MALDIVES MACROECONOMIC FORECASTING

A COMPONENT-DRIVEN QUARTERLY BAYESIAN
VECTOR AUTOREGRESSION APPROACH

Anthony Baluga and Masato Nakane

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Anthony Baluga is an economics consultant and Masato Nakane is a senior economist at the Regional Cooperation and Operations Coordination Division, South Asia Department, Asian Development Bank.

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6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
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ABSTRACT

This study aims to establish a small-scale macroeconometric model for Maldives. We examine the ability of sector- or component-driven Bayesian vector autoregressions (VAR) to produce accurate macroeconomic (output and inflation) and tourist arrival forecasts in Maldives. We implement a standard Bayesian shrinkage technique and evaluate the information content of 49 quarterly macroeconomic and tourism variables in a Bayesian VAR context, using 4.5 years of in sample forecasting period from the first quarter (Q1) of 2015 to Q1 2019 to compute measures of forecast accuracy. Overall, the empirical results reveal that Bayesian VARs, using sector or component variables and coupled with the appropriate level of shrinkage, outperform the univariate and single equation model-specification benchmarks. The forecasting superiority of Bayesian VARs is clear. The empirical evidence suggests that these models can significantly improve the directional forecasting accuracy of output in Maldives.

ABBREVIATIONS

ARDL	–	autoregressive distributed lag model
ARIMA	–	autoregressive integrated moving average
CPI	–	consumer price index
GDP	–	gross domestic product
RMSE	–	square root of the mean squared error
T&T	–	travel and tourism
US	–	United States
VAR	–	vector autoregression
WTTC	–	World Travel and Tourism Council

I. INTRODUCTION

1. Two fundamental goals for any quantitative model are (i) to represent correctly the structure of the system being studied, which variables are linked to others and how they connect; and (ii) to forecast new observations accurately. The challenge arises in designing a framework that captures closely the underlying economic structure and in choosing the variables that would carry sufficient informational content on the macro-indicators of interest. The forecasting framework needs to be contextualized to the country being evaluated—being mindful that complex models involving many macroeconomic equations do not always perform as well as parsimonious models. Additional difficulty in the econometric exercise occur in creating model representations of developing economies considering that the time series data can be more volatile for such countries, and oftentimes the needed variables are unavailable.
2. To circumvent the limitations in empirical modeling of developing economies, researchers have learned to rely on parsimonious system specifications in their work. Relevant examples of small and simple macroeconomic models consisting of a number of pre-specified simultaneous equations in developing county context include those for Fiji (Wainiqolo 2013); Namibia (Tjipe, Nielsen, and Uanguta 2004); India (Mundle, Bhanumurthy, and Das 2011); and the Philippines (Bautista 2004).
3. For a more flexible modeling design, the vector autoregression (VAR) approach is a typical model that comprises ad hoc selection of variables, either representing a theoretical long-term macroeconomic relationship or simply comprising of indicators that are understood to be important determinants of the process or system being modeled. However, the VAR model can prove to be an unwieldy approach as parameters tend to increase with the number of variables being considered. In this environment, an econometric approach developed specifically to address the “curse of dimensionality” may be highly relevant. In particular, the class of Bayesian VAR models that has been recently developed (De Mol et al. [2008], Banbura et al. [2010], Giannone et al. [2012a], Banbura et al. [2014], and Baurle et al. [2018]) is known to produce adequate results even when a relatively large number of variables, compared with the sample time series, are included in the model simultaneously.
4. Empirical economic modeling in Maldives is supposed to be straightforward, given the simplicity of its macroeconomic structure. Yet, it can be a problematic task because of the significant limitations in data availability, and the insufficient length of the time series that make estimation of a comprehensive econometric model very tough. Arguably, a Bayesian VAR model estimated as a representation of the Maldives economy may be regarded as a novel and valuable tool for forecasting.
5. The derived model may be used for mainly nonstructural analysis, including scenario testing and counterfactual projections. The scenario testing is of obvious value for policymakers in Maldives, since producing forecasts conditioned on certain assumptions, like tourist arrivals, is highly relevant in the context of Maldives. A Bayesian VAR model is suitable for such an exercise because this type of model tends to produce more stable results for a set of variables compared with established econometric models. The model’s usability in counterfactual simulations (Giannone et al. [2012b]) may be helpful in detecting misalignments and irregularities in the path of observed variables in Maldives.
6. This study substantially benefited from the literature survey, methodology, and findings of a similar study conducted by Baurle et al. (2018). Section II presents relevant literature on component-driven Bayesian VAR; section III sets up the model; section IV describes the dataset and corresponding patterns; section V reports the forecast results; and section VI concludes.

II. RELATED LITERATURE

7. VAR models have gained traction as a practical forecasting tool in macroeconomics ever since Sims' (1980) seminal contribution to this branch of empirical analysis. This type of modeling has become popular due to its simple construction and ability to fit the data and produce fairly accurate forecasts (Karlsson 2013). However, the rich parameterization arising from its standard unrestricted specification poses limitations to real-world applications. As a recourse, researchers often scale down their VAR modeling by limiting specification to a small number of endogenous variables at a time. Recent methodological development has allowed for the imposition of parameter shrinkage techniques that circumvent over-fitting of the data and improve forecasting. A convenient and reasonably simple way to shrink the VAR parameters is through the Bayesian VAR method, particularly the so-called "Minnesota" prior approach proposed by Doan et al. (1984) and Litterman (1986). This methodology enables parameter shrinkage towards a predetermined representation of the data set.

8. Banbura et al. (2010) popularized the use of a modified Minnesota prior in forecasting applications that involve VAR models with numerous variables. They were able to show that large-scale VARs could outperform their factor-based counterparts in forecasting employment, inflation, and interest rates for the United States (US) economy. Their study highlights that successfully controlling for over-fitting could be achieved as the parameters' shrinkage becomes tighter even as the size of the VAR model grows larger. Furthermore, since most of macroeconomic variables are nearly collinear (i.e., they usually share common information), the high level of parameter shrinkage does not affect the ability of the model to exploit the information content of these set of macroeconomic variables.

9. Along the same line, Koop (2013) examined the forecasting performance of medium- and large-scale VARs by using various versions of the Minnesota prior and other non-conjugate priors. Koop's empirical study, also based on a US macroeconomic dataset, suggests that medium-scale VARs (up to 20 variables) combined with a simple Minnesota prior produce superior gross domestic product (GDP), inflation, and interest rates forecasts. In addition, Gupta and Kabundi (2010) show that large Bayesian VARs outperform the dynamic stochastic general equilibrium (DSGE) models in a forecasting exercise regarding the South African economy.

10. Since Bayesian VAR allows for an efficient estimation of medium- to large-scale number of variables versus a limited sample time series, it serves perfect use for an investigation of the joint evolution of sectoral/component heterogeneity, particularly those arising from the cross-sectional distribution of production sectors that, together, constitute the real economy.

11. There is a strand of literature that compares the forecasting performance of models that use aggregate data with those that employ sectoral component-disaggregated information. An important theoretical argument commonly cited in literature is that an optimally aggregated model tends to trade-off and disregard potential model misspecification and increased estimation uncertainty because of the often unmanageable nature of the higher number of parameters in component-disaggregated models (e.g., Hendry and Hubrich [2011]). Taylor (1978) conjectured based on analytical considerations that the trade-off depends on the extent of co-movement between the disaggregate series. Models using aggregate series or univariate models for disaggregate series are inefficient, if the disaggregate series exhibit heterogeneous dynamics. At the same time, gains of multivariate disaggregate models are predicted to be rather small if the series move homogeneously.

