Economics and Finance in Indonesia

Volume 62 | Number 2 Article 4

8-1-2016

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Recommended Citation
Rachman, Faisal (2016) "Is Inflation Target Announced by Bank Indonesia the Most Accurate Inflation Forecast?," *Economics and Finance in Indonesia*: Vol. 62: No. 2, Article 4.
DOI: 10.47291/efi.v62i2.539
Available at: https://scholarhub.ui.ac.id/efi/vol62/iss2/4

Economics and Finance in Indonesia
Vol. 62 No. 2, August 2016 : 98-120
98
p-ISSN 0126-155X; e-ISSN 2442-9260

Is Inflation Target Announced by Bank Indonesia the Most Accurate Inflation Forecast?

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Abstract

This article investigates whether following Bank Indonesia's explicit inflation targets (forward-looking) is a more accurate method of predicting inflation rate in Indonesia than forecast methods utilizing past information of macroeconomic data (backward-looking). The analysis is conducted by performing naive, univariate, and multivariate time-series models with an out-of-sample forecast evaluation period of January 2014–December 2016. It is found that the backward-looking approach outperforms the forward-looking approach at all forecast horizons, indicating that Bank Indonesia still does not succeed to anchor inflation expectation towards the desired level.
Keywords: Inflation; Forward-Looking; Backward-Looking; ARMA; VAR

Abstrak
Artikel ini mencoba untuk meneliti apakah mengikuti target inflasi yang dikeluarkan oleh Bank Indonesia (forward-looking) adalah metode yang lebih akurat untuk memprediksi tingkat inflasi suatu periode tertentu di Indonesia ketimbang metode peramalan inflasi dengan menggunakan data informasi makroekonomi lampau (backward-looking). Analisa dilakukan dengan membandingkan model runtun waktu naif, satu peubah, dan peubah ganda dengan periode Januari 2014–Desember 2016 digunakan sebagai periode evaluasi sampel peramalan. Tulisan ini menyimpulkan bahwa performa peramalan metode backward-looking lebih unggul dari pada metode forward-looking untuk setiap jangka waktu peramalan yang mengindikasikan bahwa Bank Indonesia masih belum berhasil dalam mengendalikan ekspektasi publik terhadap inflasi ketingkat yang diinginkan.
Kata kunci: *Inflasi; Forward-Looking; Backward-Looking; ARMA; VAR*

JEL classifications: C22; C32; E31; E37; E52

1. Introduction

Inflation is an economic phenomenon characterized by continuing rise in the overall price-level of goods and services in one country over specific time-period. All countries elude persistently high inflation rate since it engenders many disadvantages to society, such as lower real money balance, variability in relative prices leading to resource allocation inefficiency, indirect higher tax liability for individual and rise in uncertainty for debtors and creditors (Mankiw 2012). It furthermore erodes purchasing powers in general, gives a disruption to both savings and investments leading to vagueness in the business environment and depreciates exchange rate of domestic currency resulting in plunging economic competitiveness of a country in the global market. In consequence, it may hamper the economy to grow.

Inflation therefore has become one of pivotal economic and financial indicators for every country not only to ensure its stability, but also to predict and further influence its path. To do so, some countries nowadays have adopted inflation targeting (IT) as their monetary policy framework. According to Bernanke et al. (1999), IT is a framework which sets relatively low and stable inflation rate as the ultimate policy objective by using explicit numeri-

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cal target point or ranges for certain time-period in order to anchor public expectation on inflation. The target itself is determined by the central bank (CB)'s intermediate target which is the inflation forecast based on forward-looking approach, utilizing broad available information about current and future economic conditions.

Since the accuracy of the target reflects monetary policy performance and CB's credibility, it is very crucial to delve whether the target is the most reliable available forecast tool for inflation. This article thus attempts to scrutinize the precision of the target relative to the realized inflation rate by comparing forecast following the target to some other time-series forecast methods. The article limits the study scope by focusing on one IT country, namely Indonesia, and investigates whether following Bank Indonesia (BI)'s explicit inflation target is the best rule-of-thumb for market agents in predicting inflation, which also means that BI has provided a reliable ex ante inflation targeting device and has credibility in steering public expectation towards the target.

BI announced IT framework in 2000, but has effectively implemented it since July 2005. It replaces its previous monetary policy regime, money-base targeting (MT), which was preceded by switching exchange rate regime from highly managed to free floating exchange rate in 1997 (Tiwari 2003). The reason is that MT has been proven failing to encumber soaring annual inflation rate during the Asian Financial Crisis (AFC) 1997/1998 due to its inflexibility in adjusting money supply (Inoue, Toyoshima, & Hamori 2012), which was also exacerbated by the struggles in maintaining foreign exchange reserves under tightly controlled exchange rate regime. Under the Bank Indonesia Act No. 23/1999, it stipulates that the focal goal of BI is to maintain the Rupiah currency stability in relation to the price of goods and services, and foreign currencies (Bank Indonesia n.d.). This clarifies BI's monetary policy target, focuses its responsibility and makes BI institutionally independent. Implementation is monitored under coordination between BI and the Government by establishing the Ministerial-Level Inflation Targeting, Monitoring and Control Team in 2005. The targets are set for a three-year period with the Memorandum of Understanding between BI and the Government, and announced through the Decree of the Minister of Finance.

Table 1 displays the comparison of the target and the actual annual inflation rate. The realized inflation rate has relatively declined, but it hardly achieved the target point. It is noticed that the targets were missed in the first two-year implementations and became quite reliable in the period 2007–2012, with exception of 2008 when the Global Economic Crisis 2008/2009 hit. The actual inflation rates nevertheless were out of the target ranges again in the next three years (2013–2015) but it was back to the target in 2016. To find out whether the targets are still considered as reliable forecasting tools for market agents to follow, their accuracies are then contrasted to forecast performances of some econometric models based on backward-looking approach. This article finds that the forecast using past information yields smaller forecast errors than the forecast relying on the target, meaning that forecast based on backward-looking approach is relatively more reliable than the one based on forward-looking approach.

This finding implicitly suggests that the outcome of monetary policy is still below an optimal condition, and generates less accurate inflation reference for market agents. It also may give a hint that the policy implementation has some potential problems which can harm BI's credibility. Forecasting based on forward-looking approach is inherently very difficult, especially for long-term period, because it is almost impossible for CB to have perfect control over future inflation due to long and variable lags of the implementation (Mishkin 2001). However, the possibility of BI not adopting the full-fledged IT regime needs to be really considered. It is because the under-performance of the forward-looking approach can be more likely due to institutional reasons. The policy implication of the finding hence should be addressed very scrupulously.

This article gives a contribution to monetary economics literatures regarding the IT performance evaluation in terms of inflation target accuracy, especially in the case of developing country or emerging market since most of other existing articles use industrial country as their study cases. This study can be said to be more thorough than many other related studies in comparing the accuracy between forecast methods because it applies monthly periodical datasets for estimation and the Diebold-Mariano test rather than just mean square prediction errors comparison.

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DOI: 10.47291/efi.v62i2.539

Table 1: Indonesia's Actual Inflation Rate and the Target

Year	Inflation Target	Actual Inflation Rate	On Target Range?
2005	6 ± 1%	10.45%	No
2006	8 ± 1%	13.11%	No
2007	6 ± 1%	6.41%	Yes
2008	5 ± 1%	10.23%	No
2009	4.5 ± 1%	4.39%	Yes
2010	5 ± 1%	5.13%	Yes
2011	5 ± 1%	5.36%	Yes
2012	4.5 ± 1%	4.28%	Yes
2013	4.5 ± 1%	6.41%	No
2014	4.5 ± 1%	6.39%	No
2015	4 ± 1%	6.36%	No
2016	4 ± 1%	3.53%	Yes
2017	4 ± 1%	-	-
2018	3.5 ± 1%	-	-

Note:
- Actual annual inflation rate is based on Consumer Price Index (CPI) change.
- Targets for 2005, 2006, and 2007 are set under the Decree of the Minister of Finance No. 399/KMK.011/2004 ratified on September 6th, 2004.
- Due to oil shock, targets for 2006 and 2007 (5.5% ± 1% and 5% ± 1%) are revised on March 17th, 2006.
- Targets for 2008, 2009, and 2010 are set under the Decree of the Minister of Finance No. 1/KMK.011/2008 ratified on January 3rd, 2008, but for 2010, the target (4% ± 1%) is revised under the Decree of the Minister of Finance No. 143/PMK.011/2010.
- Targets for 2010, 2011, and 2012 are set under the Decree of the Minister of Finance No. 143/PMK.011/2010 ratified on August 24th, 2010.
- Targets for 2013, 2014, and 2015 are set under the Decree of the Minister of Finance No. 66/PMK.011/2012 ratified on April 30th, 2012.
- The target for 2016, 2017, and 2018 are set under the Decree of the Minister of Finance No. 93/PMK.011/2014 ratified on May 21st, 2014.

Source: Bank Indonesia

The rest of the article is outlined as follows. Section 2 generally explains the economic theory of IT, arguments between forward and backward-looking, and reviews some empirical studies. Section 3 expounds econometric models and methodology to ensure robustness of forecasting procedure, and describes the dataset. Section 4 explicates the statistical result and discusses some main findings. Section 5 concludes.

