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FORECASTING MONTHLY INFLATION: AN APPLICATION TO SURINAME

Gavin Ooft

Johns Hopkins Institute for Applied Economics,
Global Health, and the Study of Business Enterprise

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About the Author

Gavin Ooft is the Deputy Head of the Research Department of the Central Bank of Suriname and a lecturer at the Anton de Kom University of Suriname. He completed an MS in Applied Economics at the Zanvyl Krieger School of Arts and Sciences of the Johns Hopkins University.

Abstract

An accurate forecast for inflation is mandatory in the conduction of monetary policy. This paper presents models that forecast monthly inflation utilizing various economic techniques for the economy of Suriname. The paper employs Autoregressive Integrated Moving Average models (ARIMA), Vector Autoregressive models (VAR), Factor Augmented Vector Autoregressive models (FAVAR), Bayesian Vector Autoregressive models (BVAR) and Vector Error Correction (VECM) models to model monthly inflation for Suriname over the period from 2004 to 2018. Consequently, the forecast performance of the models is evaluated by comparison of the Root Mean Square Error and the Mean Average Errors. We also conduct a pseudo out-of-sample forecasting exercise. The VECM yields the best results forecasting up to three months ahead, while thereafter, the FAVAR, which includes more economic information, outperforms the VECM, based on the assessment of the pseudo out-of-sample forecast performance of the models.

Keywords: Inflation, Forecasting, Time-Series Models, Suriname

JEL codes: E31, C32

1. Introduction

Maintaining price stability, which is crucial for a healthy macroeconomic and investment climate, is at the core of monetary policymaking. Hence, an accurate forecast for inflation is mandatory for monetary policymaking (Orphanides & Williams, 2005). This paper presents an empirical foundation for modelling and, in particular, forecasting monthly inflation rates for the economy of Suriname, given the available data of relevant economic variables. As far as can be ascertained, no research has been published before on modelling and forecasting monthly inflation for the economy of Suriname.

We employ Autoregressive Integrated Moving Average (ARIMA) models, Vector Autoregressive (VAR) models, Factor Augmented Vector Autoregressive (FAVAR) models, Bayesian Vector Autoregressive (BVAR) models and Vector Error Correction (VECM) models to model monthly inflation for Suriname over the period 2004 to 2018. Consequently, the forecast performance of the models is evaluated by comparing the Root Mean Square Error, the Mean Average Errors and the Theil inequality coefficient.

The remainder of the paper is structured as follows. Section 2 briefly reviews some theoretical and empirical literature on modelling and forecasting inflation. The following section, Section 3, sheds light on the econometric methods and forecasting evaluation techniques utilized. The fourth section discusses the data-analysis and results. Thereafter we conclude and present some recommendations.

2. Literature Review

Numerous empirical studies endeavored to model inflation, utilizing determinants proposed by theory. Policymakers, especially from central banks, are interested in the path that future inflation will follow. Numerous studies have attempted to provide accurate forecasts for this indicator. The accuracy of the forecast is often assessed by the forecast diagnostics, in general by minimizing the root mean square error of the inflation forecast (Zarnowitz, 1979; Faust and Wright, 2011).

Faust and Wright (2011) evaluate seventeen main inflation forecast models (i.e. simple autoregressive models, vector autoregression VAR with and without a time-varying trend, Phillips-curve-based models, random-walk models, equal-weighted averaging, Bayesian-model averaging, factor-augmented VAR and Dynamic Stochastic General Equilibrium [DSGE] models) by comparing their recursive out-of-sample root mean square prediction error (RMSPE). The authors point out that incorporating a slowly-varying trend, τ_t, in an inflation forecast, where the gap between inflation and the trend component $g_t = \pi_t - \tau_t$ is treated as a stationary process, considerably improve the inflation forecast. The best performance in terms of minimizing RMSPE is noted by autoregressive (AR) gap models.

Stock and Watson (1999) point out that the conventional starting point of many inflation forecasts for the U.S. has been the unemployment-based Phillips curve. These have been more accurate than forecasts with macroeconomic variables such as interest rates, monetary variables and commodity prices. The study revealed that by replacing unemployment with real economic activity in an ordinary least squares (OLS) and ridge regression framework, the inflation forecast for the U.S. was even more accurate and reliable. In a more recent study, Stock and Watson (2009) state that Phillips-curve based inflation forecasts are no improvement upon "good univariate benchmark models." However, the type of model used to forecast inflation depends on the sample period. In stable and "quiet" economic periods, univariate models seem to perform best in forecasting inflation. On average, the unobserved components-stochastic volatility (UC-SV) model[1] proposed by Stock and Watson (2007) performed best in forecasting inflation in the U.S. Meyer and Pasaogullari (2010) come upon similar evidence: simple, single-specification inflation models seem to estimate and forecast inflation well. Additionally, the authors find that inflation expectations are a reasonable determinant of future inflation forecasts.