12. In order to test the dependence of the relative forecast performance of component-disaggregated models on the characteristics of data, several papers have provided empirical assessments. A few studies

looked at the production-side component-disaggregation of GDP. These empirical researches focused on the point forecast performance of component-disaggregated models, concentrating on short-term forecasts. For the Euro area, Hahn and Skudelny (2008) found that choosing the best-performing bridge equations for each sector of production outperforms an autoregressive model forecasting aggregate GDP directly. Drechsel and Scheufele (2012) analyzed the performance of a production-side disaggregation and a disaggregation into the expenditure components of German GDP. They compared the estimated forecasts with those of aggregate benchmarks and found only limited evidence that bottom-up approaches lead to better predictions. However, Drechsel and Scheufele showed that in certain cases, the production-side approach produces statistically significant smaller forecast errors than the direct GDP forecasts. More recently, Martinsen et al. (2014) and Baurle et al. (2018) found that disaggregate survey data at regional and sectoral levels improve the performance of factor models in forecasting overall output growth.

13. In the realm of indicator-based modeling, there is literature on testing the optimal number of indicators needed to forecast a specific aggregate target variable. Barhoumi et al. (2012) and Boivin and Ng (2006) provided evidence that a medium-sized number of indicators often leads to better performance than those carrying large numbers of indicators. They attributed this to the finding that idiosyncratic errors are often cross correlated. However, a major shortcoming of most of these indicator-based models is that they are unable to capture sectoral linkages and co-movement explicitly. To this regard, Horvath (1998) and more recently Carvalho et al. (2016) argued that production networks play a crucial role in the propagation of shocks throughout the economy, and can even cause low-level shocks to lead to sizeable aggregate fluctuations. As sectoral linkages are important amplifiers of aggregate movements, their direct inclusion in a model should help improve forecasts of aggregate variables.

14. Applying also to inflation forecasting, some studies have measured the forecasting performance of models that take linkages from component-disaggregation into account, and have compared these with aggregated models. Bermingham and D’Agostino (2011) emphasized in their study that the benefits of disaggregation increased with the number of disaggregate series. But this benefit only manifested when the model picked up common factors and feedback effects in factor augmented or Bayesian VAR models. Dees and Gunther (2014) employed a panel of sectoral price data from five geographical areas to forecast different measures of inflation. They found that the disaggregated approach improved forecast performance, especially for medium-term horizons.

15. This study tests whether modeling the production side of GDP through the use of dynamic component-disaggregated and -linked system of equations is beneficial. We evaluate the forecasting performance of time series models that utilize value-added series of production sectors summing up to the aggregate output of Maldives. To the best of our knowledge, we are the first to do so. We focus on the forecast performance of these component-driven models—capturing the joint dynamics of the sectoral series and important macroeconomic variables—relative to several simpler benchmark models.

III. MODEL SPECIFICATION

16. In light of the growing VAR literature, we aim to contribute in the following ways. First, we examine the ability of Bayesian VARs to deliver accurate forecasts in Maldives. Consequently, we utilize a data set of 49 quarterly macroeconomic and tourism variables, and we compare the forecasting ability of these medium-scale Bayesian VARs against two benchmark specifications. Second, our study concentrates not only on forecasting macroeconomic activity (GDP and inflation), but also on movement in tourist arrival variables as this approach aptly puts the exercise into the Maldives economic context. Third, we emphasize the critical information content of tourism variables regarding their ability to contribute to accurate macroeconomic forecasts. Finally, not only do we examine the efficiency of point forecasts, we also pay attention to the direction of change of target variables as most economists are interested in the general economic path of a country. Therefore, we evaluate the forecasting performance of the various VAR specifications by considering not only their ability to minimize the magnitude of the forecasting errors but also their ability to deliver accurate directional forecasts. The former is assessed via the conventional mean squared forecast error commonly used in related studies (Carriero et al. 2009; Banbura et al. 2010; and Koop 2013), whereas the latter is assessed via the qualitative views on economic coherence and consistency with observed regularities in the data.

A. Bayesian Vector Autoregressions Model

17. Following the specification of Baurle et al. (2018), we denote quarter-on-quarter growth of a single sector or component s at time t by x_t^s and the stacked vector of x_t^s in all S sectors by X_t^s . The vector of macroeconomic variables is denoted by X_t^M . The vector of X_t^s and X_t^M stacked into one vector is denoted by X_t . This contains all data that is jointly used for the baseline models for GDP, tourism, and price inflation.

18. We set up a VAR model using all appropriate macroeconomic variables and sectoral or component series, and estimate the model with Bayesian methods. The stacked vector is assumed to depend linearly on its lags and some disturbances :

$$X_t = c + \sum_{i=1}^p \Phi_i X_{t-i} + \sum_{k=1}^4 \beta_k qs_k + \varepsilon_t$$

19. where the constant c , $\Phi_i, i=1, \dots, p$, and $\beta_k, k=1, \dots, q$, are coefficient matrices for the lags of stacked vector X_t and quarterly season dummy variables qs_k , respectively; and ε_t is a vector of innovations, which are assumed to be Gaussian white noise, i.e., $\varepsilon_t \sim N(0, \Sigma)$.

20. With X_t reaching a large dimension, the number of parameters to be estimated becomes large, relative to the number of available observations. Thus, some shrinking of the parameter space is needed. Following much of the literature, our implementation follows a Minnesota type prior.¹

B. Benchmark Models

21. To assess the forecast accuracy of the baseline Bayesian VAR model for Maldives, its results are compared with the forecast accuracy values under two benchmark models. We employ a univariate process and a single-equation estimation technique.

¹ The Bayesian VAR structural estimation module of Eviews version 10 has been used. Appendix 1 describes the Eviews interpretation of a Minnesota type prior. Only loose prior settings about the parameter values are imposed to allow ample room for data to speak. The Hyper-parameters used are: Mu: 0, Lamda1: 0.99, Lamda2: 0.99, Lamda3: 1.

22. The univariate process allows us to exploit and extract information by using the variable's own dynamics or behavior over time. Time-series data typically exhibit pattern over time, and the pattern can be used to forecast future values. The univariate approach employs the Box-Jenkins specification of the aggregate output or GDP, tourist arrivals, and consumer price series where the series is specified as an autoregressive integrated moving average (ARIMA) (p, d, q) process (ARIMA process $d = i$).

$$y_t = \alpha_0 + \varepsilon_t + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{i=1}^q \beta_i \varepsilon_{t-i} + \sum_{k=1}^4 \beta_k qs_k$$

23. where y_t is either the quarter-on-quarter growth rate of GDP, tourist arrivals, or price, and quarterly season dummy variables qs_k . The series is specified to be explained by its own lag values (autoregressive process) and by current and previous values of the error term (moving average, MA process). This specification hinges on the belief that time-series data have persistence or memory, such that past behavior is carried forward; the lags define the length of the memory or how far along information from the past affect the present.

