Forecasting Annual Inflation in Suriname

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EI2019-32

September 2019

Abstract

For many countries, statistical information on macroeconomic variables is not abundant and hence creating forecasts can be cumbersome. This paper addresses the creation of current year forecasts from a MIDAS regression for annual inflation rates where monthly inflation rates are the explanatory variables, and where the latter are only available for the last one and a half decade. The model can be viewed as a hybrid New-Keynesian Philips curve (NKPC). Specific focus is given to the forecast accuracy concerning the high inflation period in 2016-2017.

Key words: Inflation, New Keynesian Phillips curve, Rational Expectations, MIDAS Regression, Forecasting

JEL codes: E12, E17

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Introduction

For macroeconomic policy it is helpful to have reliable forecasts for key variables like real Gross Domestic Product growth, unemployment and inflation. Typically, such forecasts are made for annually observed variables in the current year and for the next year. This paper addresses creating accurate current year forecasts for inflation.

To predict annual inflation, one may use various variables, see Stock and Watson (1999), and rely on modern variable-selection techniques to choose the best predictors. For many countries, there is however no abundant availability of timely observed variables. Also, at the same time, for many countries the sample span can also be short. One possible avenue may now be to consider so-called MIDAS regression models. These are models that connect for example annual inflation rates with explanatory variables that are observed at a higher frequency, like months. In this paper we consider the case of Suriname (in South America), where we rely on a particular inflation forecasting model, where the input is again inflation but then 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 show that a MIDAS model for annual inflation with monthly inflations rates as explanatory variables makes sense from an economic theory perspective. Next, we illustrate the model for the sample 2004-2015, where we focus on the forecast accuracy for the years 2016-2018, where in particular for Suriname the years 2016 and 2017 were very high inflation years. We document that our model can deliver highly accurate forecasts, in particular when the summer months are included. In brief, when we know the annualized inflation rate in May or June, the subsequent forecasts for the entire year are very accurate. Finally, we conclude with limitations and further research topics.

Background

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 is closely connected to the concept of rational expectations (RE) (Gali et al. 2005), whereas the traditional NKPC model builds upon the micromodel of Calvo (1983). Point of departure is

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

where π_t is the annual inflation rate[1], $E_t \pi_{t+1}$ is the one-year-ahead expected inflation at time t and x_t is a measure of marginal costs. Gali and Gertler (1999) modify this model by assuming that some firms are able to change prices, but they rather choose not to do so in the short-run. This assumption leads to the HNKPC, given by

$$\pi_t = \mu + \alpha E_t \pi_{t+1} + \rho \pi_{t-1} + \gamma x_t \tag{2}$$

[1] Denote the annual average of the consumer price index (CPI) as CPI_t, then the annual inflation rate is defined as $100(\log \frac{CPI_t}{CPI_{t-1}})$, where log is the natural logarithm.

The HNKPC augments the 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 inflation rates as predictors for the expected inflation. In year *t,* the annualized inflation rate in month *s* is

$$\pi_{s,t} = 1200\big(\log CPI_{s,t} - \log CPI_{s,t-1}\big) \tag{3}$$

where $CPI_{s,t}$ is the consumer price index in month s of year t. For example, when the January inflation rates have been observed, Franses (2019) proposes the model in (2) to become

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

where we have collected the measure of marginal costs in the error term ε_t. Next, when February data come in, one may consider

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

but also one may consider

$$\pi_t = \mu + \alpha_1\pi_{January,t} + \alpha_2\pi_{February,t} + \rho\pi_{t-1} + \varepsilon_t \tag{6}$$

Basically, these two models are so-called MIDAS models, see Ghysels et al. (2006, 2007), Breitung and Roling (2015), and Foroni et al. (2015). From (6) it can be seen that when the December data have come in, 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 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 to 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

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \ldots + \alpha_{12} \pi_{December,t} + \rho \pi_{t-1} + \varepsilon_t \qquad (7)$$

contains 14 parameters, which, given our sample size, is infeasible. We therefore consider the restrictions

$$\alpha_i = \frac{1}{1+\beta \text{ex} \ (-\gamma i)} \qquad (8)$$

with $\beta, \gamma > 0$. Depending on the size of these 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 seems to have face value.

Results

A graph of the annual inflation rates for the period 2004-2018 is presented in Figure 1. The 12 annualized monthly inflation rates are presented in Figure 2. The high inflation rates around 2016 and 2017 are clearly visible. To examine whether our HNKPC model has any useful predictive power, we estimate the parameters of the models for 2004-2015 and we reserve 2016-2018 to evaluate predictive accuracy.