Loungani and Swagel (2001) investigate the sources of inflation over a time span of 34 years in a set of 53 developing countries. The main sources of inflation investigated in this paper are (1) fiscal view: money growth and exchange rates, (2) the output gap as in business cycle theory, (3) commodity cost shocks and (4) inertia. The authors posit that the exchange rate regime should be taken into strong consideration when analyzing sources of inflation. The findings of the study suggest that money supply and the exchange rate are key determinants of inflation especially in countries with floating exchange-rate regimes.

There is not much empirical literature on econometric-based modelling and forecasting of monthly inflation for Suriname. Narain, Ooft and Sonneveld (2014) employ a Dynamic Ordinary Least Squares (DOLS) regression model a la DaCosta and Greenidge (2008) to identify the determinants of inflation for Suriname, utilizing annual data. The study points out that the key determinants of annual inflation in Suriname are the exchange rate in particular, the money supply, economic activity, and trade openness, in order of importance. This study will take into account these determinants of inflation for Suriname to construct econometric models.

[1] In the UC-SV model: π_t has a stochastic trend, a serially uncorrelated disturbance, and a stochastic volatility.

3. Empirical Methods

Econometric Models

This study employs various econometric techniques to model monthly inflation.

- **Autoregressive (AR) and Moving Average (MA) models**

  ARMA models with possible integration of variables (ARIMA) utilize past and current values of a selected indicator for forecasting purposes. Often, ARIMA models perform well in short-term forecasting. The autoregressive model is of the form $y_t = \beta_0 + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \epsilon_t$ and the moving average model is of the form $y_t = \beta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \epsilon_t$ where θ's are the coefficients of the autoregressive process and φ's are the coefficients of the moving average process (Studenmund, 2006).

- **Seasonal ARMA (SARMA) models**

  An extension of the standard ARMA models is the Seasonal ARMA. This model identifies and adds common seasonal factors to the ARMA model. Since monthly inflation often includes seasonality due to weather or holidays, we expect this method to improve the standard ARMA results.

- **Vector Autoregressive models (VAR)[2] and VAR models with exogenous variables (VARX)**

  VARs are useful tools in modelling complex and dynamic interrelationship between macroeconomic indicators. Especially on the topic of monetary transmission mechanisms, there is a vast amount of research employing these models. The results of these analyses have proved to be empirically plausible. The standard VAR model has the form $y_t = A_0 + A(L)y_t + e_t$, where y is a (n × 1) vector of variables, A_0 is the (n × 1) vector of constant terms, A(L) is the polynomial matrix of coefficients in the lag operator (L) and e_t is the (n × 1) vector of error terms, which are considered to be iid. Useful tools in the VAR models are impulse responses and variance decomposition (Sims, 1980). An extension of the regular VAR model is the VARX model, which includes exogenous variables that follow a specific exogenous forecast.

- **Vector Error Correction Model (VECM)**

[2] Bernanke, Boivin and Eliasz (2005) posit some issues with regular VAR models:

a. A well-known issue with VAR models is the issue of dimensionality. As the degrees of freedom in the VAR model decrease exponentially, these models are often limited to at most eight variables. Hence, the criticism on the loss of important information due dimensionality of these models might be justified. This may result in biased results (e.g. omitted variable bias) with no proper reflection of reality.

b. Even though standard VAR models are suitable for forecasting purposes, another famous critique on these models is the lack of theoretical foundations. Results obtained from the impulse response functions are purely obtained from the variables the researcher inputs in the model.

Economic time series are often trending and contain common stochastic trends. Hence, we might find a stationary I(0) linear combination of two or more I(1) variables; these variables might be cointegrated. Employing OLS techniques with trending or non-stationary variables will yield biased and spurious regression results. When we impose cointegrating relationships in the regular VAR model, we reconstruct this model as a VECM, which can be expressed as:

$$\begin{bmatrix} \Delta y_{1,t} \\ \Delta y_{2,t} \end{bmatrix} = \begin{bmatrix} -\alpha_1 \beta_c \\ -\alpha_2 \beta_c \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} 1 & -\beta_y \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix}$$

Where [1 - β_y] presents the error-correction mechanism. This accounts for possible long-run relationship between non-stationary variables.