2. Literature Review

2.1. Inflation Targeting

There are at least four prerequisites for CB in adopting IT, which are adoption of floating exchange rate, capability to have assured degree of independence in performing monetary policy so it is free from any fiscal dominance, very well-developed banking and financial systems and solid commitment to achieve single monetary objective which is to steer inflation rate towards the target by exerting effective monetary transmission mechanism through interest rate (Jahan 2012). IT implementation also has some fundamentals including proclaiming an explicit mandate to pursue price stability as main objective of monetary policy by setting quantitative inflation target for certain period of time, declaring the target clearly and unambiguously to the public in order to anchor the inflation expectation, stressing on accountability and transparency in achieving the objective and employing credible inflation forecast through forward-looking approach in setting the target (Mishkin 2004; Heenan, Peter, & Roger 2006).

Batini & Haldane (1999) explained how IT framework in practice is applied. It simply uses feedback from expected inflation policy rule in order to make the gap between expected inflation and the target narrower. This specification takes a generic form as Equation (1) demonstrates.

$$\mathrm{r_t} = \gamma \mathrm{r_{t-1}} + (1-\gamma)\mathrm{r_t^*} + \theta(\mathrm{E_t}\pi_{\mathrm{t+j}} - \pi^*) \tag{1}$$

where $\mathrm{r_t}$ denotes real interest rate, $\mathrm{r_t} = \mathrm{i_t} - \mathrm{E_t}\pi_{\mathrm{t+1}}$; $\mathrm{i_t}$ is nominal interest rate controlled by CB; $\mathrm{r_t^*}$ denotes equilibrium real interest rate; $\mathrm{E_t}(.)$ is expectation function which is conditioning on the most up-to-date information set available at time t; π_{t} explains inflation rate which is the difference of log of CPI at time t and $\mathrm{t}-1$; and π^* is inflation target. Here, expected inflation rate is invoked as the feedback variable, and the deviation from the inflation target provokes an action from CB. There are three policy choice variables for CB to use, which are γ, θ and j. The parameter γ represents the degree of interest rate smoothing (CB's gradual responses to an economic shock by moving the interest rate step-by-step in the same direction over specific period of time), and θ represents the size of policy feedback coefficient. When $\gamma = 0$, it means there is no instrument smoothing, and the higher the value of parameter θ is, the more aggressive the response to the given deviation of the inflation forecast from the target will be. The parameter j is targeting horizon for CB in performing forecast. Together, three parameters determine the speed of inflation to be dragged back to the target, subsequent to an inflationary shock.

They also explicated that forecast based on forward-looking approach embodies some rules in determining the target. The rules are:

1. Lag encompassing, meaning that CB very well knows and fully awares of the lags between policy execution and its first impact on inflation. The lags must be conformed with the choice of parameter j of inflation-forecast-based rule. It thus captures transmission lags on expected inflation formation.
2. Information encompassing, meaning that inflation expectation is a good variable for inflation forecast since it is carrying all information available today regarding the path of inflation tomorrow. This rule is absent in the backward-looking approach, which relies on the past-information.
3. Output encompassing, meaning that albeit hitting the inflation target is the focal objective of the policy, it is not the only outcome which is taken into account by the rule. In principle, the target horizon parameter and the feedback parameter may indirectly influence output stabilization. During the aggregate demand shock in the economy, there will be no trade-off between inflation and output stabilization in IT execution since inflation and output shall shift in the same direction.

IT is usually chosen as the new monetary policy regime because of its short-run stabilization property for a shock coming from the aggregate-demand

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DOI: 10.47291/efi.v62i2.539

side. Furthermore, Cobham (2002) explains theoretically that IT is a monetary regime which gives the best outcome in terms of interpretability amongst all since it gives the highest visible information regarding inflation rate goal to the public, yielding the best influence not only on anchoring public expectation but also in overcoming time-inconsistency problem in monetary policy (Kydland & Prescott 1977; Barro & Gordon 1983). Time-inconsistency problem results from a discretionary policy of CB in pursuing low inflation. CB prefers both low unemployment and inflation rates, and its announcement to keep inflation low as a monetary goal may result in a zero inflation expectation. Discretion however gives an incentive to CB to relax monetary policy in order to reduce unemployment, which turns out triggers inflation. Market agents realize this so that inflation expectation will never be zero, causing high inflation in the long-run. Rule-based monetary policy, IT, therefore is more effective in persuading market agents that CB is serious about achieving low inflation. IT also has good verifiability because the data on price-level are highly accessible for public and less likely to be revised. Moreover, Cukierman (1996, 2006) explains that on average IT countries with highly independent CB backed-up and applied by law more seriously, and with lower turnover of CB Governors are empirically proved to have lower inflation rates. He further opines that this condition is mostly found in industrial countries and very few in emerging markets and former socialist economies.

IT adoption unfortunately comes with shortcomings that may cause policy objective sometimes departing from the target quite often. It is very deficient in regard to control, which is lack of precise and induces some lags during the operation. It needs around 18–24 months to make an impact on inflation (Cobham 2002). Roger & Stone (2005) reported that in the period 1991–2001 most IT countries missed the target substantially with tendency to happen less in countries aiming stable inflation rate (30% of the time) than countries in the stage of disinflation (60% of the time), less in industrial countries than emerging economies.

2.2. Inflation Targeting Framework in Indonesia

There are four key features in Indonesia's IT framework, namely the main instruments, operational target, intermediate target, and policy objective. The main instruments are fully-controlled monetary operations for BI to deliver the operational target. According to Article 10 of the Bank Indonesia Acts, BI has an authorization to conduct four monetary operations in the attempt of controlling inflation. They are open market operations (OMOs), discount rates (standing facilities), minimum reserve requirement and management of credit and financing.

OMOs refer to actions of buying (selling) Bank Indonesia Certificates (SBI) or Government Securities (SBN) by BI in order to manipulate short-term inter-bank money market rates resulting in injection (absorption) of liquidity into (from) the money market. Standing facilities are monetary operations used by BI to manage volatility of overnight inter-bank rates. There are two kinds of standing facilities, which are lending facilities (fund provision to banks experiencing liquidity problems) that expand money supply, and deposit facilities (fund placement to BI by banks with excess of liquidity) that shrink the money supply. Reserve requirement, also known as cash reserve ratio, is a stipulation regulating minimum portion of public notes and deposits which banks cannot use for lend-out activities. The banks therefore must hold the portion as reserves. Decrease (increase) in reserve requirement leads to increase (decrease) in the money supply. Management of credit and financing is an act to influence money market rate for credit and financing activities.

These instruments in effect shall shift the money supply in the money market which affects the next key feature, the operational target. The BI rate (now BI 7-Day Repo rate) is chosen as the operational target since BI has a full-power in controlling the rate in order to conduct monetary operations in daily basis. So, the rate acts as the monetary policy transmission. The rate moreover has a position to influence the third key feature, the Intermediate target. It indicates a macroeconomic variable that may directly affect the policy objective. BI's intermediate target is an inflation forecast based on forward-looking approach. It links the operational target to the objective of the monetary policy framework, which is low and stable inflation target.

The targets are announced to the public through the Decree of the Minister of Finance. So far, there are six decrees (see note in Table 1) that have been published of which two were the revisions in 2006 and 2010 due to the oil shock and the Global

Economic Crisis 2008/2009 respectively. In the end of each year, inflation movement is evaluated and projected to check whether the target is still reliable. If it is not, an intervention applying main instruments is taken to push back the movement towards the desired path. Furthermore, BI publishes regularly explanations regarding the inflation conditions to maintain public trust on BI and the target.

2.3. Forward vs. Backward-Looking

According to some economists, forward-looking approach seems to be imperative in forecasting inflation rate. As what Keynes (1923) opines, "if we wait until a price-movement is actually afoot before applying remedial measures, we may be too late." Giannoni & Woodford (2003) supports this notion of the importance of forward-looking component. Using the Taylor rule, they found that forecasting method relies more on expected inflation rate for most of the cases. Similar result is also obtained in the study using the post-war U.S. data conducted by Gali, Gertler, & López-Salido (2005), which applied a hybrid variant of the New Keynesian Phillips Curve (NKPC) model. The study suggested that forward-looking component dominates backward-looking component since although the coefficient of lagged inflation variables is statistically significant, the coefficient of expected inflation variable is considerably higher. Applying the same model for the case of Austria and Spain, the study by Dorich (2009) nonetheless concluded that the forward-looking component prevails, but does not exclusively describe the dynamic of inflation for these countries. Past behavior of inflation also appears to play an important role in shaping public expectation on the inflation rate because it exhibits persistence of inflation rate for a certain time period. It hence makes backward-looking component is more to be a complement to the forward-looking component.

