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Forecasting Indonesian Inflation within an Inflation-Targeting Framework: Do Large-Scale Models Pay Off?

Solikin M. Juhro, Bernard Njindan Iyke

Forecasting Indonesian Inflation within an Inflation-Targeting Framework:

Do Large-Scale Models Pay Off?

Abstract

We examine the usefulness of large-scale inflation forecasting models in Indonesia within an inflation-targeting framework. Using a dynamic model averaging approach to address three issues the policymaker faces when forecasting inflation, namely, parameter, predictor, and model uncertainties, we show that large-scale models have significant payoffs. Our in-sample forecasts suggest that 60% of 15 exogenous predictors significantly forecast inflation, given a posterior inclusion probability cut-off of approximately 50%. We show that nearly 87% of the predictors can forecast inflation if we lower the cut-off to approximately 40%. Our out-of-sample forecasts suggest that large-scale inflation forecasting models have substantial forecasting power relative to simple models of inflation persistence at longer horizons.

Keywords: Forecasting inflation; Inflation-targeting framework; Large-scale models; Dynamic model averaging

JEL Classification: E37

Introduction

We evaluate the performance of an inflation model consisting of a large set of exogenous predictors and lags of inflation against a simple model of inflation persistence for Indonesia within an inflation-targeting framework. The simple inflation persistence model regresses inflation on the first four lags of inflation. Theoretically, several macroeconomic and financial variables can forecast inflation (Sharma, 2019). Accordingly, we follow prior studies (Koop and Korobilis, 2012; Groen, Paap, and Ravazzolo, 2013) and regress inflation on 15 exogenous predictors and four lags of inflation. To estimate these models, we use the dynamic model averaging (DMA) approach developed by Raftery, Kárný, and Ettler (2010). The advantage of this approach is that it allows for time variation of the forecasting model, the predictors, and the parameters in each model.

We evaluate both the in- and out-of-sample forecasting performance of these models. We use posterior inclusion probabilities (PIPs) to determine which predictors can forecast inflation. Predictors with PIPs of approximately 0.50 (50%) or higher are considered good predictors of inflation. In the out-of-sample forecast evaluation, we compare the mean squared error (MSE) and log-predictive likelihood difference (PLD) values of the large-scale model to those of the inflation persistence model for out-of-sample forecast horizons $h = 1$, 5, and 9 months. We set the burn-in to 32 months, such that the forecast evaluation starts in September 1992. The sample period is from January 1990 to June 2018. This covers the inflation-targeting regime and the period immediately before its implementation.

We find that the first lags of inflation, industrial production, import and export prices, global food prices, the global prices of agricultural raw materials, the money supply, the exchange rate between the Indonesian rupiah (IDR) and the US dollar (USD), consumption expenditures, and the unemployment rate are important predictors of inflation. In other words, 60% of the 15 exogenous predictors can forecast inflation for a PIP cut-off of approximately 50%. This share rises significantly, to nearly 87%, if we lower the cut-off to approximately 40%, since consumer confidence, business confidence, stock exchange capitalization, and crude oil prices can be included in the model. The relevance of these variables, particularly the unemployment rate, consumption expenditures, and confidence indicators, is consistent with the literature (Ang, Bekaert, and Wei, 2007; Stock and Watson, 2008; Groen, Paap, and Ravazzolo, 2013). The large-scale model is more powerful out of sample at longer forecast horizons. We find that the simple model of inflation persistence outperforms the large-scale model for an out-of-sample forecast horizon $h = 1$ month. However, the large-scale model outperforms the persistence model for out-of-sample forecast horizons of $h = 5$ months and $h = 9$ months. Koop and Korobilis (2012) and Groen, Paap, and Ravazzolo (2013) find similar evidence, controlling for parameter and model uncertainty, where inflation models with a large set of predictors have greater forecast accuracy relative to naïve or simple models.