- **Bayesian VAR (BVAR)**

  Bayesian econometrics have become increasingly popular. Litterman (1986) and Doan, Litterman & Sims (1984) proposed a methodology to combine likelihood functions with prior distributions and standard VAR models in order to improve forecast performance. Often is specifying the priors a challenge in the BVAR methodology. Literature suggests setting the tightness of the prior as such that the out-of-sample forecasting model performance is maximized.

- **Factor Augmented VAR (FAVAR)**

  Bernanke, Boivin and Eliasz (2005) combine factor analysis with the standard VAR methodology in order to utilize larger data sets in a VAR environment. Large subsets of data can be successfully compressed to a small number of estimated indexes or factors. Consequently, these factors are modeled as endogenous variables in the VAR model. This procedure is advantageous to VAR modelling with large data sets, i.e. dealing with the loss of degrees-of-freedom. The authors come across evidence that application of this procedure could improve some classical results for the monetary-policy reaction function in the US.

  A standard FAVAR model is of the form: $\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + v_t$,

  where F_t is the vector of factors, which are unobserved, $\Phi(L)$ is the polynomial lag structure of the relation between F_t and Y_t and v_t is the error term.

Forecast Evaluation

We perform both in-sample and pseudo out-of-sample forecast evaluations. For the in-sample forecast evaluation, we use the sample period 2004 to 2018. Consequently, we compare the obtained forecasts based on the smallest Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Theil Inequality coefficient.

4. Data Analysis and Results

This section sheds light on the data, the estimated model, and forecast results. The variables used in this study are the headline consumer price index (CPI), the exchange rate, banking credit extended to the private sector, the money supply, narrow money, bank interest rates, and exogenous variables, namely the WTI oil prices and international food prices. Forecasts for WTI oil prices are obtained from the Energy and Information Administration (EIA) while the forecasts for food prices are retrieved from the World Bank. All nominal variables utilized in this analysis are on a monthly frequency. We use the Consumer Price Index to deflate banking credit to the private sector, money supply, and narrow money. We analyze the residuals of the models and compare both the in-sample and pseudo out-of-sample performance of the obtained forecasts.

Unit Root Tests

Since we deal with time series, we need to determine the order of integration of our variables. Unit Root Tests reveal that all variables are integrated of the order 1 (I [1]), while in growth rates, the variables are stationary (see appendix 2).

(S)ARMA results

We estimate AR, ARMA and SARMA models for (1) the sample period from January 2004 to October 2015 and from January 2004 to January 2018, but with a dummy variable to correct for the period of high inflation. The optimal model is determined by the Akaike information criterion, and we included some additional dummy variables to correct for some outliers. Since inflation has a seasonality, we also consider a SARMA model using automatic lag length selection based on the Akaike criterion. The following tables summarizes the in-sample forecasting performance of the AR, ARMA and SARMA models.

Table 1: In-Sample Forecast performance of (S)ARMA models

Forecast performance of utilized AR, ARMA and SARMA models			
Variable of interest: Monthly Inflation Estimation Sample: 2004m01 to 2015m10			
Model	**RMSE**	**MAE**	**Theil Ineq**
AR(1)	0.697	0.525	0.372
ARMA(7,6)	0.660	0.518	0.348
SARMA	0.706	0.530	0.381
Estimation Sample: 2004m01 to 2017m12			
Model	**RMSE**	**MAE**	**Theil Ineq**
AR (1)	1.134	0.803	0.261
ARMA (8,7)	1.085	0.793	0.248
SARMA	1.105	0.800	0.254

Source: Author's calculations

VAR results

The utilized variables in the VAR model are the exchange rate, real money supply, credit to the private sector in constant terms, and real interest rates. However, some studies depart from the unemployment-based Phillips curve and add unemployment to the list of variables. However, this is not be feasible for Suriname due to limited availability of unemployment data. The Akaike Information Criterion points out that the optimal lag length is established at four lags. All variables are in growth rates as to account for stationarity of these time series and to avoid spurious regression results. Granger causality tests with different lag lengths support the choice of included variables in our VAR model, to the extent that causality is most likely established from the variables towards inflation than the other way around (appendix 3).

As an extension of the standard VAR model, the VARX model incorporates exogenous (i.e. conditional) forecasts of WTI oil prices and food prices. We added some dummy variables to account for some outliers and a seasonal dummy for the month of June, when local food prices often rise due seasonal effects. The VAR model yields robust results (figure 1a, 1b), and the residuals pass residual tests except for normality.