24. To extend the univariate ARIMA specification of GDP, dynamics of other time series along with own dynamics may be used to estimate this series. This single-equation process is known as an autoregressive distributed lag model (ARDL). For this specification, the series is said to be driven by its own persistence (like the autoregressive process in equation 1) and by some exogenous variable(s) current or lagged values.

$$y_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i} + \sum_{i=0}^m \beta_i x_{t-i}^j + \sum_{k=1}^4 \beta_k qs_k + \varepsilon_t, \forall j \text{ } x^j \text{ is the exogenous variable}$$

25. The exogenous variable may be based on known economic relationships. For instance, in the GDP model, the equation may be specified as a function of tourist arrivals. For the output ARDL model, own lagged values of GDP as well as lagged values of the exogenous variable, tourist arrivals, are included in the model.

$$GDP_t = \alpha_0 + \sum_{i=1}^p \alpha_i GDP_{t-i} + \sum_{j=0}^n \beta_j TourArrivals_{t-j} + \sum_{k=1}^4 \beta_k qs_k + \varepsilon_t$$

26. The number of lags per variable may differ. The ARDL model assumes that all the right-hand side (RHS) variables are exogenous. The lagged values since pre-determined at current time-period is not a concern, however, endogeneity of contemporaneous variables needs to be ascertained to ensure that endogeneity issues do not arise.

IV. DATASET, PATTERNS, AND RELATIONSHIPS

27. We fit three component-disaggregated Bayesian VAR models to production-side national account, consumer price index (CPI) by price item/category, and tourist arrivals by region data for Maldives. Real valued time series on a quarterly frequency are utilized covering an estimation sample set from Q1 2012 to Q2 2019.² A full descriptive summary of the various data series is documented in Appendix 2.

28. The GDP dataset includes the aggregate output and 16 sectoral real gross value-added series. The sectoral classification is based on the International Standard Industrial Classification of all economic activities. The numbers have been sourced from the National Bureau of Statistics, Ministry of Finance, and covers a longer quarterly series starting from Q1 2003. Overall, the national account, by kind of activity, includes a diversified set of industries and services sectors, which together sum up to GDP. Also important to consider is that the National Bureau of Statistics has revised Maldives' national accounts for the period 2003–2015, based on GDP estimates benchmarked and rebased to 2014. This has been accomplished with the assistance of the International Monetary Fund. The average rebased GDP between 2003 and 2015 is higher by about 11% annually, compared with the 2003-based GDP estimates.

29. The CPI dataset includes the aggregate/composite index, along with specific indexes for 10 commodity items or groups. The original price series is on a monthly basis, with quarterly averages derived accordingly. Data has been sourced from the monthly statistics bulletin of the National Bureau of Statistics and the Maldives Monetary Authority.

30. The tourism indicator of choice is the number of tourist arrivals by nationality and region. This serves as reference indicator that dictates the tourism sector's gross value added in the production national accounts. The original tourist arrival series is also on a monthly basis, and quarterly sums have been derived. Data has been sourced from the monthly statistics bulletin of the Ministry of Tourism and the Maldives Monetary Authority.

31. Capturing a system-wide picture of the Maldives economy, we also fit a quarterly Bayesian VAR model that incorporates variables for the real sector (output/GDP), prices, external sector (merchandise exports and imports), monetary sector (private lending rate), and the public sector (government total revenues and expenditures). This modeling technique allows the various sector variables in the system to affect each other jointly. This approach enables dynamic feedback across all the variables, treating each as endogenous to the equation system. Note that we are unable to utilize trade statistics both in goods and services as Maldives' balance-of-payment account only runs on an annual basis.

32. To motivate the estimation results, we present a brief discussion of visually observed trends and economic relationships of the key variables of interest. These patterns critically determined the specification of the forecasting models.

A. National Output

33. Maldives is considered to be a development success -- enjoying robust growth, improvement in connectivity, and provision of affordable public services for its people. These have resulted in impressive health and education indicators with a literacy rate approaching 100%, and life expectancy of more than

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² This data sample period is chosen because it represents a consistent pattern on the macroeconomy and tourism industry of Maldives, which enables an ideal model representation.

77 years. The country's GDP per capita reached \$10,449 in 2018, compared with a meager \$615 in 1984. Real GDP growth over the past 5 years (2014–2018) averaged 6.2% bolstered by tourism, construction, communications, transport, and fisheries.

34. Figure 1 shows the level and year-on-year GDP growth rate pattern and ensuing quarterly seasonality. Output growth has been severely stifled by the 2004 Indian Ocean tsunami, with a subsequent spike in 2006, reflecting massive recovery efforts. The country's output also fell during the height of the global financial crisis in 2009, which showed Maldives' vulnerability to external shock. Looking at the quarterly seasonality pattern, GDP peaks during the first quarter, tapering in the next two quarters, eventually picking up again in the year's last quarter.

Figure 1: Gross Domestic Product Level and Growth Rate: Trends and Seasonality

GDP = gross domestic product, Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, Q4 = fourth quarter, RHS = right-hand side.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

35. Much of the above output growth pattern is hinged on the behavior of the tourism industry, being the pivotal sector in the country's economy. Being an island nation, Maldives has developed a successful high-end tourism sector, with a portion of its sizable revenues being redistributed to the population to address development challenges. Travel and tourism (T&T) is an important economic activity in Maldives. As well as its direct economic impact, the industry has significant indirect and induced impacts.

36. According to the World Travel and Tourism Council (WTTC) Economic Impact Report (2018), the direct contribution of T&T to GDP in 2017 was Rf23,189.6 million (39.6% of GDP). This had risen by 2.5% to Rf23,779.7 million in 2018. This primarily reflected the economic activity generated by industries such as resorts, hotels, travel agents, airlines, and other passenger transportation services (excluding commuter services). But it also included, for example, the activities of the restaurant and leisure industries directly supported by tourists. The direct contribution of T&T to GDP is expected to grow by 5.9% per annum to Rf42,270.9 million (45.4% of GDP) by 2028.

37. Figure 2 shows the level, growth, and seasonality pattern for the tourism sector. Noteworthy is its tight similarity to the aggregate output growth patterns as indicated previously—the same 2004 and 2009 downturns and quarterly peaks and troughs. Moreover, Figure 3 illustrates the significant contribution of tourism to GDP growth.

Figure 2: Tourism Level and Growth Rate: Trends and Seasonality

Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, Q4 = fourth quarter, RHS = right-hand side.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

**Figure 3: Contributions to Real Gross Domestic Product Growth:
Year-on-Year Growth Rate, by Sector**

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

38. WTTTC recognizes that T&T's total contribution is much greater when indirect and induced impacts are considered. In its 2018 research for Maldives, it has been estimated that the direct contribution of T&T to Maldives GDP would correspond to the "internal" spending on T&T (i.e., total spending within a particular country on T&T by residents and nonresidents for business and leisure purposes) as well as government "individual" spending – referred to as spending by government on T&T services directly linked to visitors, such as in museums and recreational parks.

39. In addition WTTTC argues that the total contribution of T&T on Maldives economy would include "indirect" contributions in terms of the output and jobs supported by:

- (i) T&T investment spending, such as improvements in transport infrastructure and construction of new resorts and hotels;
- (ii) Government "collective" spending in tourism marketing and promotion, aviation administration, and security and sanitation services particularly in resort areas; and
- (iii) Domestic purchases of goods and services by sectors that deal directly with tourists, such as purchases of food and cleaning services by resorts and hotels, fuel and catering services by airlines, and information technology service purchases.