Price stability is a core mandate of all central banks. Therefore, the prediction of inflation is always an important goal. The sheer volume of this literature rules out an exhaustive review. Older studies include those of Tzavalis and Wickens (1996), Stock and Watson (1999), Forni, Hallin, Lippi, and Reichlin (2003), and, more recently, Wright (2009), Koop and Korobilis (2012), Faust and Wright (2013), and Chen, Turnovsky, and Zivot (2014), and Sharma (2019). These studies all use the Phillips curve (Stock and Watson, 1999) and its extensions to cover a broad range of financial and macroeconomic variables (Sharma, 2019) and estimation strategies (Forni, Hallin, Lippi, and Reichlin, 2003). However, as observed by Koop and Korobilis (2012), common issues affect various inflation forecasts, particularly those based on recursive regression. Structural changes shift model parameters upward or downward (Juhro, Narayan, Iyke, and Trisnanto, 2020). Such shifts, particularly those related to the coefficients, lead to time variation in the underlying relations, which are not well captured by recursive approaches. In addition, a variable's predictive content can change over time, implying that the forecasting model for inflation can also change over time. Moreover, the number of inflation predictors can be large, leading to an even larger number of model combinations to estimate.

We contribute to the general literature by sidestepping these issues and using a DMA approach in forecasting inflation. The DMA approach allows time variation of the forecasting model and the coefficients in each model and accommodates different combination of models and predictors. Another contribution of our study is in response to the skewed focus of prior studies toward developed countries (e.g., Tzavalis and Wickens, 1996; Stock and Watson, 1999; Forni, Hallin, Lippi, and Reichlin, 2003; Stock and Watson, 2003; Wright, 2009; Koop and Korobilis, 2012; Faust and Wright, 2013; Chen, Turnovsky, and Zivot, 2014). Stock and Watson (2003), D'Agostino, Gambetti, and Giannone (2013), and Clark and Ravazzolo (2015), among other, consider the United States, while Caggiano, Kapetanios, and Labhard (2011), Giannone, Lenza, Momferatou, and Onorante (2014), and Berg and Henzel (2015), for example, consider developed European countries.

As noted by Sharma (2019), this is a problem for developing countries' policymakers seeking to understand the evolution of inflation, in pursuit of price stability. Although our study and Sharma's (2019) fill this research gap by developing forecasting models for a developing country, they differ in several ways: Sharma uses a bivariate predictive regression framework, which does not allow for time variation of the forecasting model and the coefficients in each model, nor can it accommodate different combinations of models and predictors. Ramakrishnan and

Vamvakidis (2002), who assess the predictors of Indonesian inflation within a multivariate framework, have the same issue. The study closest to ours is that of Mandalinci (2017), who use time-varying parameter and stochastic volatility models to forecast inflation for nine emerging countries, including Indonesia. However, our model has more predictors, uses monthly data, and exploits a computationally efficient estimation strategy.

The Indonesian case is appealing because it is one of the few developing countries to have adopted a clear stance regarding effective policy coordination. The central bank, that is, Bank Indonesia, and the government now coordinate their policy deliberations and formulations (Juhro, Narayan, and Iyke, 2019), which became necessary in the aftermath of the 2007 global financial crisis (Juhro, 2015; Juhro and Goeltom, 2015). Central to this policy coordination is the mandate of achieving price stability under the Bank Indonesia Act of 1999, in growing recognition that both demand-pull and cost-push factors determine Indonesia’s inflation, and, consequently, Bank Indonesia’s formal implementation of the inflation-targeting framework in 2005 (Juhro, 2015; Juhro, Narayan, and Iyke, 2019). Since the early 2000s, the inflation-targeting framework has kept the inflation rate within the target range. There is no denying that a better understanding of the evolution of Indonesian inflation will help policymakers enhance the inflation-targeting framework, especially following recent pressure on the country’s exchange rate (Juhro and Iyke, 2019a). In response, our study draws attention to important issues to consider when forecasting inflation within the inflation-targeting framework. We show that, taking into account parameter and model uncertainty, Indonesian inflation forecasting models with large sets of predictors have strong out-of-sample forecasting power relative to simple models, particularly for longer horizons.

Next, Section 2 presents the inflation forecasting model and the data. Section 3 presents the results. Section 4 concludes the paper.