In contrast to that, Fuhrer & Moore (1995) argue the concept of inflation forecast favoring forward-looking approach. They conclude that there was high persistence of the inflation rate in the post-war U.S. yearly data which made backward-looking approach was more apt for forecasting. They further revealed the persistence of inflation in both level and changes of prices and wages. The outcome shows that the auto-correlation function dies off after the fourth lag and there is a strong correlation between inflation and lagged output from past two up to past four years. Rudd & Whelan (2005) also deduce parallel finding saying that backward-looking approach utilizing past experiences is more powerful to derive inflation behavior in the post-war U.S. data. Basically they tried to compare the reduced-form Phillips Curve (PC) model which has a backward-looking component (Equation (2)) and the NKPC model incorporating with forward-looking characteristic (Equation (3)).

$$\pi_t = \alpha(L)\pi_{t-1} + \gamma(L)x_t + u_t \tag{2}$$

$$\pi_t = \beta E_t \pi_{t+1} + \gamma x_t \tag{3}$$

where π_t is inflation rate at present time; π_{t-1} denotes inflation rate at one-period behind; L represents lags; x_t covers other variables influencing inflation (output gap and unemployment rate); u_t is disturbance term; and $E_t\pi_{t+1}$ shows expected inflation rate at one-period ahead conditioning on information available from present time. They found that lagged variables have a more pivotal role in determining the current inflation rate. Moreover, they concluded that the NKPC model fails to account for the relationship showing in the reduced-form PC model and it also fails because the current output gap is not a driving variable for inflation rate. The correlation between inflation rate and future labor wage is also noticeably weak.

A descriptive analysis by Woodford (2000) explains why predicting inflation rate should be more history-dependent although many economic textbooks state that CB's pre-commitment by setting and announcing an inflation target shall minimize a loss function (see Bean 1998). Theoretically, the target is able to persuade market agents to trust commitment of CB in hindering high inflation rate, which in the end shall tackle the Kydland-Prescott inflation bias resulting from a discretionary policy. According to him, achieving the target indeed depends on the arrangement of forward-looking approach in steering public expectation towards the desirable inflation path. It however only occurs when market agents have a rational expectation and this rationality is driven by past monetary policies in managing inflation. Thereby, the subsequent policy is something that they should expect. This brings up the conclusion of the essence of backward-looking approach in forecasting inflation.

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DOI: 10.47291/efi.v62i2.539

2.4. Empirical Studies on Forecasting Inflation Rate

A few empirical studies on IT countries so far have attempted to contrast backward-looking forecast relying on historical behaviors and forward-looking forecast following CB's official inflation target assuming rational public expectations on price-level move at a similar rate of the prearranged target. The realization of inflation expectation is believed capable to make the inflation rate hit or at least close to the target as the self-fulfilling prophecy theory explains. Albeit this assumption seems reasonable and is largely used by many economists, the empirical application is still questionable, especially when there is a persistent change in inflation rate. This notion leads to the opposite idea which states that the best way to approximate rational expectations is not to see present observable economic variables as the benchmark in conditioning expectation, but rather to project inflation rate based on its own past and/or other past observable economic factors.

Diron & Mojon (2008) conduct comparison study on forecast performance in several IT countries, namely the Euro Area, Australia, Canada, New Zealand, Norway, Sweden, Switzerland, and the UK by applying two general methods which are taking by granted the CB's target forecast and applying six alternative models, namely random-walk, past-mean inflation rate, three specifications of auto-regressive model and mean inflation forecast published in the professional economists' forecast of Consensus Economics Inc. They conclude that forecasting inflation rate for one and two-year horizons in all countries by following the explicit target yields the smallest forecasting errors (the mean absolute prediction errors (MAPE) and root mean square prediction errors (RMSPE)). It thus is more superior compared to the six alternatives, assuring forward-looking approach is unbeatable. The study by Falch & Nymoen (2011) for Norway which has employed IT since 2001 also states that the inflation target announced by the Norges Bank outperforms other three forecasts based on econometric models, which are random-walk, random-walk with drift, and autoregressive model, by yielding the smallest mean square prediction errors (MSPE) for 12-quarter forecast horizons. For the case of the U.S., the Fed has set the long-run constant inflation target of 2% since 2012. The most recent study on the U.S.'s inflation by Bauer & McCarthy (2015) demonstrates that market-based inflation rate forecast using the past performances of treasury inflation-protected security, break-even inflation rate and inflation swap rate data in predicting future inflation rate is the least accurate, meaning that its prediction tend to off realized inflation rate more often compared to method following constant target.

As opposed to those findings, Altug & Çakmaklı (2015) reveal that a forward-looking approach is not always more accurate in all cases. They perform a test for assessing the precision of predicted inflation rate from State-Space model using inflation target as expected inflation variable and some alternative econometrics models, namely State-Space model without inflation rate expectation using Kalman Filter, simple moving-average, auto-regressive, backward-looking PC, and hybrid NKPC models in two emerging market countries, Brazil and Turkey, which have adopted IT framework since 1999 and 2006 respectively. It was done by comparing the forecast performance of the models through RMSPE. Whilst for Turkey the model using inflation target produces the lowest forecast errors, thereby dominates other specifications at all 12-month forecast horizons, in the case of Brazil the naive model of simple average one-year moving-average (MA) process gives the lowest RMSPE of all models. It is very hard to beat at 2 up to 12 months ahead forecasts. This finding suggests that there is still no universal and absolute rule affirming that forward-looking approach is the best available forecasting method for the IT countries in predicting inflation rate.

3. Forecasting Methodology & Data

This article measures the accuracy of BI's explicit inflation target based on forward-looking approach by comparing its forecast performance to some naive forecasts and other forecast alternatives relying on backward-looking approach. Three kinds of backward-looking approach are assessed for this article, which are the naive forecasts by simply looking the average of past experiences for certain period, univariate model estimated by regressing inflation rate on its own past performances and multivariate model applying linear inter-dependencies among multi-variable time-series to capture more information regarding factors influencing inflation rate movements.

The monthly periodical data-sets are utilized to provide the most up-to-date information regarding price-level. It also compromises the concern of delayed information embodied in quarterly or annual inflation rate data-sets (Arlt & Arltová 2015). For forecast power assessment, this article uses static or one-step (ex-post) ahead forecasts with 36-month periods as forecast horizons. The approach that yields the smallest forecast errors is selected as the most accurate one.

3.1. Explanations on Forecast Methods

Forward-looking approach is simply a target model (Equation (4)).

$$\pi^{\mathrm{F}}_{\mathrm{t+s}} = \pi^* \tag{4}$$

where π^{F} is inflation rate forecast; π^* is the inflation target; t is the last time-period in the sample data used in estimation; and s is the forecast horizon.

There are three naive forecasts estimated, namely random-walk, simple one-year MA (suggested in Altug & Çakmaklı 2015) and forecast based on the average value of the inflation rate over the past five years (suggested in Diron & Mojon 2008). The three forecasts follow Equation (5), (6), and (7) correspondingly.

$$\pi^{\mathrm{F}}_{\mathrm{t+s}} = \pi_{\mathrm{t}} \tag{5}$$

$$\pi^{\mathrm{F}}_{\mathrm{t+s}} = \frac{1}{12}\sum_{\mathrm{i=1}}^{12} \pi_{\mathrm{t+s-i}} \tag{6}$$

$$\pi^{\mathrm{F}}_{\mathrm{t+s}} = \frac{1}{60}\sum_{\mathrm{i=1}}^{60} \pi_{\mathrm{t+s-i}} \tag{7}$$

where i represents the lag.

The univariate model follows Autoregressive Moving-Average (ARMA($\mathrm{p,q}$)) process (Equation (8)) consisting of auto-regressive and moving-average components with order p and q respectively, written as AR(p) and MA(q). In this model, inflation rate variable is regressed on its lagged values, so it is treated as an endogenous variable. The stationary series is said to follow this process if its auto-correlation coefficient (ACF) shows either geometric or oscillating decline after lag q, thereby its behavior in lag 1 up to q cannot be precisely specified except that ACF remains significant and its partial auto-correlation coefficient (PACF) displays a notable tendency to decline systematically (either direct or oscillatory) as well after lag p. So, ARMA($\mathrm{p,q}$) process has the main feature of both ACF and PACF showing a marked inclination to dampen out after lag q and p correspondingly.

$$\pi_{\mathrm{t}} = \mathrm{m} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \alpha_{\mathrm{j}}\pi_{\mathrm{t-j}} + \sum_{\mathrm{j=0}}^{\mathrm{q}} \theta_{\mathrm{j}}\varepsilon_{\mathrm{t-j}} \text{ ; with } \theta_0 = 1 \text{ and } \varepsilon_{\mathrm{t}} \sim \mathrm{WN}(0,\sigma^2_{\varepsilon}) \tag{8}$$

where m is drift; α is coefficient of lagged variable measuring correlation between current inflation rate and its past values; j represents the lag; and ε is white noise with θ as the respective weights. If the series is not stationary, π_{t} needs to be integrated until it becomes stationary. The series hence is required to be differenced d times in order to make it stationary (adding I(d) process). With ARMA($\mathrm{p,q}$) fitting the series, the process becomes ARIMA($\mathrm{p,d,q}$).

Unlike univariate model, multivariate model applying Vector Autoregressive (VAR) model can capture the dynamics of macroeconomic variables and simply treat all variables symmetrically as jointly endogenous. Each macroeconomic variable is regressed on its own lags and also lags of other variables, exhibiting simultaneity among them. Since it introduces more variables, the model often forecasts relatively better than univariate model because it involves more information in estimating the coefficients of the variables. Equation (9) presents VAR model with order p.

$$\mathbf{y_t} = \mathbf{m} + \sum_{\mathrm{j=1}}^{\mathrm{p}} \mathbf{A_j}\mathbf{y_{t-j}} + \boldsymbol{\varepsilon}_\mathbf{t} \text{ ; with } \mathrm{K} \text{ equations} \tag{9}$$

where K is number of variables used (also number of equations in the model); $\mathbf{y_t}$ is $\mathrm{K} \times 1$ vector of variables; $\mathbf{m}$ is vector of $\mathrm{K} \times 1$ parameters; $\mathbf{A_j}$ represents $\mathrm{K} \times \mathrm{K}$ matrices of coefficients; and $\boldsymbol{\varepsilon}_\mathbf{t}$ is $\mathrm{K} \times 1$ vector of error terms that are assumed to be white noise and independent, but allowed to be correlated with each other.