40. Then, there is the "induced" contribution, which measures the output and jobs supported by the spending of those who are directly or indirectly employed by the T&T industry.

41. In Maldives, according to WTTTC, the total contribution of T&T to GDP (including wider effects from investment, the supply chain, and induced income impacts) was Rf44,855.6 million in 2017 (76.6% of GDP) and had grown by 2.3% to Rf45,865.5 million (75.1% of GDP) in 2018. It is forecast to rise by 5.7% per annum to Rf80,191.6 million by 2028 (86.1% of GDP).

42. These aggregate output to inter-sectoral relationships or linkages are very apparent when we look at the close association of GDP and tourism growth together with tourism-related sectors of the Maldives economy (Figures 4, 5, 6, and 7).

Figure 4: Gross Domestic Product and Tourism Growth Relationship

GDP = gross domestic product.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

Figure 5: Tourism-Related Sectors

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

Figure 6: Tourism and Construction Sectors

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

Figure 7: Sector Relationships to Real Gross Domestic Product

continued on next page

Figure 7 continued

GDP = gross domestic product.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

43. Obviously, our subsequent model estimations will be driven by the above data trends and correlations. The justification becomes clear, at this point, for having a benchmark ARDL model of GDP against tourist arrivals. With the Maldives economy being accounted for substantially by tourism and related sector activities, there is much merit to measure its impact on GDP econometrically. Potentially, we can be exploiting this strong relationship in forecasting output growth.

B. Consumer Price

44. Inflation rate in Maldives averaged 4.99% from 2005 until 2018, reaching an all-time high of 21.16% in November of 2011 and a record low of -3.44% in December of 2005. Though Maldives inflation rate fluctuated substantially in 2005–2018, it tended to decrease through 2012–2018 period ending at 1.5 % in 2018. Quarterly seasonality shows peak price increase happening in the fourth quarter of each year, corresponding to the peak of tourist arrivals and highest point of output growth in the country (Figure 8).

45. During this period, the basket of goods and services and their corresponding weights (importance) used in sampling the price changes have been revised several times based on changes in the consumption behavior of Maldivians. These revisions are extracted from the household income and expenditure surveys carried out by the Department of National Planning at regular intervals.

46. A contributing factor to the somewhat declining inflation pattern is the active price stabilization policies being implemented by the government. However, there was a temporary blip in prices in the 2016–2017 period because of the food and electricity subsidy reforms initiated in October 2016 and the increase in import duties on cigarettes, and soft and energy drinks in March 2017. But the new government, which ascended to power in 2018, has reinstituted the old directive to broadly administer subsidized prices for key staple items. This is coupled by falling international commodities prices and an appreciating US dollar (to which the currency is pegged), which have maintained low and stable prices.

Figure 8: Consumer Price Index and Inflation: Trends and Seasonality

47. The overall CPI provides a measure of the average rate of price change. In calculating an average measure of this type, it is necessary to recognize that some items are more important than the others. Price changes for the more important items should have a greater influence on the average rate of price change than price changes for less important items. The relative importance of the goods and services in the CPI is determined by the relative household expenditure on each product; for example, on average, how much more households spend on fish than on vegetables.

48. In Maldives, the most important categories in the CPI are food and non-alcoholic beverages (28.44%) and housing, water, electricity, gas, and other fuels (23.29% of the total weight). The CPI also includes household appliances (8.71%), transportation (5.44%), health (5.42%), communication (4.75%), restaurants and hotels (3.02%), and education (2.5%). Figure 9 shows the inflation trends by component-item and highlights the high degree of inflation correlations across fish and other items that are significantly related to tourism.

Figure 9: Inflation Patterns and Correlations, by Component *continued on next page*

Figure 9 continued

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

49. The link between the country's GDP growth and inflation seems to be weak (Figure 10). But this disjoint appears to be artificial because of the price protection mechanisms put in place by the government to achieve social protection goals. Maldives is highly dependent on imports because of the scarcity of natural resources and a lack of a robust industrial base, which make it necessary to import almost all kinds of goods. The energy and transport sectors are entirely dependent on oil imports. The commodity import dependency and fluctuations in global oil prices should have impacted directly on domestic prices and the national economy, if not for the price protection policies.

50. Considering all the observed data patterns and correlations, we proceed to forecast Maldives' GDP growth, growth in aggregate tourist arrivals, and consumer price inflation. The forecast accuracy of our Bayesian VARs, when compared with the basic benchmark models, is crucially linked to the underlying data-generating process and cross-variable dynamics.

V. RESULTS

51. We wish to be clear that the models developed here are not intended for structural analysis; rather, the reduced form specification of the VARs are tuned more towards forecasting exercises.

52. We conduct in-sample and out-of-sample forecast evaluation exercises where we assess the models' accuracy in terms of predicting growth in the aggregate output, tourist arrivals, and composite price index. The estimation covers an in-sample forecast from Q1 2015 to Q2 2019 and two out-of-sample forecasting periods: (i) covering Q1 2017 to Q2 2019;³ (ii) covering Q3 2019 up to Q4 2024 (referring to the directional forecast). The size of the training data sample (Q1 2012–Q2 2019) is enough to produce stable estimation results.

53. As the models are geared toward capturing complex, dynamic interlinkages in the national accounts, tourist arrivals by region, and consumer price components, we do not focus on the predicted growth in any specific quarter h periods in the future, but want to assess the models' capability to show growth direction over a range of quarters. For the short run, we produce iterated forecasts for the first four periods ahead; then cumulative sum commensurate to a year-on-year growth rate.

54. The relevant measure by which we compare errors across models is the square root of the mean squared error (RMSE):

³ This will use a shortened training sample that covers the period from Q1 2012 to Q4 2016.

$$\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / h}$$

where the forecast sample is $j = T + 1, T + 2, \dots, T + h$ and denote the actual and forecasted value in period t as y_t and $\hat{y}_t$, respectively.

55. The RMSE forecast error statistics depend on the scale of the dependent variable. These are used as relative measures to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion.

56. The following sections present and discuss the relative performance of the competing models.

A. Economic Output – Gross Domestic Product

57. Table 1 summarizes the forecast error measures of the calculated projections for aggregate output growth. By RMSE criteria, the baseline GDP component-disaggregated Bayesian VAR outperforms the two benchmark and system Bayesian VAR models. This is not surprising because, previously, we have observed that the growth of sectoral variables in the production-side accounting of Maldives GDP exhibit close co-movements because of the tourism and tourism-related variable dynamics. Therefore, we have expected already that the sectoral Bayesian VAR of GDP would produce a tighter fit and better performing forecasts.

Table 1: Forecast Error Measures—Gross Domestic Product

Forecast Evaluation

In-Sample: Q1 2015–Q2 2019

GDP				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	379.5241	334.0406	2.0858	0.0114
ARDL	304.5337	237.5114	1.4427	0.0092
GDP BVAR	188.1652	147.0858	0.8627	0.0057
System BVAR	275.7669	218.0529	1.3097	0.0083

Out-of-Sample: Q1 2017–Q2 2019

GDP				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	783.9419	654.8605	3.7052	0.0219
ARDL	779.2926	571.8238	3.1289	0.0225
GDP BVAR	640.5622	458.8786	2.6157	0.0184
System BVAR	520.5556	431.4468	2.4388	0.0148

ARDL = autoregressive distributed lag model, BVAR = Bayesian vector autoregression, GDP = gross domestic product, Q1 = first quarter, Q2 = second quarter.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

58. We mentioned in the beginning of section III that we also intend to evaluate the forecasting performance of the various models, considering not only their ability to minimize the magnitude of the forecasting errors, but also their ability to deliver accurate directional forecasts. In Figure 11, we can observe the forecast path produced by the different models compared with the actual values during the in-sample period, and through cross-model comparison for the directional out-of-sample forecast period. In the case of GDP growth, it is apparent that the simple univariate and ARDL benchmark model specifications produce smoother forecast paths of GDP growth. On the other hand, the GDP Bayesian VAR shows more nuanced forecast path compared with the system Bayesian VAR. Here lies the role of expert judgement as to which forecast path best represents the outlook-for-output growth in Maldives.