Inflation Forecasting Model and Data

Inflation forecasting model

The basic building block of all inflation forecasting models is the Phillips (1958) curve, which posits an inverse relation between wages and unemployment and, by extension, an inverse relation between inflation and unemployment (Samuelson and Solow, 1960). The theoretical implication of a negative relation between inflation and unemployment can be stated as

$$\pi_t = \pi_t^e + \sigma(\mu_t - \mu_t^n) \quad (1)$$

where π_t, π_t^e, μ_t, μ_t^n, and σ are, respectively, the inflation rate, inflationary expectations, the unemployment rate, the natural rate of unemployment, and the model parameter (Ho and Iyke, 2019).

In practice, it is challenging to measure the natural rate of unemployment and inflationary expectations, because both variables are unobservable. Additionally, bidirectional causality is likely between unemployment and inflation, because they are jointly determined (Ho and Iyke, 2019). Two intuitions help us overcome these estimation challenges. First, the adaptive and rational expectation hypotheses indicate that inflation is persistent, and, second, hysteresis in unemployment indicates that steady-state unemployment is influenced by past actual unemployment (Blanchard and Summers, 1987; Jaeger and Parkinson, 1994; Camarero, Carrion-i-Silvestre, and Tamarit, 2006). Therefore, in application, Equation (1) is reformulated such that inflationary expectations and the natural rate of unemployment are replaced with the lags and/or first differences of inflation and unemployment (King, Stock, and Watson, 1995).

Stock and Watson (1999), among others, have suggested a generalized Phillips curve, which adds several predictors to the basic model. Following these studies, we can write the generalized Phillips curve as

$$\pi_t = \alpha + X'_{t-1}\beta + \epsilon_t \tag{2}$$

where π_t is current inflation; X'_{t-1} is a set of predictors, including the first four lags of inflation; α and β are model parameters; and ϵ_t is the error term. The benchmark model (inflation persistence model) is Equation (2), but excluding the exogenous predictors of inflation.

Several issues can render forecasts based on Equation (2) inefficient or inaccurate. First, the model's parameters (α and β) can change over time, due to structural changes in the economy, meaning the relations between inflation and its predictors can change over time. Second, the importance of each predictor can change over time, meaning that the forecasting model must change to adapt to this change. Third, there are large number of potential predictors of inflation, leading to an even larger number of model combinations to estimate. Given these issues, the recursive estimation of Equation (2) is less credible.

The DMA approach offers a credible solution to these issues. Let us assume a set of N models $x^{(n)}$ $\forall$ $n = 1, \ldots, N$ associated with different subsets of predictors x_t. Then, the set of models is

$$\pi_t = x_t^{(n)}\theta_t^{(n)} + \epsilon_t^{(n)} \tag{3}$$

$$\theta_{t+1}^{(n)} = \theta_t^{(n)} + \gamma_t^{(n)}$$

where $\epsilon_t^{(n)} \sim N(0, H_t^{(n)})$ and $\gamma_t^{(n)} \sim N(0, K_t^{(n)})$. Suppose that $M_t \in \{1, \ldots, N\}$ indicates the model that is used at each time period, $\Theta_t = (\theta_t^{(1)\prime}, \ldots, \theta_t^{(n)\prime})'$ and $\pi^t = (\pi_1, \ldots, \pi_t)'$. Then, the DMA approach entails computing $P(M_t = n|\pi^{t-1})$ $\forall$ $n = 1, \ldots, N$ and averaging forecasts across models using these probabilities to forecast inflation at time t using inflation predictors through time $t-1$ (for details, see Koop and Korobilis, 2012; Catania and Nonejad, 2018).

Data

We follow prior studies (Koop and Korobilis, 2012; Groen, Paap, and Ravazzolo, 2013) to gather the predictors of inflation. Most of the data are from Sharma (2019). Consistent with Sharma's study, our measure of inflation (*INF*) is the monthly change in the Consumer Price Index. The 15 exogenous predictors are the logarithms of the industrial production index (*LIP*), the consumer confidence index (*LCCI*), the business confidence index (*LBCI*), the global price of food index (*FOOD*), the global price of agricultural raw material index (*RAW*), the Jakarta stock exchange capitalization (*LCAP*), the M2 money supply (*LM2*), the IDR–USD exchange rate (*LER*), crude oil prices (*LOIL*), net wages (*LNW*), consumption expenditures (*LCON*), and the import price index (*IMPPI*); the export price index (*EXPPI*); the interest rate spread (*SPREAD*); and unemployment (*UEM*). Our sample period is from January 1990 to June 2018, due to data availability. This period also covers the inflation-targeting framework and, therefore, is more relevant to policymakers in Indonesia. Table 1 provides details on these variables, including their definitions, dates of availability, and sources.