Table 1 presents the estimation results for MIDAS model like in (4) and (5), that is, for each month separately. It can be seen that the R^2 peaks in August. Also, the parameter ρ for lagged inflation becomes insignificant when the months proceed, whereas the 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

$$\pi_t = \mu + \alpha\pi_{August,t} + \rho\pi_{t-1} + \varepsilon_t \tag{9}$$

is exceptionally good. With a mean absolute error if 0.815 for 2016, where annual inflation was 55.2%, the forecast is almost spot on. At the same time, the forecasts from the model with the May data as explanatory variable are also already quite accurate.

Since Table 1 learns that lagged inflation is rarely a useful predictor, we also consider the models like (4) and (5) without this variable, and the estimation results appear in Table 3. Needless to say that 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 (6). Until and 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 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 and 8 present the mean absolute errors for the MIDAS models with the logistic parameter restriction as in (8). 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. Figures 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 Figure 3, whereas the parameters seem to converge to a common value (around 0.084) when all months are included.

Conclusion

The novelty of this paper is that we applied an economic-theory based MIDAS-based regression model proposed in Franses (2019) to forecast inflation in Suriname that includes a high-inflation episode. We used 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 became very accurate when the models included data from May onwards. A particular parameter restriction was also useful to improve forecast accuracy.

Our approach demonstrates the merits of forecasting inflation, including high-inflation episodes, in a simple yet sound manner in small and perhaps less developed economies with the same features as that of Suriname. Typically, inflation rate forecasts presented in the literature concern western industrialized countries where statistical data are abundantly available. However, for many countries in the world, only recently people have started to collect quarterly or monthly data. We showed that such higher frequency data can be instrumental to predict (or to nowcast) current year's annual data. Of course, a limitation is that one quickly runs out of degrees of freedom, and hence smart restrictions could or should be imposed on the parameters.

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

Table 2

One-step-ahead forecast accuracy for

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

$$\ldots.$$

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

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

$$\pi_t = \mu + \alpha\pi_{January,t} + \varepsilon_t$$

$$\dots.$$

$$\pi_t = \mu + \alpha\pi_{December,t} + \varepsilon_t$$

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

$$\pi_t = \mu + \alpha\pi_{January,t} + \varepsilon_t$$

$$\ldots.$$

$$\pi_t = \mu + \alpha\pi_{December,t} + \varepsilon_t$$

Forecast sample is 2016-2018. Forecast accuracy criterion is the mean absolute error (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

Table 5

One-step-ahead forecast accuracy for

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

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

…..

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \cdots + \alpha_8 \pi_{August,t} + \rho \pi_{t-1} + \varepsilon_t$$

Forecast sample is 2016-2018. Forecast accuracy criterion is the mean absolute error (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

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t$$

$$.....$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \cdots + \alpha_8 \pi_{August,t} + \varepsilon_t$$

Forecast sample is 2016-2018. Forecast accuracy criterion is the mean absolute error (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

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

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

…..

$$\pi_t = \mu + \alpha_1 \pi_{January,t} +..+ \alpha_{12} \pi_{December,t} + \rho \pi_{t-1} + \varepsilon_t$$

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)

Month	2016	2016-2018
January	20.260	9.469
February	23.677	9.369
March	25.247	9.436
April	17.372	7.506
May	11.088	4.355
June	10.744	3.782
July	9.370	3.342
August	6.818	2.425
September	0.684	0.907
October	0.292	0.590
November	1.898	0.813
December	0.447	0.611

Table 8:

One-step-ahead forecast accuracy for

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t$$

…..

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + .. + \alpha_{12} \pi_{December,t} + \varepsilon_t$$

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)

Month	2016	2016-2018
January	33.015	15.907
February	30.315	11.710
March	25.747	12.936
April	14.709	5.836
May	9.555	3.686
June	9.037	4.214
July	8.307	3.822
August	6.506	2.766
September	2.270	1.170
October	0.117	0.322
November	1.212	0.564
December	0.436	0.920