Forecasting inflation rates in Equation (8) and (9) simply utilize Equation (10).

$$\pi^{\mathrm{F}}_{\mathrm{t+s}} = \hat{\pi}^{\mathrm{F}}_{\mathrm{t+s}} \tag{10}$$

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DOI: 10.47291/efi.v62i2.539

where $\hat{\pi}$ represents the predicted inflation rate based on the estimated coefficients.

3.2. Determining Univariate Model

Referring to the Box-Jenkins approach, the three steps in modeling robust univariate model are inspecting sample data, determining non-stationarity properties of time-series data-set and analyzing correlograms in determining order for AR and MA components (Enders 2014). The first step is about inspecting line-graph whether the series is (weakly) stationary implying that population parameters are not changing overtime and have no trend (time-independent), or non-stationary in which there is no tendency for the series to revert back to a constant mean. The next step is to detect whether the series has unit roots implying non-stationarity using the Augmented Dicky-Fuller (ADF) test under the null-hypothesis of unit roots being present. The last step is about inspecting ACF and PACF correlograms to decide lag at which estimated ACF and PCF start to die off gradually, or drop significantly to zero. Thus, order p and q can be identified appropriately. Further, the Box-Pierce-Ljung test under the null-hypothesis of π_{t} being serially uncorrelated up to lag H and the Cumby-Huizinga test for auto-correlation with null-hypothesis of π_{t} being serially uncorrelated at specified lag (see Cumby & Huizinga 1992) are performed to check whether the series is following a white noise process.

Two statistical criteria for goodness-of-fit, namely Akaike Information Criterion (AIC) and Schwarz-Bayesian Information Criterion (SBIC), are applied to compare quality of some univariate models. These two criteria solve the problem of over-fitting of increasing likelihood resulting from adding more regressors. The criteria give more penalty as the number of parameters in the model increases. The penalty is larger in SBIC than in AIC. The model has goodness-of-fit if it minimizes information criteria. In addition to that, two diagnostic tests are adopted to check the serial correlation in the residuals and the stability condition correspondingly.

3.3. Determining Multivariate Model

To get an appropriate multivariate model, the lag-length (order p) must be correctly specified since too few lags may lead to model misspecification, such as serial correlation and omitted variable bias problem, and too many lags reduces degrees of freedom causing loss of model efficiency. Unfortunately, there is no economic theory that can confidently determine optimal lag-length for the multivariate model. Some statistic tests are then conducted (referring to Lütkepohl 2005; Ivanov & Kilian 2005). Selection of optimal number of lag is done by estimating VAR model with various p orders and then choosing one specific order p that minimises AIC, SBIC, and Hannan-Quinn Information Criterion (HQIC).

Prior to that, however, it is crucial to make sure vector $\mathbf{y_t}$ is covariance-stationary. If it suffers from unit root behaviour at level, but is covariance-stationary at first-difference, VAR model is hence remodeled to Vector Error-Correction (VEC) model (Equation (11)) with the number of lags which is one less than in the VAR model. Disregarding this is sub-optimal and misspecified since it only can explain the short-run relationship and ignores cointegration among variables. Cointegration means that variables move together towards a long-run equilibrium relationship, thus they are stationary in the long-run. In order to test whether there is one or more cointegrating equations, the Johansen cointegration test is performed (Johansen 1991).

$$\mathbf{\Delta y_t} = \mathbf{m} + \mathbf{\Pi y_{t-1}} + \sum_{\mathrm{i}=1}^{\mathrm{p}-1} \mathbf{\Gamma_i \Delta y_{t-j}} + \boldsymbol{\varepsilon}_\mathbf{t} \ ; \qquad (11)$$

with K equations

where $\mathbf{\Pi} = \sum_{\mathrm{j}=1}^{\mathrm{j=p}} \mathbf{A_j} - \mathbf{I_k}$ with rank $0 \leqslant \mathrm{r} < \mathrm{K}$; r is number of linearly independent cointegrating vectors; $\mathbf{\Gamma_i} = -\sum_{\mathbf{j=i+1}}^{\mathrm{j=p}} \mathbf{A_j}$; and $\boldsymbol{\varepsilon}_\mathbf{t}$ is a $\mathrm{K} \times 1$ disturbance vector which has zero mean and i.i.d normal. If $\mathbf{\Pi}$ has rank $0 < \mathrm{r} < \mathrm{K}$, $\mathbf{\Pi} = \boldsymbol{\alpha\beta}'$ where $\boldsymbol{\alpha}$ is the adjustment coefficient matrix; $\boldsymbol{\beta}$ is the matrix of parameters in the cointegrating equations; and both are $\mathrm{r} \times \mathrm{K}$ matrices of rank r.

Next, some post-estimation tests are applied to check robustness of the model. First, the Lagrange-multiplier (LM) test is carried out for testing residual auto-correlation under the null-hypothesis of no auto-correlation at lag order. This test helps in selecting lag-length that eliminates the serial correlation. Second, some tests to check stability condition of the specification, normality of disturbances and serial correlation of the disturbances of multivariate model are executed. Lastly, the Granger-causality test is carried-out to see Granger-causality between variables at each equation, which could be unidirectional, bilateral or independent. If the Granger-causality exists, one specified variable is a useful predictor of the other variable. It also can be used to check the exogeneity of one variable with respect to others. The test is applied with the Wald test under the null-hypothesis of corresponding coefficients on specified lags of one variable for each equation separately being jointly not different from zero.

3.4. Data for Naive Forecast and Univariate Model

Both naive forecasts and univariate model estimation utilize secondary time-series datasets of *year-on-year* (y-o-y) monthly CPI growth rates for the period January 1969–December 2013 as a proxy for inflation rate variable (see Table 2 for the description). The y-o-y dataset is chosen rather than *month-to-month* (m-t-m) dataset because it compares the current month inflation rate to the inflation rate from the same month in previous year. Therefore, it may shun the seasonality issue or repeated identical pattern in some specific intervals.

3.5. Data for Multivariate Model

There are three main determinants of inflation rate in Indonesia according to Ramakrishnan & Vamvakidis (2002). They are monetary inflation, wage inflation and imported inflation. The first determinant indicates that inflation increases because domestic nominal base-money rapidly grows more than the real sector can capacitate, leading to over supply of circulated money in the market. The second determinant occurs when there is excess demand in the labor market from the real sector. Hence, it boosts unit cost of production resulting in higher price-level of consumer goods and services. Higher wage level also means higher purchasing power leading to higher demand for goods and services. Unlike the other two, the last determinant is about international transmission effect on domestic inflation rate. It impacts inflation rate both directly and indirectly. The direct effect happens when the domestic currency depreciates against foreign currency, so it now becomes more expensive for the domestic country to import the same basket of consumer goods as before. Similar to that, indirect effect takes place when goods imported are raw materials which are applied as inputs to the process of further production. They find that of all three determinants, imported inflation is the main significant variable in predicting inflation whereas monetary inflation has a limited but significant impact on inflation.

Siregar & Rajaguru (2005) also find that volatility of the exchange rate due to the adoption of a more flexible exchange rate regime and rapid base-money growth rate during the post-AFC are the two key inflation determinants in Indonesia. Wimanda, Turner, & Hall (2011) conclude similar finding saying that inflation in Indonesia is influenced significantly by its past performance, inflation expectation, output gap, exchange rate and money growth. Past performance of inflation however seems to more significantly determine inflation than inflation expectation.

Multivariate model not only employs y-o-y monthly CPI growth rates, but also introduces some additional macroeconomic variables to explain a genuine simultaneity between variables. The model, following three studies briefly explained before, adds four macroeconomic variables in attempt to estimate the behavior of inflation. In general, the first-two other variables explain monetary inflation, the third one is a proxy for wage inflation and the last one represents imported inflation (see Table 2 for the descriptions). Overnight interest rate is added as another proxy for monetary inflation because it is more market driven, which may explain better money in circulation, and industrial/manufacturing production growth rate is chosen as a proxy for wage inflation because, in theory, as industrial/manufacturing sector grows, the labor demand of this sector will increase causing the wage level to rise in the long-run. Moreover, higher wage level in industrial/manufacturing sector usually tends to spillover to service sector resulting in higher overall wage level (the neoclassical labor market theory). All variables used in multivariate model estimation are for the period January 1996–December 2013.