<Insert Table 1 Here>

Results

1.1. Summary statistics

Table 2 shows the summary statistics of the variables. Our main statistic of interest is the unit root test, since it serves as guidance regarding how the variables should enter into the inflation forecasting model in Equation (2). We employ the widely used augmented Dickey–Fuller (ADF) test. Because the frequency of the data is monthly, we include a maximum of 12 lags in each auxiliary ADF test regression and select the optimal lag using the Akaike information criterion. We report the ADF test statistic alongside the selected optimal lag. The null hypothesis of a unit root is rejected for *INF*, *LCCI*, *LBCI*, *SPREAD*, and *LNW* at conventional statistical significance levels, implying that these variables are stationary and, therefore, enter into the model as levels. The remaining variables are not stationary and enter into the model as first differences. Note that we verify these results using the test of Narayan and Popp (2010, 2013). Table 3 reports the Narayan–Popp test results. Our decision rule is to treat a variable appropriately (i.e., use its difference or leave it as a level) if both tests produce the same outcome, and to difference the variable if the outcomes are split. The Narayan–Popp test results show significant structural breaks in the variables, implying shifts in the parameters of Equation (2).

<Insert Table 2 Here>

<Insert Table 3 Here>

In-sample forecast evaluation

Having established how the variables enter into Equation (2), we prepare the model for estimation. Our benchmark model is a simple model of inflation persistence; that is, we regress inflation on the first four lags of inflation. Our generalized model follows prior studies (Koop and Korobilis, 2012; Groen, Paap, and Ravazzolo, 2013) and fits inflation as a function of the above-mentioned 15 exogenous predictors and four lags of inflation. The in-sample forecast evaluation of the generalized model is based on whether the posterior means of the coefficients of these predictors are significant. We use the PIPs of the predictors to determine the significance of the coefficients (or predictors).

Table 4 reports the DMA estimates of Equation (2). Following Iyke (2018), a predictor is said to forecast inflation in sample if its PIP is approximately 0.50 (50%) or higher. Using this rule of thumb, we find that the first lags of inflation, industrial production, import and export prices, the global food price, the global prices of agricultural raw materials, the money supply, the IDR–

USD exchange rate, consumption expenditures, and unemployment significantly forecast inflation. This means that 60% of the 15 exogenous predictors can forecast inflation when we use a 50% PIP cut-off, and even a larger share (nearly 87%) can if we lower the cut-off to approximately 40%. In addition to these predictors, consumer confidence, business confidence, stock exchange capitalization, and crude oil prices can be included in the model if we reduce the PIP cut-off to 40%.

Prior studies (Ang, Bekaert, and Wei, 2007; Stock and Watson, 2008; Groen, Paap, and Ravazzolo, 2013) also find some or all of these predictors forecast inflation. Hence, our results are broadly consistent with the literature. From the Indonesian perspective, Ramakrishnan and Vamvakidis (2002) find the exchange rate and foreign inflation forecast inflation, while Sharma (2019) finds that business confidence, stock market capitalization, and the money supply are important predictors of inflation. Our estimates confirm their findings. We find that unemployment has a positive predictive impact on inflation, implying that high unemployment is followed by high inflation. This result violates the negative relation between inflation and unemployment posited by the Phillips curve. Our study is not the first to document that the relation between inflation and unemployment can be positive. For example, Ho and Iyke (2019) and Hooper, Mishkin, and Sufi (2019) show that the relation can be nonlinear. Specifically, these studies show a threshold beyond which the relation changes from negative to positive.

