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Forecasting annual inflation in Suriname

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ABSTRACT

For many countries, statistical information on macroeconomic variables is not abundant and, hence, creating forecasts for a key variable like inflation can be cumbersome. This paper addresses the creation of current year forecasts from a MIDAS regression for annual inflation rates in Suriname where monthly inflation rates are the explanatory variables, and where the latter are only available for one and a half decade. The constructed model associates with a hybrid New-Keynesian Philips curve (NKPC). Specific focus is given to the forecast accuracy in the high inflation period in 2016–2017. The forecasts became very accurate when the models included data from May onwards. A particular parameter restriction was also useful to improve forecast accuracy.

1. Introduction

For macroeconomic policy, it is important to have reliable forecasts for key variables like real Gross Domestic Product growth, unemployment, and inflation. Typically, such forecasts are produced for annually observed variables in the current year and for the next year.[1] This paper creates accurate current-year forecasts for annual inflation, for Suriname where many data are not available.

To predict annual inflation, one may use various variables, see Stock and Watson (1999), and one can rely on modern variable-selection techniques to choose the best predictors. For many countries, and in particular for small developing countries, there is however no abundant availability of frequently observed variables. At the same time, for many of these countries the sample span can also be short. One possible avenue to create forecasts for annually observed variables is to consider a so-called MIDAS regression model[2]. This is a model that connects for example annual inflation rates with explanatory variables that are observed at a higher frequency, like months. Specific parameter restrictions on the parameters makes such a model feasible for short samples.

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[1] See for example the forecasts reported in https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/, and https://www.consensuseconomics.com/, for many industrialized countries.

[2] See Ghysels et al. (2006) and Ghysels, Sinko, and Valkanov (2007) for early studies on MIDAS regressions.

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In this paper, we consider forecasting annual inflation in Suriname, a country in South America, where we rely on a particular inflation forecasting model, where the input variables are annualized inflation rates observed at the monthly level. We show that this model matches with a version of the Hybrid New-Keynesian Phillips Curve (HNKPC), where the forward-looking behavior of agents is captured by the incoming monthly inflation rates.

Our paper proceeds as follows. In the next section we provide an overview of developments in annual inflation in Suriname. Next, we discuss the MIDAS model for annual inflation with monthly inflation rates as explanatory variables. Due to limited amount of observations on monthly inflation in Suriname (observed only since 2004), we introduce a specific but plausible restriction on the parameters. Next, we illustrate the model for the sample period 2004–2015, where we focus on the forecast accuracy for the years 2016–2018. For Suriname, the years 2016 and 2017 showed very high inflation levels. We document that our model can deliver highly accurate forecasts, in particular when the summer months are included. In brief, when the annualized inflation rate is known in May or June, the subsequent forecasts for the entire year are very accurate. We also evaluate alternative models for forecasting annual inflation, but these all have less accurate forecasts. Finally, we conclude with limitations and further research topics.

2. Inflation in Suriname

Since the country's independence in 1975, Suriname went through several phases of high inflation. For example, the country registered inflation over 500% in 1994 (Fritz-Krockow et al, 2009). High inflation was often the result of excessive money creation by the Central Bank of Suriname to facilitate the central government and of a depreciation of the parallel exchange rate. Fiscal deficits were often induced by deficits created on the trade and capital accounts of the Balance of Payments.

As Suriname depends strongly on the export of mining products (that is, oil, gold, and bauxite in the past), its economy is highly vulnerable to commodity-price shocks. For instance, in the nineties, public revenues fell sharply due to the decline in bauxite prices. Nevertheless, due to prudent fiscal and monetary policy in the period 2001–2010, inflation averaged 10% in this period compared to excessive inflation before 2001. However, more recently in 2014–2015, the plunge in global oil prices reinduced current account and fiscal imbalances (Ooft, 2019). Also, exacerbated by election spending in 2014–2015, excessive money creation accelerated inflation again in 2015–2016. Inflation jumped even further in the latter year as the new government hiked utility tariffs to alleviate pressure on government subsidies. After a short period of price stability, election-related government spending in 2019–2020 increased inflation further in 2020.

