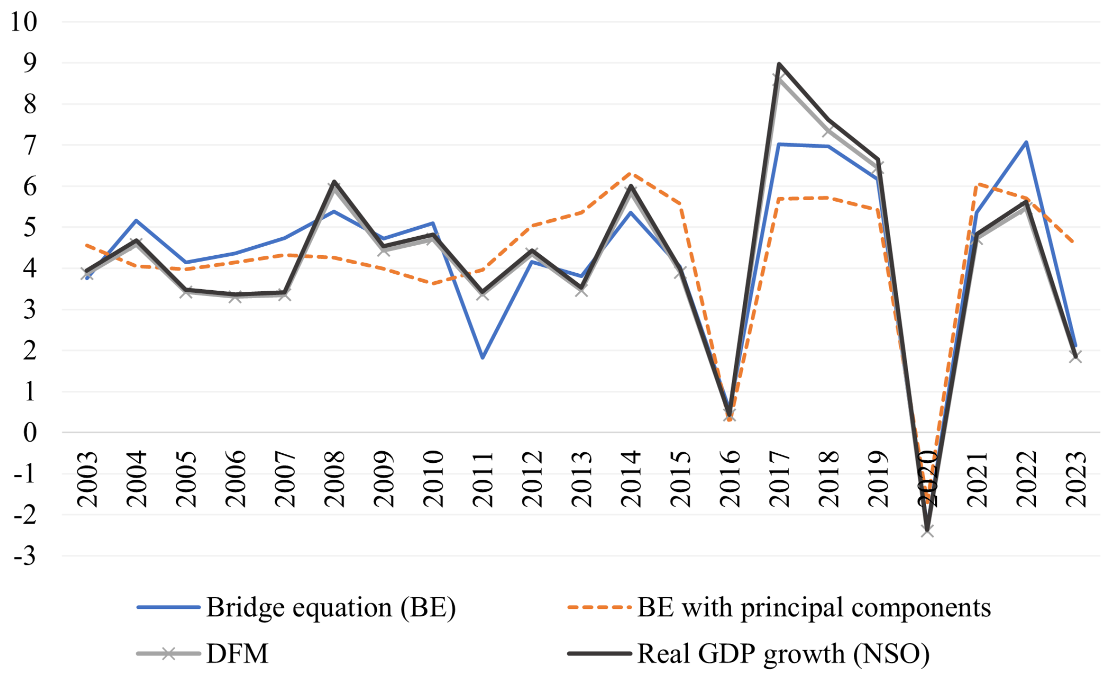
We present the results of three models: Bridge equation including all variables, Bridge equation with principal components, and dynamic factor model. In the Bridge equation with principal components, we use two principal components. The first component explains 76 percent of the variation, and the second component explains 12 percent of the variation. Thus, the first two components jointly explain 88 percent of the total variation in data. We extract these two components corresponding to eigenvalues greater than 1, as shown in Table A.3 in Appendix. The correlation of the first principal component and the log of GDP is 0.98, suggesting a similar pattern. Likewise, in the DFM, we use imports, credit, exports, MPI of India and USA, and crude oil price to extract the common factor for economic activity. We use only six variables in the DFM because of the small sample period in the estimation. Our choice of the variables in the DFM is based on the correlation with the real GDP growth.

Figure 2 presents the in-sample forecast of the nowcasting models, and actual GDP growth. In sample forecast produced all models closely follow the actual GDP growth. For model comparison, we also compute the root mean square error (RMSE), mean absolute square error (MAPE), and mean absolute error (MAE). The result in Table 2 suggests that the dynamic factor model performs better than other two models.

4.2 Benchmark comparison

We assess our forecast by comparing them against the institutional forecasters and actual GDP estimates by NSO. International Monetary Fund and Asian Development Bank regularly fore-

Figure 2: In-sample forecast of nowcasting models, and actual GDP growth



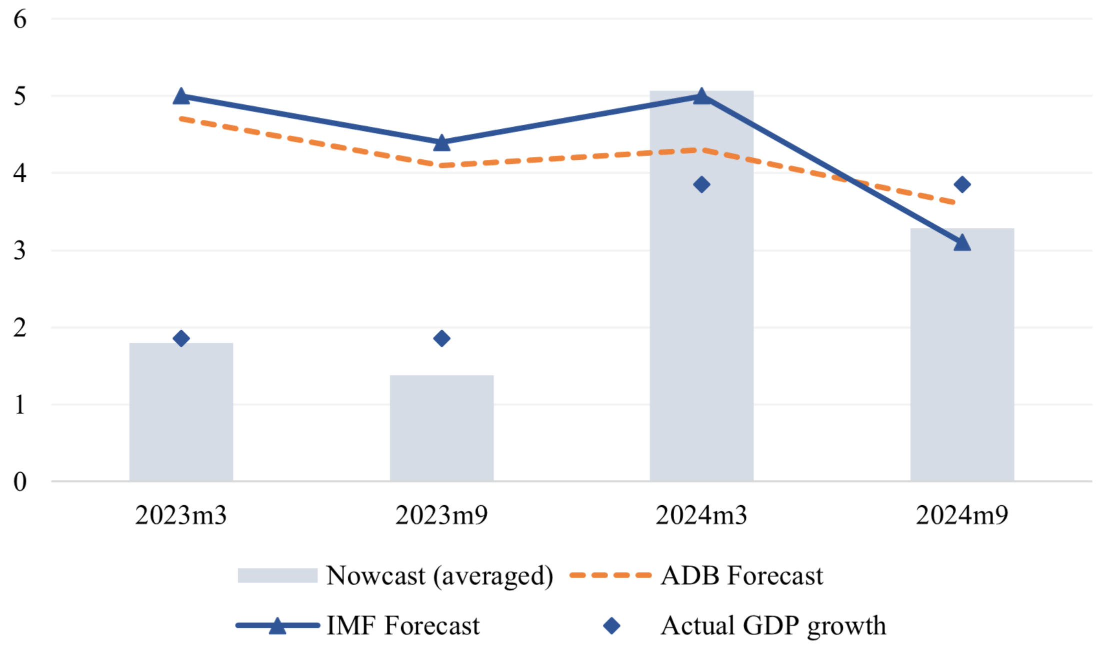
Notes: This figure shows the in-sample forecast of the nowcasting models. The solid blue line shows the in-sample forecast of bridge equation with all variables. Likewise, the solid gray line with cross sign shows the dynamic factor models, and the orange dotted line represents the bridge equation with the first two principal components. The solid dark line represents the actual GDP growth over the period.