A number of reasons can explain an upward-sloping Phillips curve. The relation between inflation and unemployment depends on the phase of the business cycle. For instance, King, Stock, and Watson (1995) show that, for the United States, the Phillips curve is unstable and the relation between inflation and unemployment is positive during normal periods and negative during business cycles. The so-called microfounded theories of the Phillips curve contend that it is costly for firms to increase output and employment in response to excess demand. Such theories rely on the capacity constraint model and assume both increasing marginal costs and fixed production capacity in the short run. The net result of these short-run rigidities is a convex Phillips curve (Dupasquier and Rickets, 1998).[1] An upward-sloping Phillips curve can also be explained by asymmetries in price adjustment. Stiglitz (1984) and Fisher (1989) use a downward nominal wage rigidity model to demonstrate that workers are more hesitant to accept a drop in their nominal wages compared to a drop in their real wages because of the money illusion. The implication is that excess supply has far less impact on inflation, compared with excess demand, resulting in asymmetries in the inflation–output gap. Gordon (2013) shows that an upward-sloping Phillips curve is the result of supply shocks, which shift the short-run supply curve. Following the theory of a backward-bending Phillips curve and assuming downward nominal wage rigidity, Palley (2003) shows a trade-off between inflation and unemployment at low inflation rates. This trade-off reverses at high inflation rates. We finding of a positive Phillips curve is consistent with these theoretical arguments.

<Insert Table 4 Here>

Out-of-sample forecast evaluation

We set the burn-in for the out-of-sample forecast evaluation, at 32-months, meaning that the forecast evaluation starts in September 1992. We then compare the *MSE* and *PLD* values of the generalized (large-scale) model to those of the inflation persistence model for an out-of-sample forecast horizon of $h = 1$ month. Panel A of Table 5 reports the results. The statistics suggest that the simple model of inflation persistence outperforms the large-scale model for an out-of-sample

[1] Ball et al. (1988) provide a different explanation to convex Phillips curves. Juhro (2004) documents a convex Phillips curve for Indonesia.

forecast horizon of $h = 1$ month. However, is this the case for longer forecast horizons? The results in Panels B and C indicate it is not. The large-scale model outperforms the persistence model for out-of-sample forecast horizons of $h = 5$ months and $h = 9$ months. This result is consistent with those of Koop and Korobilis (2012) and Groen, Paap, and Ravazzolo (2013), who find that, controlling for parameter and model uncertainty, large-scale inflation models have substantial forecast accuracy relative to naïve or simple models.

<Insert Table 5 Here>

Conclusion

We proposed a large-scale inflation forecasting model for Indonesia. We use using a DMA approach to address three issues the policymaker faces when forecasting inflation, namely, parameter, predictor, and model uncertainties. Our in-sample forecasts suggest that the first lags of inflation, industrial production, import and export prices, global food prices, the global prices of agricultural raw materials, the money supply, the IDR–USD exchange rate, consumption expenditures, and the unemployment rate significantly forecast inflation for a 50% PIP cut-off. If the cut-off is lowered to 40%, we find that consumer confidence, business confidence, stock exchange capitalization, and crude oil prices can also forecast inflation. Out-of-sample forecasts suggest that the large-scale inflation forecasting model has substantial forecasting power relative to simple models of inflation persistence at longer horizons. Overall, we document that large-scale models have significant payoffs in terms of inflation forecasting in Indonesia.

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Table 1: Definition of variables

This table shows the variables, including their definition/construction, and their available dates. Majority of the data comes from Sharma (2019).