The Central Bank of Suriname has a de jure floating exchange rate regime. However, de facto, the Bank opts towards maintaining a more managed exchange rate accompanied by monetary targeting. In the past for example, money creation caused exchange-rate imbalances in the periods 1992–1994, 1999–2000, 2015–2016 and most recently in 2020. Large fiscal deficits led to depreciation of the exchange rate. As the long-run passthrough of the exchange rate hovers between 0.7 and 0.9, exchange-rate depreciations have a direct impact on consumer prices (International Monetary Fund, 2019). A high exchange-rate passthrough is unavoidable as consumer prices consist mainly of imported goods. The share of market prices in the CPI basket is around 55% while the remaining administered prices also contain imported components, such as fuel prices.

3. The model

We aim to create a model that is based on economic theory. The New-Keynesian Phillips Curve (NKPC) proposes that the inflation rate in the current period depends linearly on next period's expected inflation rate and on marginal costs. The NKPC is derived from the basic price-setting model of Calvo (1983). Since its inception, the model was re-estimated and improved several times with various econometric specifications, see for example Gali and Gertler (1999) and Lanne and Luoto (2013). Gali and Gertler (1999) improved the NKPC model by incorporating lagged inflation. This model version is referred to in the literature as the hybrid NKPC (HNKPC). Many studies have shown the advantages of including inflation expectations in forecasting models for better outcomes. Mavroeidis et al. (2014) provide a recent overview on the inclusion of inflation expectations. Also, Woodford (2003), Preston (2005) and Gali (2008) have reiterated the importance of incorporating inflation expectations and to use these as a key input in various forecasting models.

The HNKPC model proposed in Gali and Gertler (1999) reads as

$$\pi_t = \mu + \alpha E_t \pi_{t+1} + \rho \pi_{t-1} + \gamma x_t \tag{1}$$

where t refers to years. The HNKPC model augments the NKPC model with one lag of inflation (π_{t-1}) which can substantially improve the fit of the model in empirical settings.

The key issue in practice is to find an approximation of $E_t \pi_{t+1}$. One may rely on survey expectations, or one may replace it by observable variables. Based on the ideas in Frijns and Margaritis (2008), who use early-in-the-day volatility estimates to predict end-of-day volatility of stocks with intraday data from the New York Stock Exchange, the Nasdaq and Paris Bourse, Franses (2019) proposes to use current monthly annualized inflation rates as predictors for the expected inflation. In year t, the annualized inflation rate in month s is

$$\pi_{s,t} = 1200(\log CPI_{s,t} - \log CPI_{s,t-1}) \tag{2}$$

where $CPI_{s,t}$ is the consumer price index in month $s$of year t, and "log" is the natural logarithm. For example, when the January inflation rates are observed, the model in (1) becomes

$$\pi_t = \mu + \alpha\pi_{January,t} + \rho\pi_{t-1} + \varepsilon_t \tag{3}$$

where the measure of marginal costs appears in the error term ε_t. When February data are observed, one may consider

$$\pi_t = \mu + \alpha\pi_{February,t} + \rho\pi_{t-1} + \varepsilon_t \tag{4}$$

but one may also consider

$$\pi_t = \mu + \alpha_1\pi_{January,t} + \alpha_2\pi_{February,t} + \rho\pi_{t-1} + \varepsilon_t \tag{5}$$

These two models are so-called MIDAS models, see Ghysels et al. (2006, 2007), Breitung and Roling (2015), and Foroni et al. (2015). From (5) it follows that when the year proceeds, the model contains many parameters to be estimated. Much of the literature on MIDAS models therefore addresses methods to reduce the number of parameters. When no restrictions are imposed, the model is called the Unrestricted MIDAS (UMIDAS) model, see Foroni et al. (2015).