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DOI: 10.47291/efi.v62i2.539

Table 2: Descriptive Statistics

Variable	Definition and Source	N	Mean	Std. Dev	Min	Max
CPI growth rate (inf)	Weighted average y-o-y monthly changes (%) in price of goods and services over time paid by consumers in purchasing a basket of those goods and services (Jan 1969–Dec 2016). *Source: BI*	576	11.54	11.19	-5.15	82.42
Monetary base growth rate ($\mathrm{basem\_grwth}$)	Y-o-y monthly changes (%) on number of currency in circulation, transferable deposits and other deposits (Jan 1996–Nov 2016). *Source: IFS*	251	20.63	17.36	-10.83	116.03
Monthly changes on average overnight interest rate ($\mathrm{ovintrt}$)	Y-o-y monthly changes on average money market rate (%) of one-day loans between commercial banks (Jan 1991–Dec 2016). *Source: IFS*	312	-0.03	13.34	-68.56	59.45
Industrial/manufacturing production growth rate ($\mathrm{indprod\_grwth}$)	Y-o-y monthly changes (%) in industrial productions (Jan 1994–Oct 2016). *Source: ARIC*	274	4.74	8.39	-23.09	38.58
Exchange rate growth rate ($\mathrm{exchrt\_grwth}$)	Market y-o-y monthly changes (%) of national currency (IDR) per U.S. Dollar (USD), period average (Jan 1991–Nov 2016). *Source: IFS*	311	14.05	57.37	-51.24	454.44

Note: BI – Bank Indonesia; IFS – the International Monetray Fund (IMF)'s International Financial Statistics; and ARIC – the Asian Development Bank (ADB)'s Asia Regional Integration Center

3.6. Seasonality, Structural Break and Economic Crisis Dummy Variable

The seasonal dummy model is estimated to convince the series is free from seasonality issue. Inflation rate variable here is regressed on intercept and eleven seasonal dummies. Each dummy equals to one for its specific month, for instance $\mathrm{D_{Jan}} = 1$ if the observation is January every year and $\mathrm{D_{Jan}} = 0$ otherwise. Only eleven seasonal dummies are created to avoid a perfect-multicollinearity (dummy variable trap). A significant dummy coefficient means that seasonality takes place every that particular month. Hence, the series firstly should be transformed by differencing procedure to eliminate this cyclical pattern.

Another notable feature of time-series is to detect a structural break which may produce severe forecasting errors. It happens when there is a shift in the series marked by a notable break in its pattern caused by a policy change (level-shift outliers). In order to test whether inflation rate series exhibits a break after IT implementation, the Chow test is performed under the null-hypothesis of no structural break by partitioning the full-sample at the break date: $\mathrm{t} = 1, 2, ..., \mathrm{b}-1$ and $\mathrm{t} = \mathrm{b}, \mathrm{b}+1, ..., \mathrm{T}$ in which b is July 2005.

Besides those two features, it is also necessary to include an exogenous dummy variable for AFC period (afc) into the model since it induces temporary abnormal inflation rate behavior (temporary-change outliers). It equals to one for period July 1997–June 1999 and zero otherwise.

3.7. Empirical Strategies for Forecast Evaluation

This study applies out-of-sample forecast by clustering full-sample data set for inflation rate with period $\mathrm{t} = 1, 2..., \mathrm{T}$, or $\{\pi_1, \pi_2, ..., \pi_\mathrm{T}\}$ into three partition, which are initial condition used for lagged variables $\{\pi_1, \pi_2, ..., \pi_{\mathrm{e}-1}\}$, estimation sample data $\{\pi_\mathrm{e}, \pi_{\mathrm{e}+1}, ..., \pi_\tau\}$ and post-sample data for forecast evaluation period $\{\pi_{\tau+1}, \pi_{\tau+2}, ..., \pi_\mathrm{T}\}$ stored to inspect forecast errors. The less forecast errors the model produces, the more accurate it is in forecasting. The model is firstly run on sample data, $\pi_\mathrm{t} = 1, 2, ..., \tau$, of which $\pi_\mathrm{t} = 1, 2, ..., \mathrm{e} - 1$ are the initial conditions and $\mathrm{t} = \mathrm{e}, \mathrm{e} + 1, ..., \tau$ are estimation sample, to generate parameter estimates used to predict inflation rate at time $\tau + \mathrm{s}$, which is $\hat{\pi}^\mathrm{F}_{\tau+\mathrm{s}}$. The model is then re-estimated on observation $\mathrm{t} = 1, 2, ..., \tau + 1$ to get the value of predicted inflation rate at time $\tau + 1 + \mathrm{s}$, which is $\hat{\pi}^\mathrm{F}_{\tau+1+\mathrm{s}}$. This re-estimation is carried-out repeatedly up to $\hat{\pi}^\mathrm{F}_\mathrm{T}$. So, t in the Equation (4) to (10) equals to $\tau + \mathrm{h}$.

The predicted values afterwards are compared to actual inflation rates from the post-sample data, $\mathrm{t} = \tau+1, \tau+2, ..., \mathrm{sT}$, which are previously kept in order to get forecast errors. The forecast errors are then calculated with the prediction error (PE) formula (Equation (12)).

$$\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}} = \pi_{\tau+\mathrm{h}+\mathrm{s}} - \hat{\pi}^{\mathrm{Fm}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}} \quad (12)$$

where m represents the model being used; τ is sample size used in the estimation; $\mathrm{h} = 0, 1, 2, ..., \mathrm{H}-\mathrm{s}$; and $\mathrm{s} = 1, 2, ..., \mathrm{T}-\tau$. In general, $\hat{\pi}^{\mathrm{Fm}}_{\tau+\mathrm{h}+\mathrm{s}}$ is read as forecast of $\pi_{\tau+\mathrm{h}+\mathrm{s}}$ at $\mathrm{t} = \tau+\mathrm{h}$ by the model m and H observations ($\mathrm{t} = \tau+1, \tau+2, ..., \tau+\mathrm{H}$, so $\mathrm{T} = \tau+\mathrm{H}$) at the end of estimation sample data after τ are kept for measuring forecast accuracy of the model. The model is next expected to have a small residual variance that is estimated by MSPE in Equation (13). Smaller MSPE is desired for forecasting.

$$\widehat{\mathrm{MSPE}}^{\mathrm{m}} = \frac{\sum_{\mathrm{h}=0}^{\mathrm{H}-\mathrm{s}} (\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}})^2}{\mathrm{H}-\mathrm{s}+1} \quad (13)$$

Since MSPE formula cannot show that it has a $\chi^2_{(\mathrm{H}-\mathrm{s}+1)}$ distribution, the Diebold-Mariano (DM) test is then performed to tackle this issue. The DM test measures the accuracy of the model's prediction by using loss function, $\mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}})$, where loss function can be either $\mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}}) = (\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}})^2$, $\mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}}) = (\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}})^4$, or $\mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}}) = |\widehat{\mathrm{PE}}^{\mathrm{m}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}}|$, and testing the loss function with Equation (14) under the null-hypothesis of loss differential equal to zero (forecast accuracy of two models is equal), $\mathrm{H}_0 : \mathrm{E}[\mathrm{d_h}] = \mathrm{E}[\mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m1}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}}) - \mathrm{L}(\widehat{\mathrm{PE}}^{\mathrm{m2}}_{\tau+\mathrm{h}+\mathrm{s}|\tau+\mathrm{h}})] = 0$ (see Diebold & Mariano, 1995).

$$\mathrm{DM} = \frac{\bar{\mathrm{d}}}{\left(\frac{\widehat{\mathrm{LRV}}(\bar{\mathrm{d}})}{(\mathrm{H}-\mathrm{s}+1)(1-\frac{\mathrm{s}}{\mathrm{H}})}\right)^{1/2}} \sim \mathrm{N}(0,1) \quad (14)$$

where $\bar{\mathrm{d}}$ is mean of $\mathrm{d_h}$ calculated by $\frac{\sum_{\mathrm{h}=0}^{\mathrm{H}-\mathrm{s}} \mathrm{d_h}}{\mathrm{H}-\mathrm{s}+1}$ and $\widehat{\mathrm{LRV}}(\bar{\mathrm{d}})$ is a consistent long-run asymptotic variance estimation for $(\sqrt{\mathrm{H}-\mathrm{s}+1})\bar{\mathrm{d}}$. The null can be rejected if $|\mathrm{DM}| > 1.96$ with 95% confidence, and the model with the smaller loss is said to be more powerful in forecasting the inflation rate.

This article applies post-sample data for period January 2014–October 2016 in performing static or one-step ahead forecast, encompassing 36-month forecast horizons, to analyze precision of all forecast methods.

4. Result and Analysis

4.1. ARMA(p,q) Model

Prior to determining ARMA(p,q) model, inflation rate variable is initially regressed on constant and eleven seasonal dummies to check seasonality in the series. Regression result shows that all seasonal dummy variable coefficients are insignificant, meaning that the null-hypothesis of the coefficient being zero (no effect) cannot be rejected. The series hence is free from seasonality problem.

Analysis on the Box-Jenkins methodology starts with inspecting the series by observing the plot of inflation rate in Figure 1, then checking whether it has a particular pattern. It seems that inflation rate (inf) has no significant trend with an inclination to keep reverting back to a constant mean. A closer examination actually suggests that inf has a very slight negative trend with positive mean. In spite of that, the series is graphically considered to be stationary. The next step is investigating a nonstationarity of a unit root process with statistical procedure (the ADF test for unit root). The result shows that the null-hypothesis of unit root is rejected. Test statistic for inf series in the absolute value (4.269) is greater than 1% critical values (3.43). The series thereby is already stationary, making the integer order d equal to zero and ensuring z-ratios of the lagged inflation rate variables later in the model can be appropriately examined since the regression is avoided from a spurious result.

The last step is to see ACF and PACF correlograms of the series in order to determine order p and q. From Figure 2, ACF of inf exponentially dies away and dampens out after the tenth lag. The first-ten lags of ACF are significant since they lie outside the bands. Its PACF also shows an oscillating decay with the first, second, forth, eleventh and thirteenth noticeably remaining outside the bands making it significantly different from zero.