Variable	Definition	Date	Source
INF	Change in consumer price index	1967M02-2018M06	Sharma (2019)
LIP	Logarithm of industrial production index	1991M12-2018M04	Sharma (2019)
LCCI	Logarithm of consumer confidence index	2001M04-2017M12	Sharma (2019)
LBCI	Logarithm of Business confidence index	2002M03-2017M12	Sharma (2019)
IMPPI	Import price index	1991M01-2018M05	Sharma (2019)
EXPPI	Export price index	1991M01-2018M05	Sharma (2019)
FOOD	Logarithm of global price of food index (2016 = 100).	1992M01-2019M11	Federal Reserve Economic Data
RAW	Logarithm of global price of agricultural raw material index (2016 = 100).	1990M01-2019M11	Federal Reserve Economic Data
LCAP	Logarithm of Jakarta stock exchange capitalization (value traded, USD).	1990M01-2018M05	Sharma (2019)
LM2	Logarithm of M2 money supply.	2003M12-2018M04	Sharma (2019)
SPREAD	Difference between one-month JIBOR and three-month JIBOR.	1991M01-2018M06	Sharma (2019)
LER	Logarithm of Indonesian rupiah per USD.	1967M02-2018M06	Sharma (2019)
LOIL	Logarithm of crude oil prices (West Texas Intermediate USD per barrel).	1986M01-2019M12	Federal Reserve Economic Data
LNW	Logarithm of average of net wage/salary per month of employee, interpolated from annual data	1990M01-2018M06	National Labor Force Survey of Indonesia
LCON	Logarithm of total household consumption expenditure.	1993M03-2019M03	CIEC; Juhro and Iyke (2019b)
UEM	Unemployment rate, interpolated from semi-annual data.	1983M01-2019M09	Global Financial Database

Table 2: Summary statistics

The table shows summary statistics of the variables. The dependent variable is inflation (INF). The remaining variables are the predictors. Their definitions are in Table 1. SD, JB, and ADF, denote, respectively, standard deviation, p-value of the Jarque–Bera statistic, and the Augmented Dickey–Fuller test statistic. We allow a maximum of 12 lags, and include only the intercept term in the ADF test regression. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively. The sample period is from January 1990 to June 2018.

Variable	Mean	SD	Skewness	Kurtosis	JB	ADF(Lag)
INF	36.11	40.87	1.01	2.60	0.00	4.07***(8)
LIP	12.58	0.22	0.21	2.32	0.02	-0.81(3)
LCCI	4.60	0.01	-1.06	4.49	0.00	-4.07***(1)
LBCI	4.60	0.01	-1.53	4.73	0.00	-3.61**(9)
IMPPI	0.78	0.23	-0.15	2.01	0.00	-1.28(9)
EXPPI	0.77	0.22	0.36	1.85	0.00	-1.27(2)
FOOD	4.43	0.24	0.29	1.70	0.00	-1.36(1)
RAW	4.52	0.23	0.45	2.92	0.00	-1.89(2)
LCAP	11.29	1.33	-0.24	2.02	0.00	-1.98(1)
LM2	14.92	0.42	-0.41	2.25	0.03	-1.78(12)
SPREAD	-0.18	3.51	-5.61	34.61	0.00	-4.86***(0)
LER	-0.63	6.50	0.52	1.40	0.00	0.34(12)
LOIL	3.55	0.66	0.31	1.71	0.00	-1.84(1)
LNW	13.33	1.04	-0.35	1.79	0.00	-2.86*(12)
LCON	13.57	0.32	-0.00	2.23	0.02	-1.37(12)
UEM	5.50	2.60	0.33	2.06	0.00	-1.13(12)

Table 3: Narayan–Popp structural break unit root test

The table reports the Narayan–Popp structural break unit root test results. We compute the M1 and M2 statistics and compare them to the critical values tabulated in Narayan and Popp (2010). The test accommodates two endogenous structural breaks. We include only the intercept and 12 lags in each test regression. TB1, TB2, and k are, respectively, the first and second structural break dates, and the chosen optimal lag. I(0) and I(1) denote, no unit roots and unit roots, respectively. The sample period is from January 1990 to June 2018.