Figure 11: Gross Domestic Product Level and Growth Forecast

ARDL = autoregressive distributed lag model, ARIMA = autoregressive integrated moving average, BVAR = Bayesian vector autoregression, GDP = gross domestic product.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

B. Tourism Activity – Tourist Arrivals

59. In the case of tourist arrival forecast, Table 2 shows that projections coming from the system Bayesian VAR outperform the univariate benchmark and the tourism disaggregated by region Bayesian VAR. This is an indication of the heterogeneous pattern of tourist arrivals across several regions. In particular, recent trends in tourist arrivals have shown a dramatic growth of visitors coming from the People's Republic of China. However, their numbers are quite erratic compared with the consistent level of European visitors to Maldives. Because of this, the system Bayesian VAR, where tourism is taken as an aggregate and fitted against other macro-sector variables, gave a tighter fit and forecast compared with the disaggregated Bayesian VAR.

Table 2: Forecast Error Measures – Tourist Arrival

Forecast Evaluation

In-Sample: Q1 2015–Q2 2019

Tourism				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	18,651.2700	15,903.3700	4.5432	0.0264
Tourism BVAR	28,553.4600	24,992.6600	6.7731	0.0393
System BVAR	14,519.1100	12,117.7600	3.4374	0.0205

Out-of-Sample: Q1 2017–Q2 2019

Tourism				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	62,779.9300	48,406.4500	11.9786	0.0892
Tourism BVAR	27,275.9800	21,354.2600	5.6372	0.0365
System BVAR	41,494.7200	32,406.5500	9.3018	0.0560

BVAR = Bayesian vector autoregression Q1 = first quarter, Q2 = second quarter.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

60. Looking at the directional pattern of tourist arrival forecasts (Figure 12), the system Bayesian VAR reflects more forecast fluctuations compared with the component-driven Bayesian VAR and univariate benchmark. Given the volatile nature of visitors coming from the People's Republic of China, it might be prudent to adopt the forecast path of the system Bayesian VAR after incorporating qualitative judgement.

Figure 12: Tourist Arrival Growth Forecast

ARIMA = autoregressive moving average, BVAR = Bayesian vector autoregression.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

C. Consumer Price Inflation

61. Finally, measures of forecast accuracy for price inflation projections (Table 3) show that the price component-driven Bayesian VAR outshines the univariate benchmark and system Bayesian VAR. Again, this is not surprising as we have noted previously the close pattern of price variables by item or commodity basket. This results in better estimates coming from the price disaggregated Bayesian VAR.

Table 3: Forecast Error Measures–Inflation

Forecast Evaluation

In-Sample: Q1 2015–Q2 2019

Price				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	1.7503	1.3943	1.3518	0.0085
Price BVAR	0.7308	0.6249	0.6061	0.0036
System BVAR	0.8214	0.6759	0.6569	0.0040

Out-of-Sample: Q1 2017–Q2 2019

Price				
	Root Mean Squared Error	Mean Absolute Error	Mean Absolute Percent Error	Theil Inequality Coefficient
	RMSE	MAE	MAPE	Theil
Univariate	2.7167	2.3312	2.2412	0.0129
Price BVAR	1.1924	1.0908	1.0448	0.0057
System BVAR	1.5438	1.3446	1.2875	0.0074

BVAR = Bayesian vector autoregression, Q1 = first quarter, Q2 = second quarter.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

62. The forecast path of inflation from the competing models show the highest level of variation when compared with those of GDP and tourist arrival growth projection paths (Figure 13). The univariate model produced the smoothest forecast path and the highest inflation forecast values for the out-of-sample period; the price component Bayesian VAR produced the lowest forecast values with a downward trend, while the forecast values coming from the system Bayesian VAR lie in the middle of the two. Expert judgement is needed to discern which path is applicable to foresee price developments in Maldives, with some government authorities leaning towards a declining view on inflation.

Figure 13: Consumer Price Inflation Forecast

ARIMA = autoregressive moving average, BVAR = Bayesian vector autoregression.

Source(s): Authors' estimates based on data from Maldives Monetary Authority and the National Bureau of Statistics of Maldives.

63. In evaluating the accuracy of the above forecasts, we note the efficiency (in terms of minimizing forecast errors) of our Bayesian VARs. However, when we divert focus to the directional accuracy, a huge gray area emerges in terms of the appropriate decision criteria to adopt in choosing the relevant forecast path for a variable of interest. This nicely slides us to one important implication, which is discussed in the closing section.

VI. CONCLUSIONS AND RECOMMENDATIONS

64. The main objective of this paper is to build an efficient macroeconomic forecasting tool for Maldives, while relying on limited time series data for estimation. To this effect, we apply the recently developed econometric approach that specifically addresses the “curse of dimensionality.” In this methodology, we estimate a Bayesian VAR model comprising of major domestic sectoral production, price, and tourism variables. Our results demonstrate that the Bayesian VAR methodology is appropriate for economic modeling in Maldives. The Bayesian VAR models, in consideration of the appropriate level of shrinkage, can exploit the information content of the component-disaggregated macroeconomic and tourism variables, and produce macroeconomic forecasts that outperform their small-scale benchmark counterparts.

65. The version of the model we have utilized in this study is an illustrative example of the applicability of Bayesian VAR for Maldives macroeconomic forecasting rather than the ultimate specification. The composition of the dataset employed may be further altered, depending on the required task.

66. We find that the directional meaning of the generated forecast values is hard to improve in the Bayesian VAR environment, as the forecast value nuance is diminished especially for long-term forecasting horizons. Nevertheless, in the case of price inflation, there is evidence that Bayesian VARs can improve the directional forecasting performance in the medium-term horizon.

67. Further, the forecasting results, based on qualitative evaluation accounting for the directional inclination and the magnitude of the forecasting errors, clearly support the use of Bayesian VARs for both macroeconomic and tourism variables.

68. In the forecasting process, both the results of macroeconomic modeling and expert judgements are used. In preparation for the forecasting exercise, a thorough descriptive analysis of past economic developments is conducted. Then the macroeconomic modeling is undertaken, with forecast estimates compared to actual developments and the causes of discrepancies analyzed. The results of the model are eventually judged in the context of both domestic and foreign economic and political developments. Expert judgement is factored in to assess the future output position. Verification of the results is done through comparison of macroeconomic forecasts against those of other relevant domestic and foreign institutions. These steps show that forecasting is a multi-staged iterative process. It is important to stress that internal consistency of the macroeconomic forecasting process should always be maintained.

APPENDIX 1: EVIEWS MINNESOTA TYPE PRIOR

To illustrate this prior type, extracted here is the derivation detail in the Eviews User Manual.