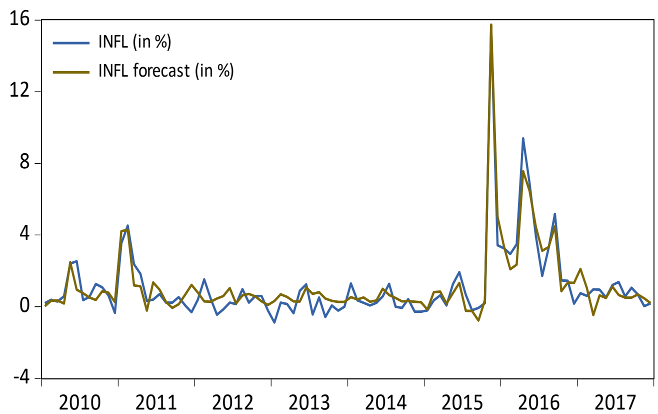

Figure 1a: VAR in-sample forecast

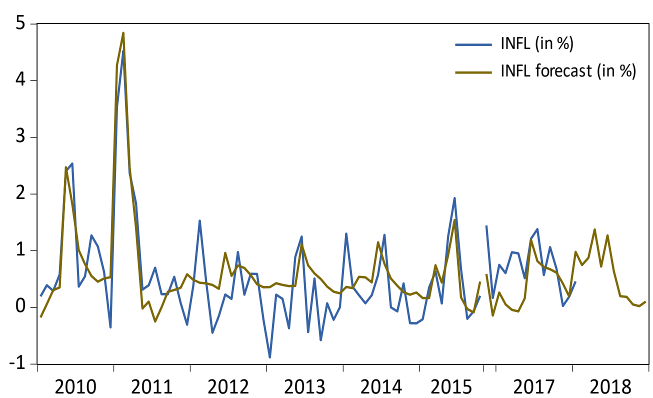

Figure 1b: VAR in-sample forecast (excl. high inflation)

Source: GBS and author's calculations

VECM results

We utilized the consumer price index, the average official exchange rate, real private sector credit, and the credit interest rates. Since these variables are not stationary in levels, we examined for possible long-run relationships. The Johansen Cointegration test points to one cointegrating relationship. Not surprisingly, the Engle-Granger test for cointegration points out that a long-run relationship can be established between CPI and the average exchange rate. Therefore, the VECM is estimated with 3 lags (one lag less than the VAR). We added some seasonal and impulse dummy variables to improve the fit. We also added exogenous WTI oil prices to this model. The error correction term is negative and significant. The errors of the VECM pass the residual test. The model has a good fit (see figure 4) and has a determination coefficient of about 0.87.