	M1					M2				
Variable	Test statistic	TB1	TB2	k	Status	Test statistic	TB1	TB2	k	Status
INF	-5.48	1999M06	1999M07	9	I(0)	-5.55	1999M06	2000M08	9	I(0)
LIP	-9.50	1995M02	2004M07	12	I(0)	-10.99	1995M02	2001M05	12	I(0)
LCCI	-8.94	2004M03	2009M08	12	I(0)	-8.92	2003M02	2004M03	12	I(0)
LBCI	-8.22	2005M03	2007M05	12	I(0)	-8.12	2007M05	2008M06	12	I(0)
IMPPI	-6.10	1995M04	1996M05	10	I(0)	-6.33	1994M03	1995M04	10	I(0)
EXPPI	-7.15	1995M04	1996M05	12	I(0)	-7.16	1996M05	1997M06	12	I(0)
FOOD	-7.57	1996M02	2004M07	4	I(0)	-7.94	2004M07	2005M07	4	I(0)
RAW	-7.56	1995M03	2004M07	4	I(0)	-7.44	2004M07	2005M08	4	I(0)
LCAP	-3.93	1994M02	2005M08	2	I(0)	-3.21	2004M07	2005M08	2	I(1)
LM2	-3.80	2009M03	2011M06	2	I(1)	-3.99	2009M03	2010M05	2	I(1)
SPREAD	-4.76	2009M03	2011M06	5	I(0)	-8.34	2009M03	2010M05	5	I(0)
LER	-8.47	1998M04	2002M06	4	I(0)	-8.84	1998M04	2001M06	4	I(0)
PP	-8.15	1998M05	1999M05	4	I(0)	-7.47	1999M05	2000M06	4	I(0)
LOIL	-6.61	2000M05	2004M08	3	I(0)	-6.73	1997M04	2000M05	3	I(0)
LNW	-7.93	2001M06	2002M06	4	I(0)	-8.42	2002M06	2003M07	4	I(0)
LCON	-7.88	1997M02	1998M03	4	I(0)	-7.98	1998M03	1999M04	4	I(0)
UEM	-1.28	1990M07	1999M06	2	I(1)	-0.68	1990M07	1999M06	2	I(1)

Table 4: In-sample forecasts

The table reports the in-sample forecasts using the DMA approach. We report the estimated posterior means of the regression coefficients (PMs), posterior inclusion probabilities (PIP), and their standard deviations (SDs). The constant is always included in the model. A predictor is important if its PIP is approximately 0.50 or more. The sample period is from January 1990 to June 2018.

Variable	PM	SD(PM)	PIP	SD(PIP)
Constant	0.97	2.03	1.00	0.00
INF_{t-1}	0.63	0.26	0.61	0.26
INF_{t-2}	0.12	0.10	0.28	0.06
INF_{t-3}	0.08	0.05	0.23	0.07
INF_{t-4}	0.10	0.06	0.21	0.06
ΔLIP_{t-1}	0.03	0.07	0.50	0.00
$LCCI_{t-1}$	0.19	0.63	0.40	0.03
$LBCI_{t-1}$	0.18	0.62	0.40	0.03
$\Delta IMPPI_{t-1}$	0.12	0.19	0.49	0.01
$\Delta EXPPI_{t-1}$	0.17	0.19	0.48	0.01
$\Delta FOOD_{t-1}$	-0.09	0.31	0.48	0.01
ΔRAW_{t-1}	-0.11	0.31	0.47	0.01
$\Delta LCAP_{t-1}$	-0.33	0.28	0.43	0.03
$\Delta LM2_{t-1}$	0.37	0.37	0.49	0.00
$SPREAD_{t-1}$	0.06	0.31	0.29	0.11
ΔLER_{t-1}	0.16	0.18	0.48	0.01
$\Delta LOIL_{t-1}$	0.13	0.34	0.39	0.06
LNW_{t-1}	0.30	0.32	0.30	0.02
ΔCON_{t-1}	0.14	0.22	0.50	0.00
ΔUEM_{t-1}	0.12	0.30	0.46	0.04

Table 5: Out-of-sample forecasts

The table shows the out-of-sample forecast evaluations. We set the burn-in to 32 meaning that the evaluation starts from September 1992. The out-of-sample forecast accuracy measures are mean squared error (*MSE*) and log-predictive likelihood difference (*PLD*). We compare the *MSE* and *PLD* of the full model to the benchmark over $h = 1$, $h = 5$, and $h = 9$ month ahead out-of-sample forecast horizons. The sample period is from January 1990 to June 2018.

Panel A: $h = 1$	
MSE	*PLD*
2.12	134.94
Panel B: $h = 5$	
0.41	386.44
Panel C: $h = 9$	
0.26	524.67