Suppose that we have VAR(p) model:

$$y_t = a_0 + \sum_{j=1}^p A_j y_{t-j} + \epsilon_t$$

where y_t for $t = 1, \dots, T$ is an $m \times 1$ vector containing observations on m different series and ϵ_t is an $m \times 1$ vector of errors where we assume ϵ_t is i.i.d. $N(0, \Sigma_\epsilon)$. For compactness, we may rewrite the model as:

$$Y = XA + E$$

or

$$y = (I_m \otimes X)\theta + e$$

where Y and E are $T \times m$ matrices and $X = (x_1, \dots, x_T)'$ is a $T \times (mp + 1)$ matrix for $x_t = (1, y'_{t-1}, \dots, y'_{t-p})$, I_m is the identity matrix of dimension m , $\theta = \text{vec}(A)$, $e \sim N(0, \Sigma_\epsilon \otimes I_T)$, and . The likelihood function then becomes

$$l(\theta, \Sigma_\epsilon) \propto |\Sigma_\epsilon \otimes I_T|^{-1/2} \exp \left\{ -\frac{1}{2} (y - (I_m \otimes X)\theta)' (\Sigma_\epsilon \otimes I_T)^{-1} (y - (I_m \otimes X)\theta) \right\}$$

To illustrate how to derive the posterior moments, let us assume Σ_ϵ is known and a multivariate normal prior for θ :

$$\Pi(\theta) \propto |V_0|^{-1/2} \exp \left\{ -\frac{1}{2} (\theta - \theta_0)' V_0^{-1} (\theta - \theta_0) \right\}$$

where, θ_0 is the prior mean and V_0 is the prior covariance. When we combine this prior with the likelihood function, the posterior density can be written as

$$\begin{aligned} \Pi(\theta|y) = \exp \left\{ -\frac{1}{2} \left((V_0^{-1/2}(\theta - \theta_0))' (V_0^{-1/2}(\theta - \theta_0)) \right) \right. \\ \left. + \left\{ (\Sigma_\epsilon^{-1/2} \otimes I_T) y - (\Sigma_\epsilon^{-1/2} \otimes X) \theta \right\}' \left\{ (\Sigma_\epsilon^{-1/2} \otimes I_T) y - (\Sigma_\epsilon^{-1/2} \otimes X) \theta \right\} \right\} \end{aligned}$$

which is a multivariate normal probability density function. For simplicity, define

$$w \equiv \begin{bmatrix} V_0^{-1/2} \theta_0 \\ (\Sigma_\epsilon^{-1/2} \otimes I_T) y \end{bmatrix}$$

$$W \equiv \begin{bmatrix} V_0^{-1/2} \\ (\Sigma_\epsilon^{-1/2} \otimes X) \end{bmatrix}$$

Then, the exponent in the previous equation can be written as

$$\Pi(\theta|y) \propto \exp\left\{-\frac{1}{2}(w - W\theta)'(w - W\theta)\right\} \propto \exp\left\{-\frac{1}{2}(\theta - \bar{\theta})'W'W(\theta - \bar{\theta}) + (w - W\bar{\theta})'(w - W\bar{\theta})\right\}$$

where the posterior mean $\bar{\theta}$ is

$$\bar{\theta} = (W'W)^{-1}W'w = [V_0^{-1} + (\Sigma_\epsilon^{-1} \otimes X'X)]^{-1}[V_0^{-1}\theta_0 + (\Sigma_\epsilon^{-1} \otimes X)'y]$$

Since Σ_ϵ is known, the second term of the above equation has no randomness about $\bar{\theta}$. Therefore, the posterior may be summarized as

$$\pi(\theta|y) \propto \exp\left\{-\frac{1}{2}(\theta - \bar{\theta})'W'W(\theta - \bar{\theta})\right\} = \exp\left\{-\frac{1}{2}(\theta - \bar{\theta})'\bar{V}^{-1}(\theta - \bar{\theta})\right\}$$

and the posterior covariance $\bar{V}$ is given as

$$\bar{V} = [V_0^{-1} + (\Sigma_\epsilon^{-1} \otimes X'X)]^{-1}$$

The Minnesota family of priors assumes that Σ_ϵ is known; replacing Σ_ϵ with its estimate $\widehat{\Sigma}_\epsilon$. This assumption yields simplifications in prior elicitation and computation of the posterior. Our choice of an estimator of Σ_ϵ is the univariate autoregressive process, wherein Σ_ϵ is restricted to be a diagonal matrix, where $\widehat{\sigma}_{iv}^2$ the (i, i) -th element of $\widehat{\Sigma}_\epsilon$, is the standard OLS estimate of the error variance calculated from an univariate autoregressive regression using the i -th variable.

Since Σ_ϵ is replaced by $\widehat{\Sigma}_\epsilon$, we need only specify a prior for the VAR coefficient θ . The Litterman prior assumes that the prior of θ is $\theta \sim N(\theta_0, V_0)$, $\theta_0 = 0$ (where the hyper-parameter $\mu_1 = 0$, which indicates a zero mean model) and nonzero prior covariance $V_0 \neq 0$. Note that, although the choice of zero mean could lessen the risk of over-fitting, theoretically any value for μ_1 is possible.

To explain the Minnesota/Litterman prior for the covariance V_0 , note that the explanatory variables in the VAR in any equation can be divided into own lags of the dependent variable, lags of the other dependent variables, and finally any exogenous variables, including the constant term. The elements of V_0 corresponding to exogenous variables are set to infinity (i.e., no information about the exogenous variables is contained within the prior).

The remainder of V_0 is then a diagonal matrix with its diagonal elements v_{ij}^l for $l = 1, \dots, p$

$$v_{ij}^l = \begin{cases} \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 & \text{for } (i = j) \\ \left(\frac{\lambda_1 \lambda_2 \sigma_i}{l^{\lambda_3} \sigma_j}\right)^2 & \text{for } (i \neq j) \end{cases}$$

where σ_i^2 is the i -th diagonal element of Σ_ϵ .

This prior setting simplifies the complicated choice of specifying all the elements of V_0 down to choosing three scalars λ_1 , λ_2 and λ_3 . The first two scalars λ_1 and λ_2 are overall tightness and relative cross-variable weight, respectively. λ_3 captures the lag decay that, as lag length increases, coefficients are increasingly shrunk toward zero. Note that changes in these hyper-parameter scalar values may lead to smaller (or larger) variances of coefficients, which is called tightening (or loosening) the prior.

Given this choice of prior, the posterior for θ takes the form $\theta \sim N(\bar{\theta}, \bar{V})$, where

$$\bar{V} = [V_0^{-1} + (\widehat{\Sigma}_\epsilon^{-1} \otimes X'X)]^{-1}$$

and

$$\bar{\theta} = \bar{V} [V_0^{-1}\theta_0 + (\widehat{\Sigma}_\epsilon^{-1} \otimes X)'y]$$

A primary advantage of the Minnesota/Litterman prior is that it leads to simple posterior inference. However, the prior does not provide a full Bayesian treatment of Σ_ϵ as an unknown; so, it ignores uncertainty in this parameter.