We also consider a version of the MIDAS model with restrictions, where we tailor the restrictions to the case at hand. Below, we present an analysis of annual inflation rates for Suriname for 2004–2015, and we create forecasts for 2016–2018. As explanatory variables we consider the annualized monthly inflation rates, which we only have available for these same years. UMIDAS does require many degrees of freedom, and the model in (5) becomes infeasible. We therefore consider the following restrictions

$$\alpha_i = \frac{1}{1 + \beta\exp(-\gamma i)} \tag{6}$$

With $\beta, \gamma > 0$. Depending on the size of these two parameters, there is a tendency for α_1 to approach 0, and α_{12} (or the last one in the sequence) to approach 1. This largest weight for the most recent month has face value.

4. Results

The annual inflation rates in Suriname for the period 2004–2018 are presented in Fig. 1. The annualized monthly inflation rates are presented in Fig. 2. The high inflation rates around 2016 and 2017 are clearly visible. To examine whether our HNKPC model has relevant predictive power, we estimate the parameters of the models for 2004–2015 and we leave out the years 2016–2018 to evaluate predictive accuracy.

Table 1 presents the estimation results for MIDAS model like in (2) and (3), that is, for each month separately. The R^2 peaks in August. Also, the parameter ρ for lagged inflation becomes insignificant when the months proceed, whereas the

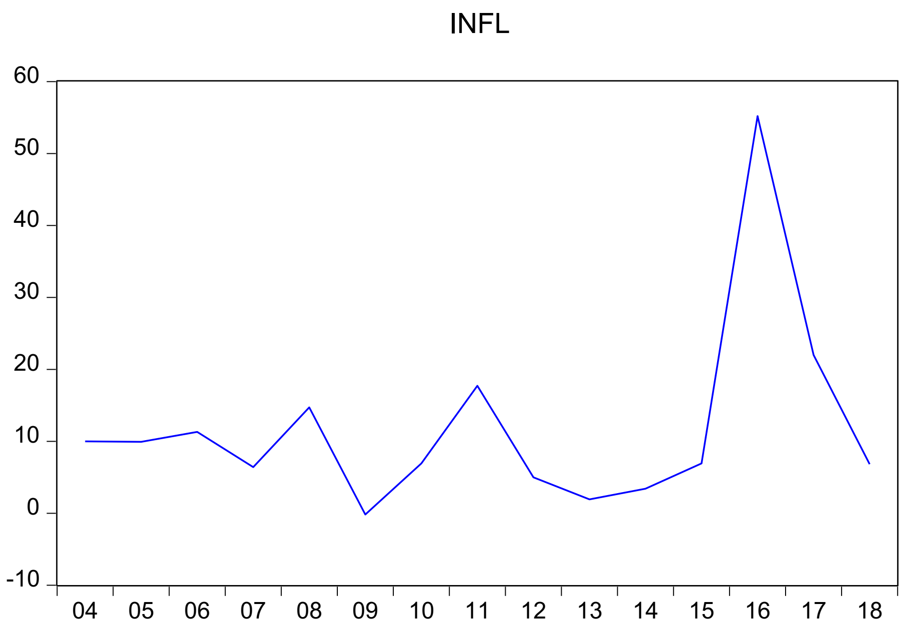

Fig. 1. Annual Inflation (in percentages) for the years 2004–2018 (source: World Bank).