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DOI: 10.47291/efi.v62i2.539

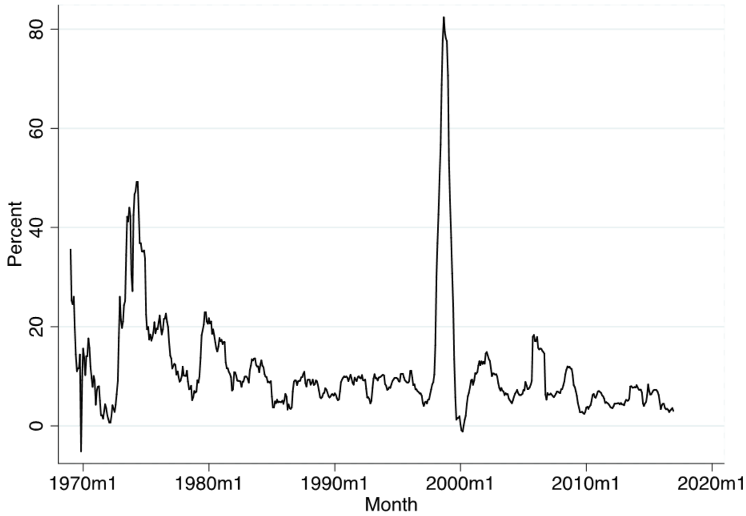


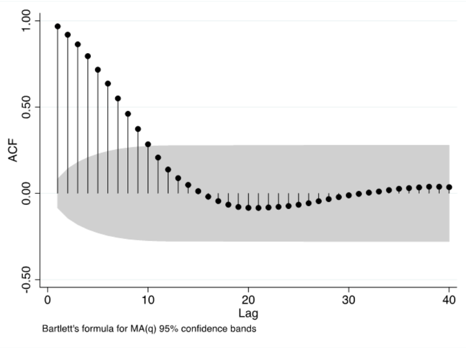
Figure 1: Indonesia's y-o-y Monthly Inflation Rate (January 1969–December 2016)
Source: Author's calculation based on data from Bank Indonesia

The residual analysis applying the Box-Pierce-Ljung statistic is further computed to check whether inflation rate follows a white noise process. Using 40 lags, the result shows that the null-hypothesis of no serial correlation up to the 40th lag is rejected since Q_H-statistic of each lag is larger than its respective critical value. Thus, the residuals are serially dependent up to lag 40. The Box-Pierce-Ljung statistic merely checks whether any serial correlation exists in the range of lags of the series, not at specific lag. The Cumby-Huizinga test under the null-hypothesis of no serial correlation at one specific lag is then carried-out. The result indicates that the test statistic for auto-correlation of inf series is significantly large at $q = 1$ until $q = 10$, so the null-hypothesis can be rejected. The test however fails to reject the null at $q > 10$. Therefore, the series seems to follow a mixed ARMA(p,q) process. It is decided to regress several ARMA(p,q) specifications with p =1, 2, 4, 11, or 13 and $q = 10$. To select the model going to be used for forecasting, AIC, and SBIC for goodness-of-fit comparisons are performed.

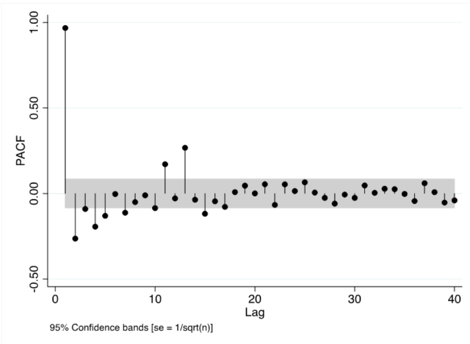
It is better not to interpret the estimated parameters of ARMA(p,q) model one by one since there is no convincing economic theory regarding the relationship between variable and its lagged values. The analysis will be more focused on scrutinizing how fit the model is to the data. The goodness-of-fit statistic recommends that the fourth specification (ARMA(11,10)) is the most fitted among others. It yields both the lowest AIC and SBIC, whilst ARMA(13,10) has the second lowest AIC and ARMA(4,10) has the second lowest SBIC.

The test for stability condition is then performed to check whether selected ARMA specification is stationary and invertible (sum of AR coefficients is less than one, which is a necessary condition for the process to be convergent). An invertible model must have all AR and MA roots outside the unit circle, or equivalently, inverse roots must lie inside the unit circle. Inverse roots of ARMA(11,10) and ARMA(13,10) polynomials are calculated to see if inverse AR and MA roots lie inside the unit circle (all inverse roots are less than one, meaning that AR and MA processes are convergent). The results show that some inverse roots of the MA-polynomial lie outside the unit circle (the values are bigger than one), indicating that the specifications are not stable, or in other words MA process tends to be explosive. This implicates that inflation is impossible to forecast with both specifications (Figure 3b and 3c). In contrast to that, all inverse AR and MA roots for ARMA(4,10) are less than one in magnitude, so they lie inside the unit circle, signifying that the stationarity and invertibility conditions are satisfied (Figure 3a). It is thereby recommended to use ARMA(4,10) for forecasting. Another thing is worth to notice. Inverse roots of ARMA(4,10) are less than but relatively close to one, meaning that inflation has a high level of persistence. This supports the finding of Wimanda, Turner, & Hall.

Economics and Finance in Indonesia, Vol. 62 [2016], No. 2, Art. 4

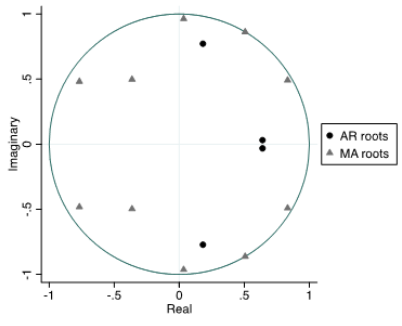


(a) Autocorrelation Function

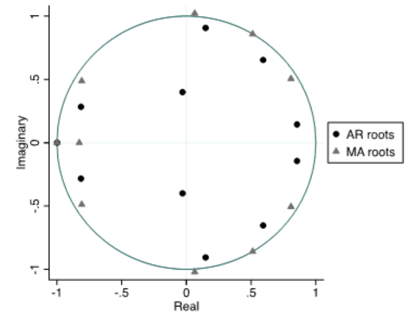


(b) Partial Autocorrelation Function

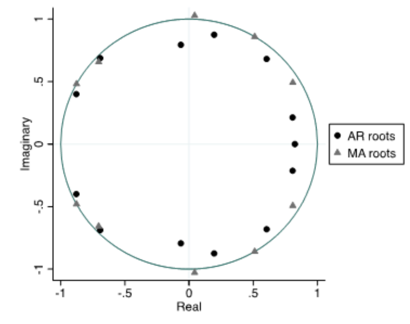
Figure 2: Correlogram of Inflation Rate



(a) ARMA(4,10)



(b) ARMA(11,10)



(c) ARMA(13,10)

Figure 3: Inverse Roots of ARMA Model

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DOI: 10.47291/efi.v62i2.539

Although ARMA(4,10) seems to adequately fit the series, it is necessary to review two diagnostic tests for its residuals. First test is to check whether the residuals have a normal distribution. It is obtained that the distribution of residuals does not fit perfectly the bell-shaped distribution. It has zero mean with fraction of outliers at both tails (kurtosis). The second one is to check the ACF and PACF correlograms of the residuals whether there is any serial correlation left from the estimation. The result shows that there are two significant serial correlations of residuals (at lag 10 and 11). So, the residuals are not completely independent. This is a striking finding because the serial correlation has not been entirely removed from the estimation in which the series is already in y-o-y form and proven by the seasonal dummy model to be free from seasonality. This suggests that there is a probability of undetected outliers remaining in the series. ARMA(4,10) specification has considered temporary-change outliers by adding the crisis dummy (afc), but has not examined level-shift outliers. The Chow test is then taken to inspect a structural break in the series due to IT implementation as a policy change. The result indicates that the null-hypothesis of no structural break cannot be rejected since F-statistic (0.92) is smaller than its critical values (2.07 at 1%, 1.68 at 5%, and 1.5 at 10%). This puts forward into consideration that there is maybe another structural breaks which is unknown, or there is an additive and/or innovational outlier in the series. The article fails to detect completely what kind of outlier resides in the series, but gives a meaningful detection regarding the issue. In spite of that, ARMA(4,10) may still be appropriate in representing inflation rate series.

4.2. VAR Model

VAR model analysis starts with investigating whether other macroeconomic variables are stationary at level or first-difference. The null-hypothesis of unit roots being exist is rejected for change on overnight interest rate $(\mathrm{ovintrt\_chng})$, industrial/manufacturing production growth rate $(\mathrm{indprod\_grwth})$ and exchange rate growth rate variable $(\mathrm{exchrt\_grwth})$ variables at 1% critical value. Test statistic for monetary-base growth rate variable (basem_grwth) in absolute value (2.34) is less than any critical value (3.48 at 1%, 2.88 at 5%, and 2.57 at 10%), but its first difference has large test statistic (4.99 in absolute value). This concludes that $\mathrm{basem\_grwth}$ is first-differenced stationary and the other three are already stationary at a level. Since not all variables are stationary at a level, the Johansen test is required to check cointegration amongst the series. Order p of the VAR model is firstly determined by looking which lag gives the lowest AIC, SBIC, and HQIC. It is decided to use either $\mathrm{p} = 1$ (lowest SBIC), $\mathrm{p} = 3$ (lowest HQIC), or $\mathrm{p} = 13$ (lowest AIC).