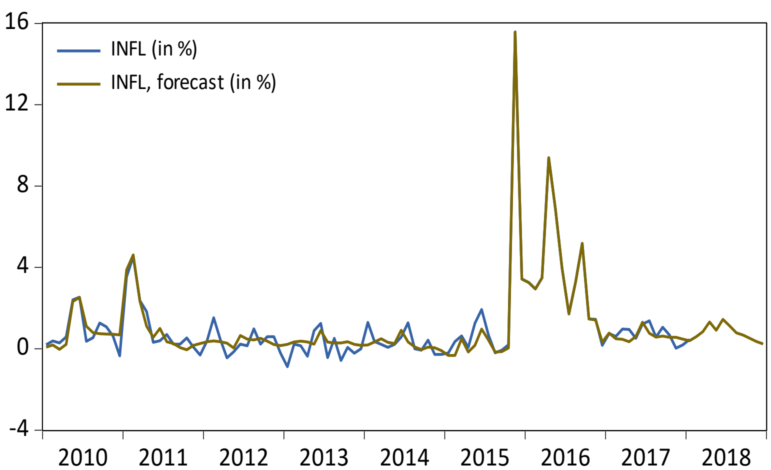

Figure 2a: VECM in-sample forecast
Source: GBS and author's calculations

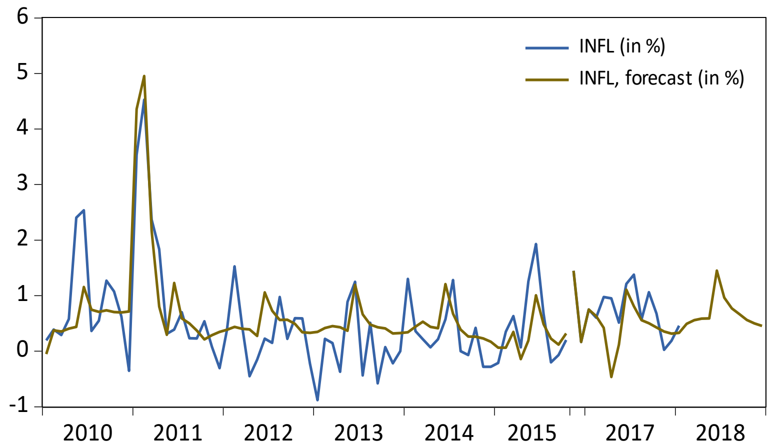

Figure 2b: VECM in-sample forecast (excl. high inflation)
Source: GBS and author's calculations

BVAR results

BVARs are famous for their ability to improve forecast performance. We departed from the optimal standard VAR model to estimate the BVAR model. We opted for the Litterman-Minnesota Priors with values μ=0.4; λ1= 0.6; λ2=0.99; λ3=1. The autoregressive prior of 0.4 is obtained from a simple autoregressive inflation model. When capturing the whole sample period, we encountered some serial correlation and heteroscedasticity issues. When the high inflation period is excluded, the residuals of the model behave well.

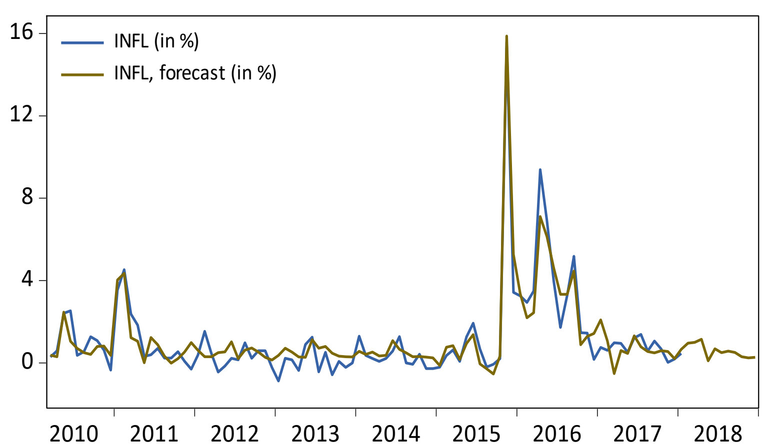

Figure 3a: BVAR results
Source: GBS and author's calculations

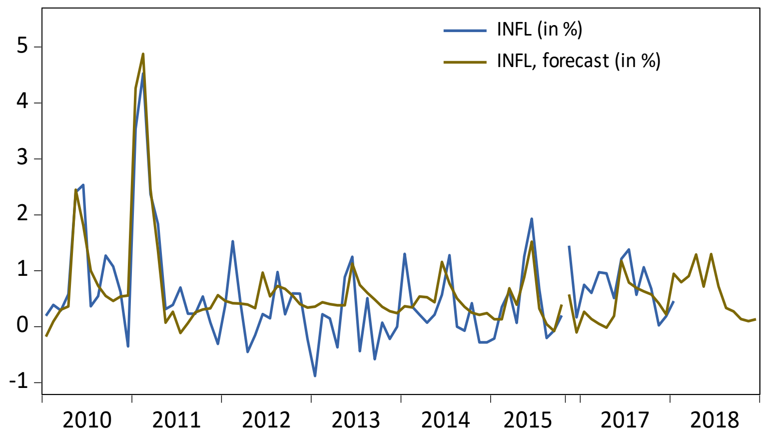

Figure 3b: BVAR in-sample forecast (excl. high inflation)
Source: GBS and author's calculations

Factor Augmented VAR results

We employ principle component analysis, based on correlations between variables, to extract common factors from monetary variables[3] and exchange rates[4]. The Eigenvalue cumulative proportion graph depicts that three principle components are sufficient in explaining more than 60% of the underlying factors (figure 4).