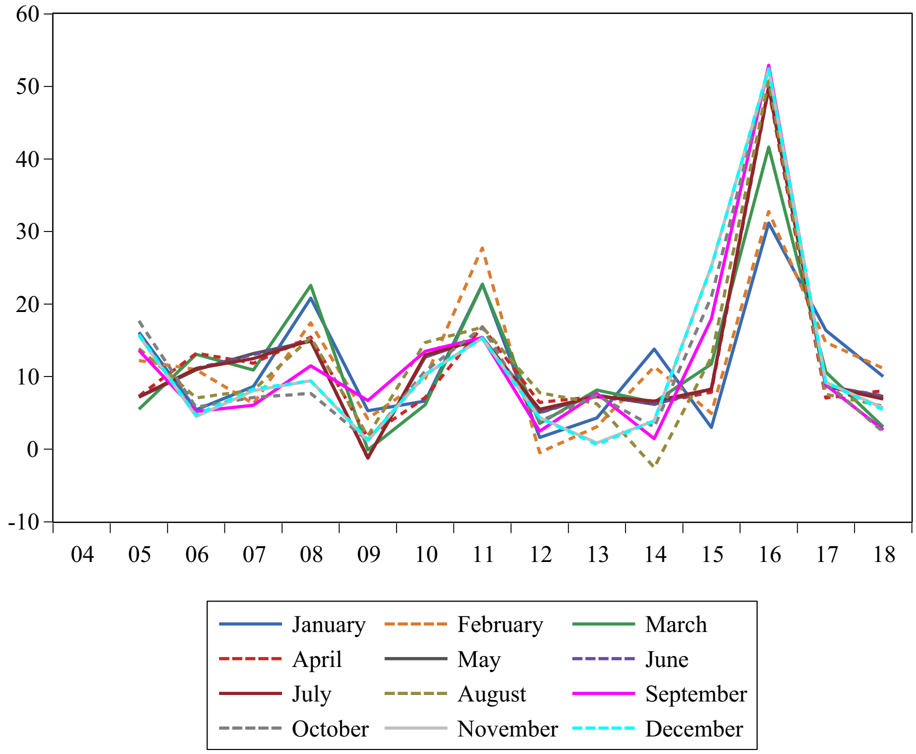

Fig. 2. Annualized Monthly Inflation rates (in percentages) for the years 2004–2018 (Source: General Bureau of Statistics Suriname).

Table 1
Estimation results for $\pi_t = \mu + \alpha\pi_{January,t} + \rho\pi_{t-1} + \varepsilon_t$ .... $\pi_t = \mu + \alpha\pi_{December,t} + \rho\pi_{t-1} + \varepsilon_t$ Effective sample size is 2004–2015. Standard errors are in parentheses.

Month	μ		α		ρ		R^2
January	4.704	(1.759)	1.200	(0.232)	−0.752	(0.205)	0.774
February	4.379	(1.708)	0.881	(0.161)	−0.414	(0.168)	0.793
March	4.025	(1.538)	0.776	(0.123)	−0.274	(0.144)	0.836
April	3.413	(1.271)	0.717	(0.089)	−0.141	(0.115)	0.893
May	1.746	(1.337)	0.795	(0.095)	0.005	(0.112)	0.900
June	1.137	(1.775)	0.790	(0.123)	0.080	(0.144)	0.840
July	0.539	(1.420)	0.782	(0.092)	0.151	(0.115)	0.902
August	1.034	(1.145)	0.774	(0.075)	0.093	(0.095)	0.931
September	0.886	(1.260)	0.808	(0.086)	0.090	(0.103)	0.919
October	1.895	(2.131)	0.713	(0.144)	0.059	(0.177)	0.759
November	2.285	(3.743)	0.534	(0.229)	0.089	(0.285)	0.416
December	4.156	(4.139)	0.365	(0.238)	0.023	(0.323)	0.243

parameter α is significant for almost all months. Table 2 presents the associated forecast accuracy, measured by the Mean Absolute Error (MAE), of these 12 models in Table 1, and there we see that the predictive accuracy for the model

$$\pi_t = \mu + \alpha\pi_{August,t} + \rho\pi_{t-1} + \varepsilon_t \tag{7}$$

is exceptionally good. With a MAE if 0.815 for 2016, where annual inflation was 55.2%, the forecast is very accurate. At the same time, the forecasts from the model with the explanatory variable of May are also already quite accurate.

As Table 1 shows that lagged values of inflation are rarely a useful predictor. We also consider the basic NKPC models like (3) and (4) without this variable, and the estimation results are reported in Table 3. The R^2 values are smaller, but not to a very large extent. The associated forecast accuracy is reported in Table 4 and we see a slight deterioration of the predictive ability of the models. Still, starting from May and until October, the forecasts are quite accurate.