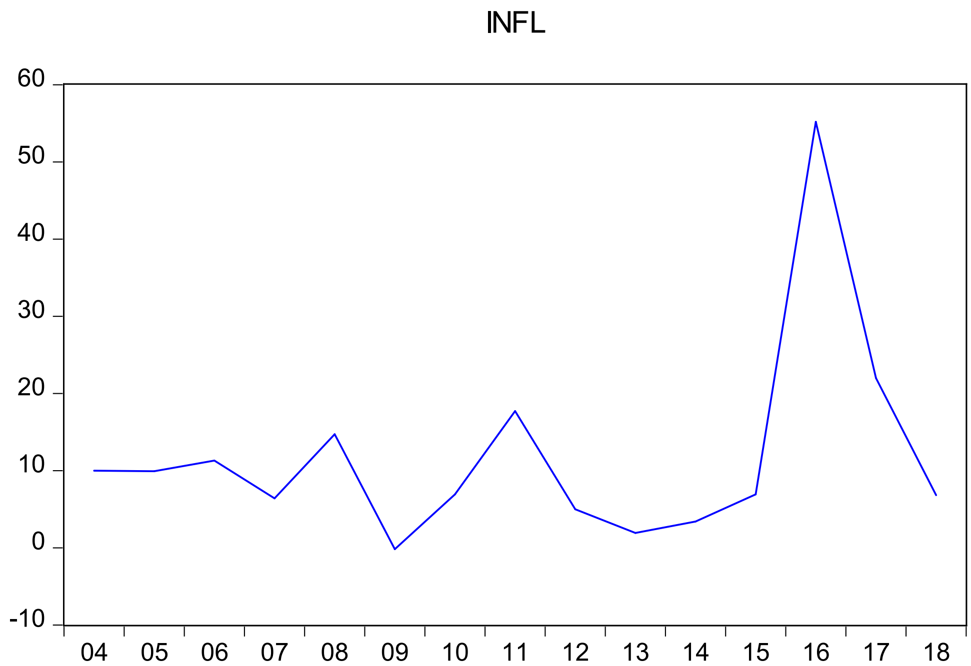

Figure 1: Annual Inflation, 2004-2018 (source: World Bank)

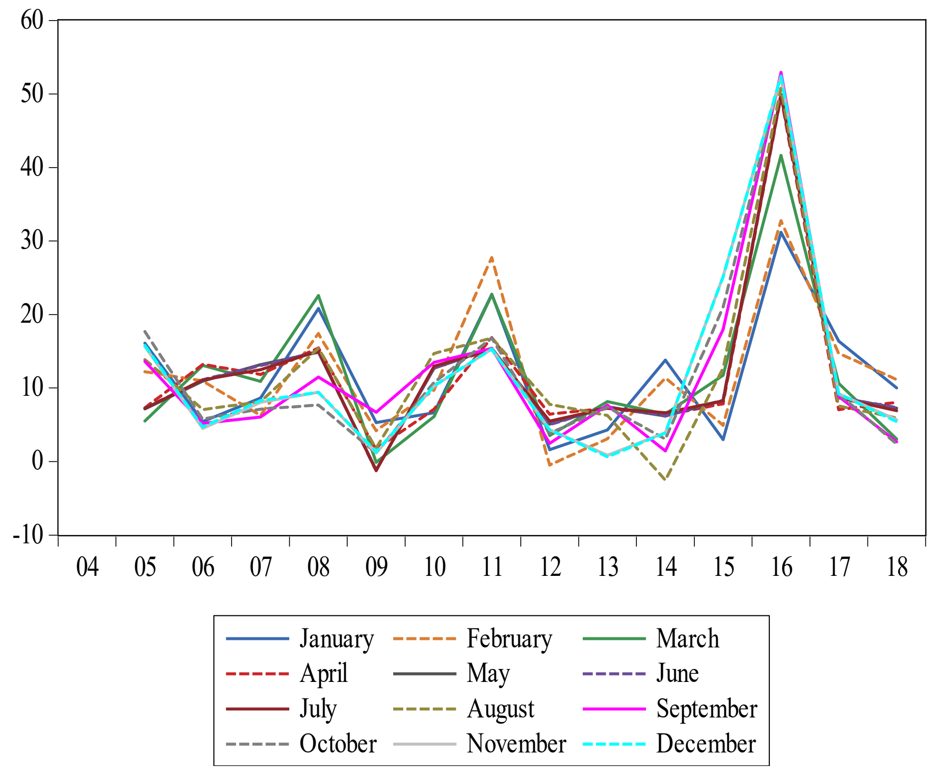

Figure 2: Annualized Monthly Inflation rate (source: Central Bureau of Statistics Suriname)