Table 2: Evaluation of the nowcasting models

Criterion	Bridge equation	BE with principal Components	DFM
RMSE	0.82	1.37	0.42*
MAPE	0.15	0.29	0.02*
MAE	0.63	1.11	0.11*

Note: This table shows the root mean square error(RMSE), mean absolute square error(MAPE), and mean absolute error (MAE) of the nowcasting models. * represents best performing model from each criterion.

Figure 3: Benchmark comparison of nowcast



Notes: This figure shows the comparison of nowcast, derived from combining nowcast of three models based on RMSE, with the actual GDP growth, and the forecast of the International Monetary Fund (IMF), and the Asian Development Bank (ADB)

cast Nepal's GDP growth twice a year (April and October). Since the Nepali fiscal year begins in mid-July, we compare our nowcast with those two institutions forecast for October and April. Due to small samples, and the COVID-19 period, we take the nowcasting results for 2023-2024 in our benchmark comparison.

We first nowcast annual GDP growth for three models, and estimate forecast combination based on root mean square error. Since the sample period is relatively short, and we want to nowcast annual GDP growth, it is better to use such forecast combination rather than a single model. And, we compare the RMSE weighted average GDP growth nowcast against the actual GDP growth, and the forecast of the International Monetary Fund, and the Asian Development Bank. Figure 3 shows the benchmark comparison. Our nowcast of GDP growth closely follows the realized GDP growth. Moreover, our nowcast is comparable to the forecast by the IMF and ADB.

5 CONCLUSION

This paper proposes a statistical framework to nowcast Nepal's GDP which provides a basis for real-time monitoring of economic activity. We identify 11 market moving or headline indicators available at monthly frequency for the period after 2000. We use simple bridge equation, dynamic factor model, and bridge equation with principal components to nowcast annual GDP using indicators available at monthly frequency. We evaluate these three models based on in-sample forecast, and the dynamic factor model performs better. We nowcast GDP for 2023-2024 using data for 3 months and 9 months. Our nowcast closely follows the actual GDP growth, and are comparable to the institutional forecast. One can simply use the model averaging of three models rather than relying on a single model due to the small sample period.

The simple proposed framework in this paper can be used to regularly forecast Nepal's GDP and thus monitor economic activity at shorter-frequency. One of the limitations is the availability of data for the shorter time period and the need to forecast annual GDP which significantly reduces our sample points. Thus, this work can be further extended with the availability of more high-frequency data and the regular release of quarterly GDP in Nepal.

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Table A.1: Augmented Dickey Fuller Unit Root Test Results

Variables	Level	First difference
Consumer price index	1.065	-2.903*
Private sector credit	-2.695	-4.698**
Exchange rate	-3.511	-5.672***
Exports	-1.784	-6.14***
Government expenditure	-4.228	-4.798**
Imports	-3.391	-6.396***
MPI India	-2.398	-6.515***
MPI USA	-3.794	-7.299***
Oil price	-3.142	-5.421***
Workers remittances	-2.903	-5.408***
Tourist arrivals	-3.770	-18.667***

Table A.2: Correlation matrix

Indicators	CPI	Credit	Excchange rate	Exports	Government expenditure	Imports	MPI India	MPI USA	Oil	Remittances	Tourist arrivals	RGDP
CPI	1.00											
Credit	0.39	1.00										
Excchange rate	0.48	-0.12	1.00									
Exports	0.26	-0.11	0.25	1.00								
Government expenditure	0.13	0.21	-0.15	0.19	1.00							
Imports	0.15	0.61	-0.03	0.50	0.41	1.00						
MPI India	-0.29	0.06	-0.52	0.07	0.17	0.36	1.00					
MPI USA	-0.32	-0.25	-0.45	0.30	-0.03	0.19	0.74	1.00				
Oil	-0.35	0.04	-0.56	0.30	-0.01	0.43	0.57	0.67	1.00			
Remittances	0.52	0.26	0.38	0.35	-0.06	0.32	-0.08	-0.12	0.07	1.00		
Tourist arrivals	0.22	-0.28	0.03	0.64	0.07	-0.04	-0.12	0.21	0.20	0.08	1.00	
RGDP	-0.13	0.35	-0.14	0.56	0.38	0.84	0.47	0.35	0.53	0.22	0.13	1.00

Table A.3: Principal components

Principal components	Eigenvalues	Proportion	Cumulative Proportion
1	9.06*	0.76	0.76
2	1.50*	0.12	0.88
3	0.60	0.05	0.93
4	0.41	0.03	0.96
5	0.19	0.02	0.98
6	0.09	0.01	0.99
7	0.06	0.00	0.99
8	0.04	0.00	1.00

* The first two principal components are selected.