Table 5 presents the estimation results for models like that in (5). Including August, there are enough degrees of freedom, so only for the related months we can estimate the parameters in an unrestricted MIDAS model. Clearly, the forecasts for

Table 2
One-step-ahead forecast accuracy for $\pi_t = \mu + \alpha\pi_{January,t} + \rho\pi_{t-1} + \varepsilon_t$ …. $\pi_t = \mu + \alpha\pi_{December,t} + \rho\pi_{t-1} + \varepsilon_t$ Forecast sample is 2016–2018. Forecast accuracy criterion is the mean absolute error (MAE).

Month	2016	2016–2018
January	20.260	9.469
February	24.724	9.454
March	24.627	9.137
April	17.371	7.506
May	7.539	3.412
June	5.448	2.700
July	4.791	2.855
August	0.815	1.708
September	8.534	5.256
October	3.598	4.288
November	21.692	10.643
December	31.772	15.056

Table 3
Estimation results for $\pi_t = \mu + \alpha\pi_{January,t} + \varepsilon_t$ …. $\pi_t = \mu + \alpha\pi_{December,t} + \varepsilon_t$ Effective sample size is 2004–2015. Standard errors are in parentheses.

Month	μ		α		R^2
January	2.576	(2.395)	0.664	(0.260)	0.394
February	2.061	(1.691)	0.732	(0.177)	0.631
March	2.163	(1.258)	0.745	(0.131)	0.763
April	2.538	(0.919)	0.715	(0.094)	0.853
May	1.861	(0.813)	0.799	(0.085)	0.897
June	1.914	(1.045)	0.777	(0.109)	0.836
July	2.106	(0.880)	0.750	(0.090)	0.875
August	2.119	(0.761)	0.756	(0.078)	0.905
September	1.916	(0.812)	0.791	(0.085)	0.897
October	2.584	(1.243)	0.705	(0.129)	0.749
November	3.597	(2.094)	0.496	(0.197)	0.384
December	4.793	(2.271)	0.345	(0.205)	0.221

Table 4
One-step-ahead forecast accuracy for $\pi_t = \mu + \alpha\pi_{January,t} + \varepsilon_t$ …. $\pi_t = \mu + \alpha\pi_{December,t} + \varepsilon_t$ Forecast sample is 2016–2018. Forecast accuracy criterion is the MAE.

Month	2016	2016–2018
January	33.105	15.907
February	29.073	14.858
March	25.748	12.936
April	17.389	7.087
May	7.267	3.356
June	5.987	3.812
July	6.287	3.957
August	1.625	3.100
September	7.629	6.332
October	3.224	5.186
November	23.154	12.480
December	32.353	15.506

2016 are not at all as good as before, nor are the forecasts for 2017 and 2018. Excluding the lagged inflation rate, as is done in Table 6 does give some improvement, but not much.

Table 7 presents the MAEs for the MIDAS models with the logistic parameter restriction as in (6). Now, the forecast accuracy improves, in particular starting from June/July onwards. Also, forecast accuracy seems best when all months are included, which makes sense of course. Figs. 3 and 4 present the logistic curves for the models up to and including May and December, respectively. The typical sigmoid shape is clearly visible from Fig. 3, whereas the parameters seem to converge to a common value (around 0.084, which is close to $\frac{1}{12}$) when all months are included.

To compare our findings with the outcome of alternative models, we create random walk forecasts for the remaining months of the year and averaged those with the already available months. The average absolute errors per month of origin

Table 5
One-step-ahead forecast accuracy for $\pi_t = \mu + \alpha_1 \pi_{January,t} + \rho\pi_{t-1} + \varepsilon_t$ $\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \rho\pi_{t-1} + \varepsilon_t$ ….. $\pi_t = \mu + \alpha_1 \pi_{January,t} + \cdots + \alpha_8 \pi_{August,t} + \rho\pi_{t-1} + \varepsilon_t$ where no restrictions on the parameters are imposed. Forecast sample is 2016–2018. Forecast accuracy criterion is the MAE

Month	2016	2016–2018
January	20.260	9.469
February	23.677	9.369
March	23.506	9.203
April	10.487	6.357
May	10.247	4.335
June	10.440	4.408
July	28.837	16.714
August	7.668	7.298

Table 6
One-step-ahead forecast accuracy for $\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t$ $\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t$ ….. $\pi_t = \mu + \alpha_1 \pi_{January,t} + \cdots + \alpha_8 \pi_{August,t} + \varepsilon_t$ where no restrictions on the parameters are imposed. Forecast sample is 2016–2018. Forecast accuracy criterion is the MAE.