Three possible conditions can be obtained from the Johansen test. First, $\mathbf{\Pi}$ has a full-rank $(\mathrm{r} = \mathrm{K})$ meaning that every element of $\mathbf{y_t}$ is stationary at a level. Second, $\mathbf{\Pi}$ has a rank of $\mathrm{r} < \mathrm{K}$ suggesting that the model has $\mathrm{K} - \mathrm{r}$ non-stationary linear combinations and r stationary cointegration. Third, $\mathbf{\Pi}$ has zero rank $(\mathrm{r} = 0)$ implying $\mathbf{y_t}$ is stationary at first-difference, I(1). Only when the rank of Π is $0 < \mathrm{r} < \mathrm{K}$, VEC model is preferred. Based on the result, matrix $\mathbf{\Pi}$ for all order p tested has a full-rank condition confirming that all endogenous variables are I(0) stationary. The null-hypothesis of $\mathrm{r} = 0$ (no cointegration), $\mathrm{r} \leqslant 1$ (at least there is one-cointegration), $\mathrm{r} \leqslant 2$ (at least there are two-cointegrations), $\mathrm{r} \leqslant 3$ (at least there are three-cointegrations) and $\mathrm{r} \leqslant 4$ (at least there are four-cointegrations) is rejected (trace-statistic is bigger than 5% critical value). Using max-statistic, the same finding is deduced. The null-hypothesis of $\mathrm{r} = 0$, $\mathrm{r} = 1$, $\mathrm{r} = 2$, $\mathrm{r} = 3$, and $\mathrm{r} = 4$ is rejected (max-statistic exceeds the critical value). Therefore, VAR model is chosen.

Next, post-estimations are taken to decide which VAR specification is the most robust. To find which lag-order is more appropriate for forecasting, the LM test for serial correlation with the null-hypothesis of no auto-correlation in the residual at specified lag-order is employed. The fewer significant lags, which indicate auto-correlation, are preferred. The result suggests to choose order $\mathrm{p} = 13$ because the null-hypothesis only can be rejected at the first and sixth lags, while for $\mathrm{p} = 1$ the null is rejected at all lags and for $\mathrm{p} = 3$ the null cannot be rejected at the ninth lag only. This gives a hint of less model misspecification for the model with $\mathrm{p} = 13$.

The estimation output of VAR(13) specification is very difficult to interpret since it reports numerous coefficients. To accommodate that, the Wald test is utilized for checking the significance of lags across all equations. Output of the test shows that the null-hypothesis of coefficients at a specific lag jointly being zero cannot be rejected only at lag 4, 9, and 10 in inf equation (Table 3). This specification is hence fitted in explaining inf behavior. The null-hypothesis of coefficients at lag 13 jointly being zero furthermore can be rejected in all equations but $\mathrm{exchrt\_grwth}$ equation, and the null-hypothesis that the coefficients on the first to 13th lag of the endogenous variables are zero in all five equations jointly is strongly rejected, confirming that $\mathrm{p} = 13$ is the optimal lag length for the model.

Normality test for the residuals of inf equation and stability test of the specification are subsequently carried-out. The result displays that the residuals of the equation are almost normally distributed since there is a small fraction of outliers at the right tail. The standardized normal probability (P-P) plot shows slight and trivial deviations from normal in the middle range of data, whilst the quantiles of the residuals against the quantiles of a normal distribution (Q-Q) plot shows only one significant deviation from normal at the upper tail, indicating an outlier in the series. Based on these findings, the residuals can be accepted to be close to a normal distribution. The stability test exhibits that VAR(13) specification satisfies stability condition since all the inverse roots lie inside the unit circle, and the ACF and PACF correlograms for the residuals shows no serial correlation despite two small peaks at relatively far lags (lag 12 and 20).

Lastly, the Granger-causality test is applied to examine whether the coefficients of all lags for one specified endogenous variable jointly are statistically not different to zero and to detect whether there is any block exogeneity in the specification. Table 4 indicates that all four other macroeconomic variables Granger-cause inf, which is in line with the theory. Higher $\mathrm{basem\_grwth}$ is related to a higher inflation rate as there will be more money circulated in the economy and lower $\mathrm{ovintrt\_chng}$ is predicted to increase money supply in the banking system because it is now cheaper for banks to make loans between them. Additionally, higher $\mathrm{indprod\_grwth}$ is believed to make the overall wage to rise (spillover effect on other sectors) leading to higher demands of goods and services. Higher $\mathrm{exchrt\_grth}$ is associated with depreciation of local currency, increasing the imported inflation. So, the other four macroeconomic variables are proper predictors for inf.

Another interesting finding is that $\mathrm{basem\_grwth}$ Granger-causes inf, but not the other way around. There is only unidirectional Granger-causality from $\mathrm{basem\_grwth}$ to inf. It is very surprising finding since under IT regime, BI should react and try to adjust the money supply through the policy rate when inflation in the previous period is considerably high. Thus, inf should be a good predictor for $\mathrm{basem\_grwth}$. This perhaps signifies a weak and indirect feedback effect from inf to $\mathrm{basem\_grwth}$. The only good predictor for $\mathrm{basem\_grwth}$ is $\mathrm{indprod\_grwth}$, while $\mathrm{ovintrt\_chng}$ is only marginally significant. This can be explained by the economic theory. Higher industrial/manufacturing output growth means that there are more economic activities in the economy, associated with more money in circulation. Despite all that, every variable is proven to Granger-cause at least one other variable. Therefore, it is concluded that there is no block exogeneity in the specification (all variables are correctly treated as endogenous).

The two estimation models are appropriate for representing inflation rate series, but they are not fully free from unobservable outliers. Merely considering outliers resulted from seasonality and economic turmoil episode is not enough. IT adoption also cannot be proven statistically as level-shift outliers (structural break). Treating this issue however must be done with full of good reasoning. One cannot simply identify an observation as an outlier just because of its extreme value. There should be an economic reason behind that. Investigating the nature of outlier is very pivotal because it can arise from either human error in entering data, combining data from different sources, or an important factor or event missed from the model (Gujarati 2004). Dealing with outliers is more difficult to do for the multivariate time-series model since a multivariate outlier also depends on the size and dynamic structure in the specification (Tsay, Peña, & Pankratz 2000). Outlier is one of a big issue in performing regression because it can increase the variance of the residuals and decrease power of the test statistic. Fortunately, the outlier problem in this article is not severe. ARMA(4,10) and VAR(13) specifications thereby are still appropriate to use in forecasting inflation rate.

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Table 3: Wald Test for VAR(13)

Lag	Chi-squared (χ^2)					All
	inf	basem_grwth	ovintrt_chng	indprod_grwth	exchrt_grwth	
1	408.17***	56.27***	52.28***	8.78	250.19***	766.47***
2	9.33*	19.05***	41.37***	4.19	9.66*	98.52***
3	10.35*	7.80	13.52**	14.82**	26.44***	81.39***
4	8.34	12.30**	9.42*	6.92	37.94***	67.81***
5	16.18***	2.63	14.65**	9.91*	59.41***	98.95***
6	28.79***	13.56**	17.34***	2.35	54.14***	118.18***
7	12.56**	2.64	23.97***	4.74	19.11***	60.98***
8	23.84***	2.07	6.77	9.79*	9.72*	53.49***
9	5.82	2.37	3.69	1.45	26.91***	40.08**
10	5.79	0.80	21.40***	4.87	9.04	48.98***
11	26.85***	16.94***	20.06***	6.52	40.92***	115.71***
12	42.09***	19.12***	6.19	16.34***	17.49***	115.01***
13	54.97***	33.93***	12.56**	27.98***	8.64	163.32***

Note: z-statistic in parentheses and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Granger-causality Test for VAR(13)

Equation	χ^2					All
	inf	basem_grwth	ovintrt_chng	indprod_grwth	exchrt_grwth	
1st	-	41.348***	42.50***	28.29***	75.48***	520.46***
2nd	15.41	-	21.38*	37.03***	15.60	181.08***
3rd	25.02**	39.97***	-	33.44***	115.17***	541.56***
4th	31.05***	19.09	33.05***	-	24.98**	113.86***
5th	33.48***	17.30	201.65***	20.05*	-	330.01***

Note: First to fifth equations represent inflation rate, monetary base growth rate, overnight interest rate change, industrial/manufacturing production growth rate, and exchange rate growth rate equations respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3. Forecast Evaluation

One-step (ex-post) ahead forecasts are performed afterwards. The graphical comparison of predicted inflation rate generated from ARMA and VAR models and actual inflation rate in the post-sample (period January 2014–December 2016) shows that both models have relatively good performance in forecasting inflation (Figure 4). However, the dashed-lines of VAR model move more closely to the actual inflation line. VAR model therefore is graphically more accurate than ARMA model in forecasting inflation.