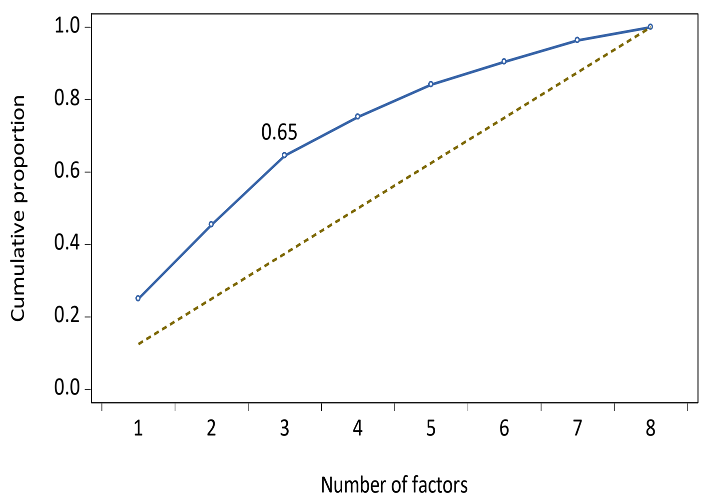

Figure 4: Eigenvalue Cumulative Proportion
Source: Author's calculations

[3] Credit growth, narrow money growth, broad money growth and interest rates
[4] Official exchange rate and parallel exchange rate

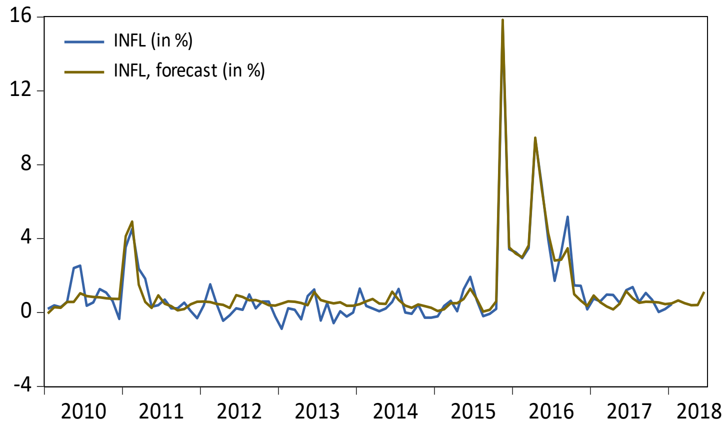

Figure 5a: FAVAR in-sample forecast
Source: GBS and author's calculations

Consequently, we estimate the FAVAR utilizing three principle components extracted from aforementioned variables. We added a seasonal dummy for June and some impulse dummy variables to improve the fit. The FAVAR yield good results (figure 5a, 5b). The determination coefficient is around 0.89 and the residual passes all diagnostics tests.

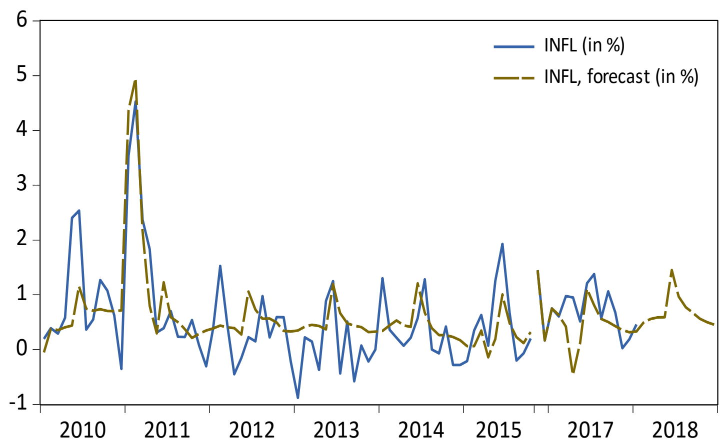

Figure 5b: FAVAR in-sample forecast (excl. high inflation)
Source: GBS and author's calculations

Forecast Evaluation

In this section, we compare the dynamic forecasts of the various models based on the forecast evaluation statistics: the RMSE, MAE and the Theil Inequality Coefficient. Not surprisingly, the forecast of the models estimated without the period of high inflation performed better than the models estimated over the whole sample period. Over the whole sample period, the FAVAR model and the VECM model yield the best results, while the BVAR and standard VAR performed best over the sample period excluding high inflation (table 2).