Month	2016	2016–2018
January	33.015	15.907
February	30.315	11.710
March	26.382	10.810
April	9.338	5.970
May	7.809	3.481
June	8.058	4.266
July	9.744	4.272
August	3.142	5.899

Table 7
One-step-ahead forecast accuracy for $\pi_t = \mu + \alpha_1 \pi_{January,t} + \rho\pi_{t-1} + \varepsilon_t$ ….. $\pi_t = \mu + \alpha_1 \pi_{January,t} + .. + \alpha_{12} \pi_{December,t} + \rho\pi_{t-1} + \varepsilon_t$ with the parameter restriction that $\alpha_i = \frac{1}{1+\beta\exp(-\gamma i)}$ Forecast sample is 2016–2018. Forecast accuracy criterion is the mean absolute error (MAE).

	$\rho \neq 0$		$\rho = 0$	
Month	2016	2016–2018	2016	2016–2018
January	20.260	9.469	33.015	15.907
February	23.677	9.369	30.315	11.710
March	25.247	9.436	25.747	12.936
April	17.372	7.506	14.709	5.836
May	11.088	4.355	9.555	3.686
June	10.744	3.782	9.037	4.214
July	9.370	3.342	8.307	3.822
August	6.818	2.425	6.506	2.766
September	0.684	0.907	2.270	1.170
October	0.292	0.590	0.117	0.322
November	1.898	0.813	1.212	0.564
December	0.447	0.611	0.436	0.920

over the years 2016, 2017, 2018 are 11.550, 11.175, and 1.367, respectively, where the important outcome is that forecast errors do not get smaller as the year proceeds.

As an alternative to forecasting annual inflation, we can also look at a model for only annual data. The annual data are available from 1960 onwards (World Bank). An autoregression of order 2 fits the data well, although there are of course a few outliers, mainly in the mid 1990ies. Recursive estimation with samples ending in 2015, 2016 and 2017, give the absolute forecast errors 36.6, 38.9 and 4.4 for the years 2016, 2017 and 2018, respectively. So again, our economic theory-based MIDAS model gives much more accurate forecasts.

Finally, as of 2011, there is a monthly indicator available for Suriname. We experimented with a few months of this variable to see if there is any forecasting power, but there was none[3].

[3] A frequently observed stock market index could also be useful. An attempt to create one appears in Bodeutsch and Franses (2015), but this has no official status. And, the exchange rates of Suriname show little fluctuation and are characterized by occasional jumps, making this variable not very useful.