APPENDIX 2: DATA SUMMARY STATISTICS

Table A2.1: Gross Domestic Product and Components: Level Numbers

Sample: Q1 2003–Q2 2019

	RS_GDP	RS_TAX	RS_AGRI	RS_FISH	RS_MFG	RS_ELECTR	RS_WATER	RS_CONSTRN	RS_WHOLESALE	RS_TOURISM	RS_TRANSCOMM	RS_FINSERV	RS_REALSTATE	RS_PROFSCITECH	RS_PUBLICADMN	RS_EDUC	RS_HEALTHSOCWORK	RS_ENTRECOTHR
Mean	12,268.31	1,257,778	189,671	613,901	293,453	178,002	669,039	669,039	1,06,097	315,626	1,41,611	503,649	844,873	164,707	930,204	385,337	306,618	251,950
Median	11,829.83	1,273,055	188,075	593,91	280.8	153,015	622,585	622,585	1,08,614	313,915	1,32,947	553,075	837.4	174.62	884,485	372.3	309,865	252.01
Maximum	20,026.4	2,410.56	212.34	939,65	470.29	360.35	1,242.28	1,242.28	1,67,744	549,477	2,538.16	744.79	1,210.17	266.71	1,679.04	672.24	567.73	377.73
Minimum	6,833.99	629.41	162.02	318.77	215.25	63.53	183.96	183.96	647.69	139,734	527.58	124.67	466.18	50.48	363.8	225.79	93.75	110.05
Std. Dev.	3,255.447	372,352	11,834.39	139,924	55,816.28	84,327.34	261,669.9	261,669.9	244,688.6	81,658.72	562,633.4	177,740.1	235,727.9	56,175.52	352,047.9	121,710.4	141,620.2	58,985.74
Skewness	0.388385	0.546654	-0.067603	0.256734	1.33215	0.445409	0.438968	0.438968	0.371636	0.42742	0.19636	-0.798596	-0.06193	-0.443115	0.414964	0.312021	0.014593	-0.12014
Kurtosis	2.327318	3.149027	2.690624	2.60162	4.33998	1.991041	2.399821	2.399821	2.250144	3.327392	1.757943	2.556326	1.681422	2.233481	1.955366	1.978551	1.90088	2.710598
Jarque-Bera	2.903648	3.348211	0.313483	1.161477	24.45862	4.981772	3.110212	3.110212	3.065527	2.30433	4.66657	7.556637	4.823473	3.775623	4.895113	3.940162	3.324523	0.389093
Probability	0.234143	0.187476	0.854925	0.559485	0.000005	0.082837	0.211167	0.211167	0.215938	0.315952	0.096977	0.022861	0.089659	0.151403	0.086505	0.139446	0.189709	0.823208
Sum	809,708.7	83,013.34	1,2518.29	40,517.48	19,367.94	11,748.19	44,156.6	44,156.6	73,002.41	208,357.1	934,633.5	33,240.84	55,761.63	10,870.71	61,393.5	25,432.24	20,236.38	16,628.75
Sum Sq. Dev.	6.89E+08	9,011,999	9,103,429	1,272,617	202,504.7	462,221.5	4,450,622	4,450,622	3,891,713	43,342,951	20,576,166	2,053,451	3,611,896	205,119.8	8,055,953	962,872.3	1,303,659	226,155.6
Observations	66	66	66	66	66	66	66	66	66	66	66	66	66	66	66	66	66	66

Source(s): Maldives National Bureau of Statistics.

Figure A2.1: Gross Domestic Product and Components: Year-on-Year Percent Change

rs_GDP	Gross domestic product at market price
rs_Tax	Taxes less subsidies
rs_Agri	Agriculture
rs_Fish	Fisheries
rs_Mfg	Manufacturing
rs_Electrwater	Electricity and water
rs_Constrn	Construction
rs_Wholereail	Wholesale and retail trade
rs_Tourism	Tourism
rs_Transcomm	Transportation and communication
rs_Finserv	Financial services
rs_RealEstate	Real estate
rs_Profscitech	Professional, scientific, and technical activities
rs_Publicadm	Public administration
rs_Educ	Education
rs_Healthsocwork	Human health and social work activities
rs_EntrecOther	Entertainment, recreation, and other services

Estimated using production approach

In Rf million at 2014 constant prices

Source(s): Maldives National Bureau of Statistics.

Table A2.2: Tourism by Region and Country of Origin: Level Numbers

Sample: Q1 2012–Q2 2019

	TOUR- ARRIVAL	TOUR- REGAFR	TOUR- REGAMER	TOUR- REGASIA	TOUR- REGEURO	TOUR- REGMIDEAST	TOUR- REGOCEA	TOUR- REGUNPASS	TOUR- REGGER	TOUR- REGITALY	TOUR- REGUK	TOUR- REGRUSS	TOUR- REGPRC
Mean	318,162.5	2,725,033	12,418.67	136,219.2	149,738.1	10,446.2	6,558.3	57,03333	26,688.93	19,495.2	24,811.27	15,860.83	77,954.9
Median	308,549.5	2,423.5	11,896.5	137,819.5	143,238	9,576	6,005	63.5	26,018.5	15,158.5	23,779	14665	76,678
Maximum	482,978	4,693	25,804	168,636	269,619	20,578	11,594	107	37,279	52,848	36,116	26284	115,589
Minimum	202,201	1,232	5,885	73,693	102,167	4,344	3,462	0	19,496	8,934	20,640	8836	44,486
Std. Dev.	58,564.83	976,9569	4,655.338	24,086.5	41,944.64	3,908.828	2,325.044	35,61042	4,997,876	10,353.63	3,850,103	4,808,125	17,812.01
Skewness	0.654233	0.66059	0.804094	-0.924003	1.02147	1.035149	0.816707	-0.489105	0.659599	1,440,406	1,274,421	0.544063	0.34605
Kurtosis	3.759819	2.269134	3.542057	3.664919	3.719573	3.782289	2.515387	1.914966	2.53604	4.994904	3.956018	2.349366	2.79021
Jarque-Bera	2.861758	2.849599	3.600116	4.821556	5.864237	6.122633	3.628613	2.667743	2.444428	15.3484	9.263211	2.009178	0.653767
Probability	0.239099	0.240557	0.165289	0.089745	0.053284	0.046826	0.162951	0.263455	0.294577	0.000465	0.009739	0.366195	0.721168
Sum	9544874	81,751	372,560	4086575	4,492,142	313,386	196749	1,711	800,668	584,856	744,338	475825	2,338,647
Sum Sq. Dev.	9.95E+10	27,678,899	6.28E+08	1.68E+10	5.10E+10	4.43E+08	1.57E+08	36774.97	7.24E+08	3.11E+09	4.30E+08	6.70E+08	9.20E+09
Observations	30	30	30	30	30	30	30	30	30	30	30	30	30

Tourarrival = Tourist arrivals, TourregEuro = Tourists from Region - Europe, TourregAsia = Tourists from Region - Asia, TourregAfr = Tourists from Region - Africa, TourregAmer = Tourists from Region - Americas, TourregOcea = Tourists from Region - Oceania, TourregMidEast = Tourists from Region - Middle East, TourregUNpass = Tourists from Region - United Nations passport holders and others, TourregGer of which = Tourists from Region - Germany, TourregItaly of which = Tourists from Region - Italy, TourregRuss of which = Tourists from Region - Russian Federation, TourregUK of which = Tourists from Region - United Kingdom, TourregPRC of which = Tourists from Region - People's Republic of China.

Source(s): Maldives Monetary Authority and Ministry of Tourism.