Table 2: In-Sample Forecast Evaluation Statistics

Variable of interest: Monthly Inflation Estimation Sample: 2004m01 to 2018m01 Evaulation Sample: 2010m01 to 2018m01				Excluding high inflation period Estimation Sample: 2004m01 to 2015m10 Evaulation Sample: 2010m01 to 2015m10			
Model	**RMSE**	**MAE**	**Theil Ineq**	**Model**	**RMSE**	**MAE**	**Theil Ineq**
AR	1.134	0.803	0.261	AR	0.697	0.525	0.372
ARMA	1.085	0.793	0.248	ARMA	0.660	0.518	0.348
SARMA	1.105	0.800	0.254	SARMA	0.706	0.530	0.381
VAR	0.665	0.509	0.139	VAR	0.521	0.424	0.259
VECM	0.605	0.444	0.126	VECM	-	-	-
BVAR	0.676	0.508	0.142	BVAR	0.510	0.412	0.254
FAVAR	0.586	0.446	0.122	FAVAR	0.591	0.450	0.300
CBvS model	0.842	0.600	0.179	CBvS model	0.788	0.545	0.510

Source: Author's calculations

We have also performed a pseudo out-of-sample forecast evaluation for one to twelve steps ahead to compare the different models over various forecast horizons (table 3). Up to three months ahead, the VECM produces the best forecasting results, while the FAVAR outperformed all other models from 4-months ahead on, based on the RMSE.

Table 3: Pseudo Out-of-Sample[5] Forecast Evaluation – Root Mean Square Errors

Variable of interest: Monthly Inflation Sample period: 2004m01 - 2017m12							
Periods Ahead	**AR**	**ARMA**	**SARMA**	**VARX**	**VECM**	**BVAR**	**FAVAR**
1 Month	0.760	0.769	0.795	0.462	0.003	0.465	0.382
2 Months	1.042	1.024	1.057	0.482	0.116	0.490	0.377
3 Months	1.200	1.107	1.154	0.521	0.229	0.521	0.376
4 Months	1.301	1.156	1.219	0.657	0.490	0.704	0.378
6 Months	1.536	1.282	1.412	0.660	0.545	0.741	0.348
12 Months	1.920	1.590	1.828	0.767	0.727	0.852	0.531

Source: GBS and author's calculations

[5] Number of rolling samples set at 24

Conclusion

This study deploys various econometric techniques to model and forecast monthly inflation for the economy of Suriname. With the available data, we construct several univariate and multivariate time series models such as VAR, BVAR, FAVAR and VECM models. Consequently, the optimal forecast is selected based on the smallest RMSE, MAE, and Theil Inequality coefficient. The estimated models perform better when a recent period of high inflation is excluded from the sample. The best model is the BVAR model based on the in-sample forecast. However, more interesting is the pseudo out-of-sample forecast performance. The VECM yields the best results up to three months ahead, while the FAVAR, which includes more economic information, outperforms the VECM in many instances. Modelling inflation using a VECM can be justified by the long-run relationship between the exchange rate and inflation in Suriname, i.e. a high exchange-rate pass-through.

Recommendations

Though the results of this paper are satisfactory, we consider the following methods to improve the monthly inflation forecasts:

- Econometric disaggregated approach to forecast inflation. This approach is useful in the case where some components of the CPI basket can be forecasted using time series models while other components follow other patterns or are comprised of administered prices.
- Markov-switching VAR models. Since the economy went through a regime change, including a period of high inflation, we can consider utilizing a Markov-switching VAR in follow-up research to possibly improve our estimations and forecast results.

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Appendix

Appendix 1a – Descriptive Statistics (variables in levels)

	CPI	CR	CRL	ERPAVG	EROAVG	IRCRD	IRDBT	M0	M2	IRCRD	IRDBT
Mean	58.07	3619.30	2005.44	4.17	4.00	13.55	7.11	1569.26	6466.59	13.55	7.11
Median	52.73	3265.35	1948.80	3.76	3.55	12.45	6.80	1510.83	5683.08	12.45	6.80
Maximum	130.47	8411.50	3942.98	8.55	8.21	21.10	9.32	3246.00	17030.03	21.10	9.32
Minimum	29.16	611.30	292.93	3.01	3.03	11.40	6.10	455.55	1485.26	11.40	6.10
Std. Dev.	26.38	2312.75	1236.92	1.49	1.46	2.43	0.86	762.03	4301.07	2.43	0.86
Skewness	1.49	0.58	0.16	1.98	2.12	1.57	0.89	0.23	0.96	1.57	0.89
Kurtosis	4.43	2.30	1.64	5.43	6.00	4.69	2.73	2.03	3.04	4.69	2.73
Obs	166	166	166	166	166	166	166	166	166	166	166

Source: Author's calculations

Appendix 1b – Descriptive Statistics (in growth rates)