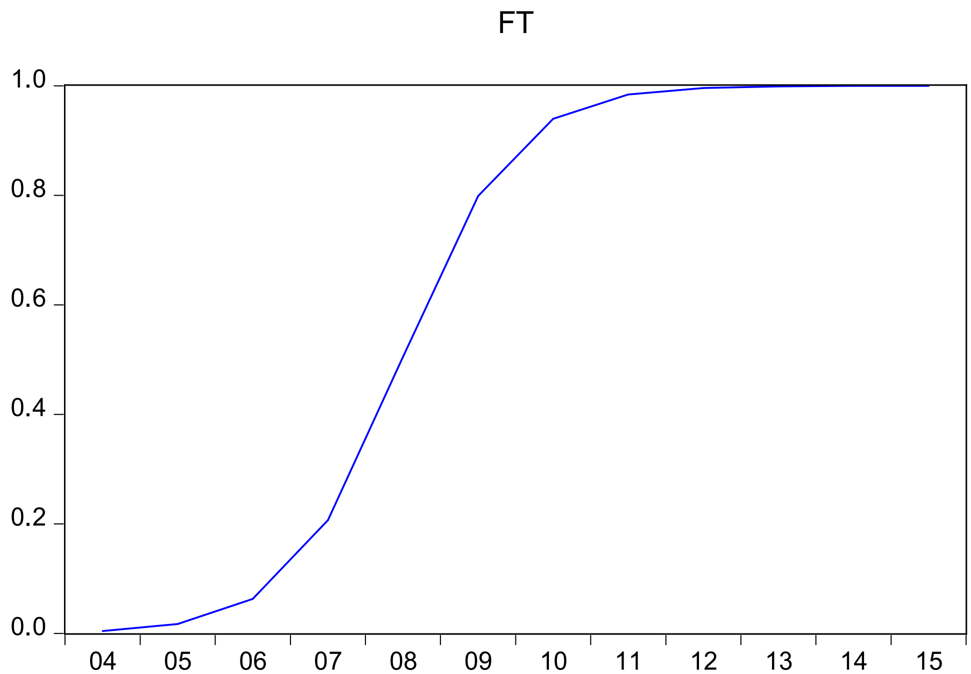

Figure 3: Parameters in

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t$$

$$\ldots..$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} +..+ \alpha_5 \pi_{May,t} + \varepsilon_t$$

with the restriction

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

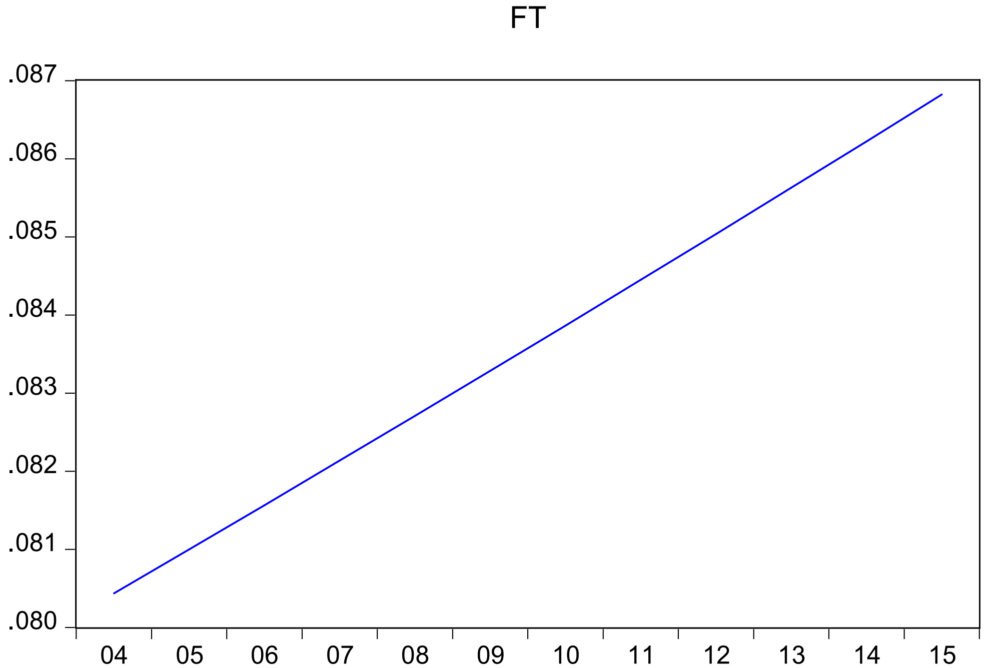

Figure 4: Parameters in

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \varepsilon_t$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} + \alpha_2 \pi_{February,t} + \varepsilon_t$$

$$\ldots..$$

$$\pi_t = \mu + \alpha_1 \pi_{January,t} +..+ \alpha_{12} \pi_{December,t} + \varepsilon_t$$

with the restriction

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

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