Figure A2.2: Tourism by Region and Country of Origin: Year-on-Year Percent Change

Tourarrival	Tourist arrivals
TourregEuro	Tourists from Region - Europe
TourregAsia	Tourists from Region - Asia
TourregAfr	Tourists from Region - Africa
TourregAmer	Tourists from Region - Americas
TourregOcea	Tourists from Region - Oceania
TourregMidEast	Tourists from Region - Middle East
TourregUNpass	Tourists from Region - United Nations passport holders and others
TourregGer	of which Tourists from Region - Germany
TourregItaly	of which Tourists from Region - Italy
TourregRuss	of which Tourists from Region - Russian Federation
TourregUK	of which Tourists from Region - United Kingdom
TourregPRC	of which Tourists from Region - People's Republic of China

Source(s): Maldives Monetary Authority and Ministry of Tourism.

Table A2.3: Prices by Commodity Basket: Consumer Price Index

Sample: Q1 2012–Q2 2019

	PRICE- ALLITEMS	PRICE- FOODBEV	PRICE- FOOD	PRICE- FISH	PRICE- HOUSWEG	PRICEFUR- NHHQMNMT	PRICE- HEALTH	PRICE- TRANSPORT	PRICE- COMMS	PRICE- EDUC	PRICE- RESTHOT	PRICE- ALLEXCLFISH	PRICEALL- EXCLFOODBEV
Mean	100.6392	100.0527	100.8107	96.17851	100.0004	104.6734	99.0634	96.76895	98.64199	106.5683	99.49692	101.2229	101.3513
Median	100.8719	100.0442	100.2402	97.28417		104.4981	103.0857	96.58066	98.55264	107.5432	100.0352	101.1935	101.6824
Maximum	105.087	106.9287	107.2161	102.1434	104.3937	107.6825	106.4721	100.3037	99.87346	119.6501	111.1539	108.5322	104.823
Minimum	92.5969	88.71953	93.79198	78.18679	92.04179	102.3773	82.18006	93.38221	97.01651	89.7879	81.45853	94.19005	95.95734
Std. Dev.	3.446726	4.607935	3.771833	5.23368	3.241735	1.437916	7.252037	1.661781	0.767226	10.98284	6.80224	3.55695	2.604644
Skewness	-0.73113	-0.637645	0.070716	-2.342393	-0.941229	0.364488	-1.185868	0.280765	-0.044972	-0.234055	-1.219429	-0.221709	-0.591784
Kurtosis	2.81032	3.164859	2.041783	8.60117	2.979109	2.356016	2.948479	2.772515	2.262939	1.56281	4.367556	2.400406	2.249848
Jarque-Bera	2.717732	2.066928	1.094546	66.65041	4.43011	1.18265	7.034729	0.458831	0.689185	2.855801	9.772795	0.695166	2.29082
Probability	0.256952	0.355772	0.578525	0	0.109148	0.553593	0.029678	0.794998	0.708509	0.239812	0.007549	0.706393	0.318093
Sum	3,019.175	3,001.58	2,822.699	2,885.355	3,000.013	3,140.202	2,971.902	2,903.068	2,959.26	3,197.049	2,984.908	3,036.686	2837.835
Sum Sq. Dev.	344.5176	615.7589	384.1215	794.3506	304.7566	59.96048	1,525.169	80.08397	17,070.43	3498.06	1341.843	366.9049	183.1726
Observations	30	30	28	30	30	30	30	30	30	30	30	30	28

Source(§): Maldives Monetary Authority and National Bureau of Statistics.

Figure A2.3: Inflation by Commodity Basket

priceAllitems	All items
priceFoodBev	o/w Food and non-alcoholic beverages
priceFood	o/w Food
priceFish	o/w Fish
priceHousweg	Housing, water, electricity, gas, and other fuel
priceFurnhheqmnt	Furnishing, household equipment, and routine maintenance of the house
priceHealth	Health
priceTransport	Transport
priceComms	Communications
priceEduc	Education
priceResthot	Restaurants and hotels
priceallexclFish	Total, excluding fish
priceallexclFoodbev	Total, excluding food and non-alcoholic beverages

Consumer Price Index

(June 2014 = 100)

Source(s): Maldives Monetary Authority and National Bureau of Statistics.

Table A2.4: Macroeconomic Variables: Level Numbers

Sample: Q1 2012–Q2 2019

	RS_GDP	PRICE-ALLITEMS	ESEXPORT	ESIMPORT	MONEY-INTRATE	GOVEXP-TOTAL	GOVREV-TOTAL	FXUSD
Mean	15187.21	100.6392	1168.268	8081.063	10.86358	5027.181	4081.338	15.38844
Median	14903.26	100.8719	1188.943	7577.138	10.81975	5012.095	4317.024	15.39
Maximum	20026.4	105.087	1842.817	11314.48	11.48814	9232.243	5889.568	15.41
Minimum	11647.23	92.5969	569.6293	6063.688	9.895593	2948.681	2285.999	15.34333
Std. Dev.	2143.257	3.446726	283.1698	1552.831	0.543196	1417.464	1081.091	0.018419
Skewness	0.418233	-0.73113	0.191613	0.770211	-0.356223	0.658671	-0.114986	-0.874592
Kurtosis	2.471558	2.81032	2.94095	2.484602	1.772002	3.807112	1.787652	3.193565
Jarque-Bera	1.223657	2.717732	0.187937	3.298172	2.519445	2.983523	1.903343	3.871391
Probability	0.542358	0.256952	0.910311	0.192226	0.283733	0.224976	0.386095	0.144324
Sum	455616.2	3019.175	35048.05	242431.9	325.9074	150815.4	122440.1	461.6533
Sum Sq. Dev.	1.33E+08	344.5176	2325369	69927255	8.556798	58266940	33893976	0.009839
Observations	30	30	30	30	30	30	30	30

Source(s): Maldives Monetary Authority and National Bureau of Statistics.

Figure A2.4: Macroeconomic Variables: Year-on-Year Percent Change

RS_GDP	Gross domestic product at market price*
PRICEALLITEMS	Consumer price index all items**
ESEXPORT	Total exports f.o.b.*
ESIMPORT	Total imports c.i.f.*
MONEYINTRATE	Interest rate of commercial banks on loans and advances to private sector***
GOVEXPTOTAL	Government total expenditure*
GOVREVTOTAL	Government total revenue*
FXUSD	Exchange Rate****

f.o.b. = free on board; c.i.f. = cost, insurance, and freight

* In Rf million at 2014 constant prices

** June 2014 = 100

*** Local currency, weighted average; in % per annum, end of period

**** Rufiyaa per US dollar; average of period mid rates

Sources: Maldives Monetary Authority and National Bureau of Statistics.

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Maldives Macroeconomic Forecasting

A Component-Driven Quarterly Bayesian Vector Autoregression Approach

This study aims to build an efficient small-scale macroeconomic forecasting tool for Maldives. Due to significant limitations in data availability, empirical economic modeling for the country can be problematic. To address data constraints and circumvent the “curse of dimensionality,” Bayesian vector autoregression estimations are utilized comprising of component-disaggregated domestic sectoral production, price, and tourism variables. Results demonstrate how this methodology is appropriate for economic modeling in Maldives. With the appropriate level of shrinkage, Bayesian vector autoregressions can exploit the information content of the macroeconomic and tourism variables. Augmenting for qualitative assessments, the directional inclination of the forecasts is improved.

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