	CPI	CR	CRL	ERPAVG	EROAVG	IRCRD	IRDBT	M0	M2	IRCRD	IRDBT
Mean	0.93	1.56	1.58	0.63	0.64	-0.04	0.00	1.23	1.52	-0.04	0.00
Median	0.51	1.39	1.36	0.20	0.00	0.00	0.00	1.43	1.15	0.00	0.00
Maximum	15.58	11.09	8.33	16.28	20.67	0.60	0.20	11.95	15.68	0.60	0.20
Minimum	-3.17	-6.40	-2.18	-10.78	-4.23	-1.80	-1.10	-7.30	-6.00	-1.80	-1.10
Std. Dev.	1.86	1.89	1.55	2.79	3.05	0.25	0.11	3.67	2.43	0.25	0.11
Skewness	3.92	1.27	0.96	1.58	4.06	-2.81	-5.91	0.31	2.59	-2.81	-5.91
Kurtosis	27.66	12.39	5.67	12.93	23.54	20.35	59.75	3.43	16.01	20.35	59.75
Obs	165	165	165	165	165	165	165	165	165	165	165

Source: Author's calculations

Appendix 2a – Unit Root Test Results (variables in levels)

Null Hypothesis: Unit root (individual unit root process)
Series: CPI, CR, CRL, ERPAVG, EROAVG, IRCRD, IRDBT, M0, M2, IRCRD, IRDBT
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 6
Total number of observations: 1819
Cross-sections included: 11

Method	Statistic	Prob.**
ADF - Fisher Chi-square	10.716	0.979
ADF - Choi Z-stat	1.629	0.948

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results

Series	Prob.	Lag	Max Lag	Obs
CPI	0.331	5	13	161
CR	0.408	2	13	165
CRL	0.311	3	13	164
ERPAVG	0.875	6	13	162
EROAVG	0.885	1	13	167
IRCRD	0.621	0	13	167
IRDBT	0.728	0	13	167
M0	0.739	0	13	167
M2	0.960	2	13	165
IRCRD	0.621	0	13	167
IRDBT	0.728	0	13	167

Source: Author's calculations

Appendix 2b – Unit Root Test Results (variables in growth rates)

Null Hypothesis: Unit root (individual unit root process)
Series: INFL, G_CR, G_CRL, G_ERPAVG, G_EROAVG, G_IRCRD,
G_IRDBT, G_M0, G_M2, G_IRCRD, G_IRDBT
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 2
Total number of observations: 1822
Cross-sections included: 11

Method	Statistic	Prob.**
ADF - Fisher Chi-square	620.386	0.000
ADF - Choi Z-stat	-22.266	0.000

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results

Series	Prob.	Lag	Max Lag	Obs
INFL	0.000	0	13	165
G_CR	0.000	1	13	165
G_CRL	0.023	2	13	164
G_ERPAVG	0.001	2	13	165
G_EROAVG	0.000	0	13	167
G_IRCRD	0.000	0	13	166
G_IRDBT	0.000	0	13	166
G_M0	0.000	0	13	166
G_M2	0.000	0	13	166
G_IRCRD	0.000	0	13	166
G_IRDBT	0.000	0	13	166

Source: Author's calculations

Appendix 3 – Granger Causality Tests

Pairwise Granger Causality Tests
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
G_ERPAVG does not Granger Cause INFL	138	2.874	0.092
INFL does not Granger Cause G_ERPAVG		2.005	0.159
G_CR does not Granger Cause INFL	138	3.352	0.069
INFL does not Granger Cause G_CR		0.697	0.405
G_IRCRD does not Granger Cause INFL	138	1.649	0.201
INFL does not Granger Cause G_IRCRD		0.215	0.644

Pairwise Granger Causality Tests
Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
G_ERPAVG does not Granger Cause INFL	136	2.274	0.083
INFL does not Granger Cause G_ERPAVG		0.539	0.657
G_CR does not Granger Cause INFL	136	1.367	0.256
INFL does not Granger Cause G_CR		1.023	0.385
G_IRCRD does not Granger Cause INFL	136	2.823	0.041
INFL does not Granger Cause G_IRCRD		0.814	0.488

Pairwise Granger Causality Tests
Lags: 6

Null Hypothesis:	Obs	F-Statistic	Prob.
G_ERPAVG does not Granger Cause INFL	133	1.922	0.082
INFL does not Granger Cause G_ERPAVG		0.460	0.837
G_CR does not Granger Cause INFL	133	1.065	0.387
INFL does not Granger Cause G_CR		1.508	0.181
G_IRCRD does not Granger Cause INFL	133	1.674	0.133
INFL does not Granger Cause G_IRCRD		0.354	0.906

Source: Author's calculations