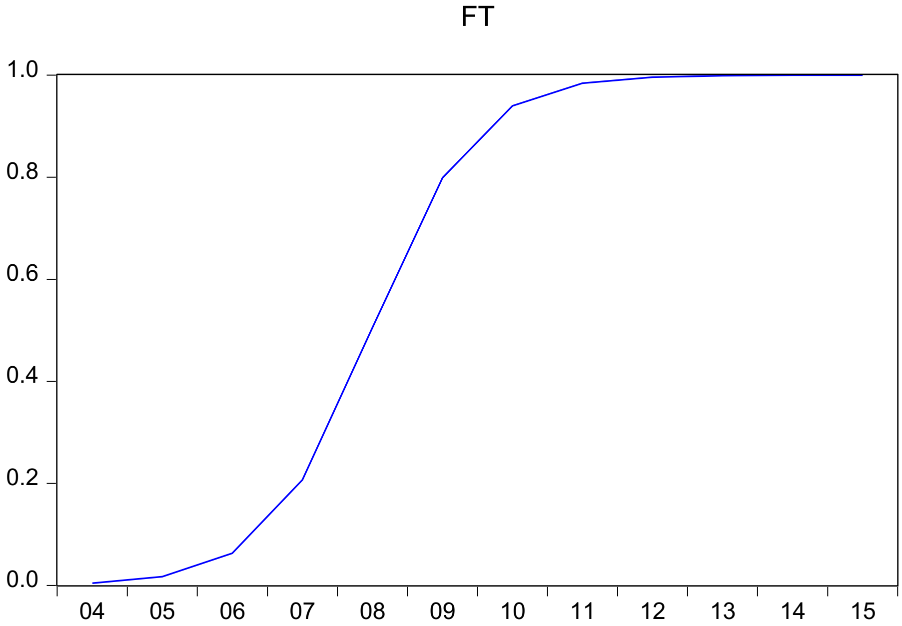

Fig. 3. Estimated parameters for the years 2004–2015 in the regression models $\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t \pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t \ldots$... $\pi_t = \mu + \alpha_1 \pi_{January,t} + .. + \alpha_5 \pi_{May,t} + \varepsilon_t$with the imposed restriction that $\alpha_i = \frac{1}{1+\beta \exp(-\gamma i)}$.

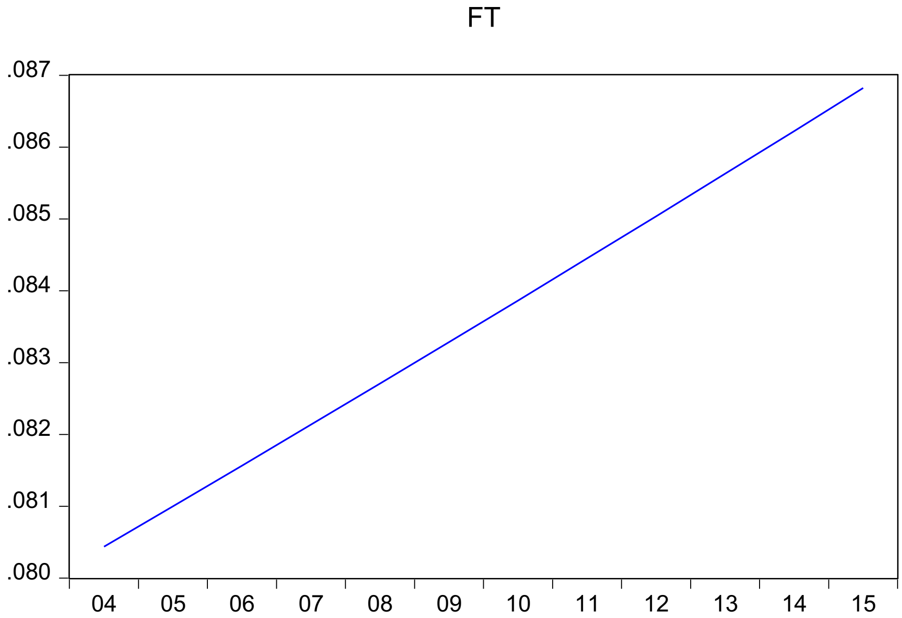

Fig. 4. Estimated parameters for the years 2004–2015 in the regression models $\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t \pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t \ldots$... $\pi_t = \mu + \alpha_1 \pi_{January,t} + .. + \alpha_{12} \pi_{December,t} + \varepsilon_t$ with the imposed restriction that $\alpha_i = \frac{1}{1+\beta \exp(-\gamma i)}$.

5. Conclusions

The novelty of this paper is based on the application of MIDAS regression models to forecast inflation in Suriname for a period that includes a high-inflation episode, where the model is based on economic theory. We use available year-on-year inflation rates in the current year that become available every month to create forecasts for the current year's annual inflation rate. The forecasts become very accurate when the models include data from May onwards. In particular, a parameter restriction is constructed to improve forecast accuracy.

We have demonstrated that even during high-inflation episodes, annual inflation can be predicted accurately. Our methodology will also work for economies with similar features as that of Suriname. For many developing countries, only recently quarterly or monthly data have been collected. We show that such higher frequency data can be instrumental to predict (or to nowcast) current year's annual data for the same variable. Of course, due to data limitations, a theory-based predictive model can come at the cost of many parameter. We therefore advocate to impose smart restrictions on the parameters.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2021.101357.

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