It is also better to analyze the forecast uncertainty by constructing the forecast intervals (FI) for the predicted values. According to Stock & Watson (2011), the errors in the predictions consist of two components, which are errors from coefficient estimates and from uncertainty of expected future inflation values. The latter tends to be more dominant in the univariate model since it contains less information compared to multivariate model. Unlike the distribution of regression residuals, the distribution of prediction errors of Equation (12) is unknown and could be not normal. They further suggest reporting FI of univariate model tighter than 95%. The study by Granger (1996) advises to use 50% FI. This however also implies that there is only 50% chance for a future inflation rate to be inside the intervals.

It is decided to use 50% FI for ARMA model and 95% FI for the VAR model. Figure 5 displays FI of predicted inflation rate from ARMA (above-graph) and VAR models (below-graph). It can be recognized that the intervals of predicted values in the VAR model are narrower than in the ARMA model even with higher FI. It means that the inflation rate predictions of the VAR model are relatively more certain. In contrast to that, ARMA model with 50% FI still shows relatively wide intervals, notifying the uncertainty of the predictions is higher.

To compare precision between forecast method following IT (forward-looking approach) and other forecast methods utilizing backward-looking approach (naive forecasts, ARMA, and VAR models), MSPE of each model is then computed to measure forecast errors. Forecast horizon can be categorized into short, medium and long–terms (12, 24, and 36-month forecast horizons correspondingly). Table 5 presents MSPE of all forecasts. It is very obvious that ARIMA(4,10) dominates in forecasting inflation rate for shorter period since it produces the lowest MSPE for 13-month forecast horizons (excluding 4 and 5-month forecast horizons), while VAR(13) yields the lowest MSPE in medium and long forecast horizons. Random-walk model is relatively accurate in forecasting inflation rate up to 6-month forecast horizons. Despite of that, all backward-looking methods are relatively more accurate than method following IT for almost all forecast horizons. This suggests that backward-looking approach is unbeatable and more reliable for forecasting inflation rate in Indonesia.

To scrutinize whether MSPE of each model statistically different to MSPE generated from the forecast following the target, the Diebold-Mariano (DM) test is then conducted. Table 6 presents the output of the test. In predicting inflation rate, it is better to apply backward-looking approach (except random-walk model) since it yields lower MSPE compared to IT model and the difference is statistically significant. One-year MA model is better to use for predicting inflation rate in medium term, while five-year MA model is more accurate in short and medium-terms than IT model. For ARMA(4,10) and VAR(13), the null-hypothesis of no significant difference in terms of accuracy to IT model can be rejected in all forecast horizons, making them superior to IT model. IT model only can beat random-walk model since forecast accuracies of two models in forecasting inflation rate are proven to be statistically equal (none of the difference is significant). Focusing only to the difference, however, IT model performs relatively better in long-term forecast compared to random-walk model. Yet, again, the accuracy difference between them is insignificant. Moreover, MSPE of IT model is apt to markedly decline in 2016. This interesting finding suggests that BI has continuously enhanced its monetary operations in order to have better capability to steer inflation towards its desired level. It is probably related to the replacement of BI rate to BI 7-Day Repo rate as a policy reference rate starting August 19th, 2016.

5. Conclusion

Whilst most of previous empirical studies favor forward-looking approach, this article challenges the popular notion by inferring backward-looking approach as the most accurate method in fore-

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DOI: 10.47291/efi.v62i2.539

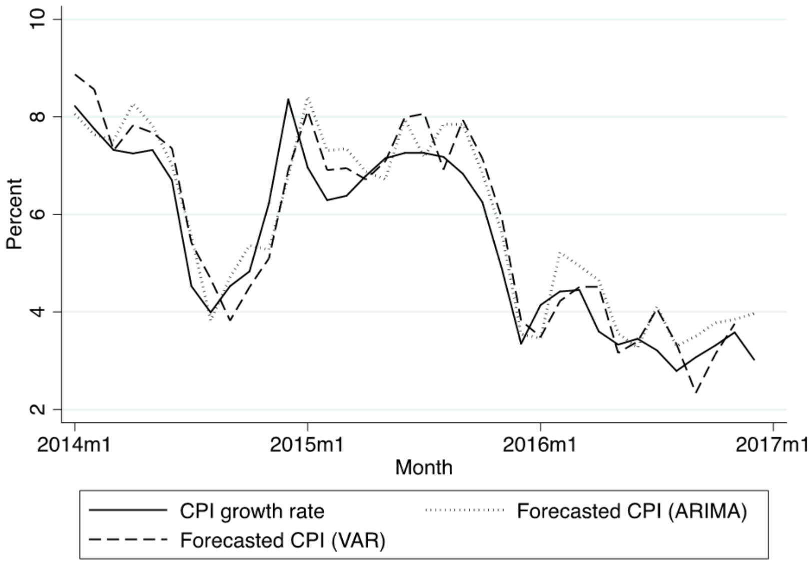

Figure 4: Forecast Comparison of ARMA(4,10) and VAR(13)

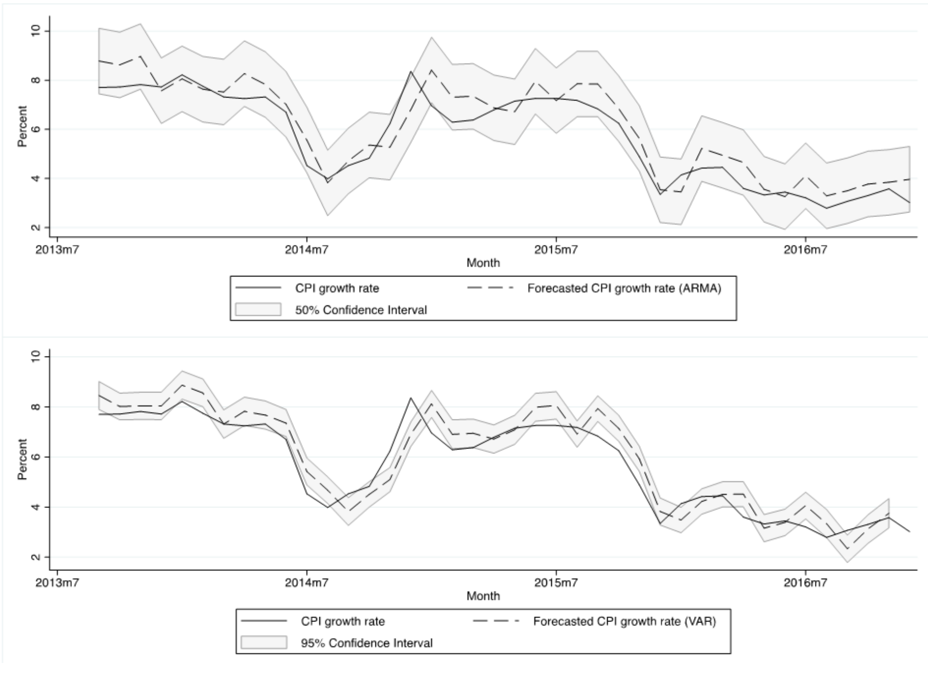

Figure 5: Forecast Interval of ARMA(4,10) and VAR(13)

Table 5: MSPE of One-Step Ahead Forecast for Inflation Rate (January 2014–December 2016)

Forecast Horizon	Inflation Target	Random Walk	One-Year MA	5-Year MA	ARMA(4,10)	VAR(13)
1	13.84	0.25	3.33	9.58	**0.03**	0.42
2	12.19	0.12	2.17	8.23	**0.02**	0.54
3	10.78	0.14	1.49	7.10	**0.03**	0.36
4	9.98	**0.16**	1.12	6.45	0.28	0.35
5	9.58	**0.16**	0.90	6.11	0.28	0.31
6	8.79	0.31	0.86	5.46	**0.25**	0.33
7	7.53	1.72	2.10	4.76	**0.36**	0.39
8	6.62	3.24	3.24	4.37	**0.32**	0.40
9	5.89	4.01	3.55	3.95	**0.29**	0.42
10	5.31	4.45	3.56	3.58	**0.29**	0.38
11	5.10	4.25	3.25	3.32	**0.35**	0.47
12	5.91	3.93	3.31	3.76	**0.52**	0.60
13	6.13	3.67	3.07	3.63	**0.64**	0.66
14	6.07	3.55	2.85	3.41	0.67	**0.64**
15	6.04	3.44	2.67	3.22	0.69	**0.62**
16	6.15	3.28	2.53	3.10	0.65	**0.58**
17	6.37	3.10	2.45	3.04	0.62	**0.55**
18	6.61	2.94	2.39	2.99	0.61	**0.54**
19	6.82	2.80	2.34	2.95	0.58	**0.55**
20	6.98	2.67	2.25	2.89	0.57	**0.53**
21	7.03	2.59	2.15	2.80	0.59	**0.56**
22	6.94	2.57	2.06	2.68	0.58	**0.57**
23	6.67	2.80	2.15	2.61	**0.58**	0.59
24	6.41	3.48	2.56	2.75	**0.56**	0.58
25	6.16	3.86	2.66	2.75	**0.56**	0.57
26	5.93	4.13	2.67	2.71	0.56	**0.55**
27	5.72	4.37	2.66	2.67	0.55	**0.53**
28	5.52	4.82	2.74	2.72	0.57	**0.54**
29	5.34	5.32	2.82	2.80	0.55	**0.52**
30	5.17	5.75	2.83	2.86	0.53	**0.51**
31	5.03	6.22	2.84	2.94	0.54	**0.51**
32	4.92	6.79	2.85	3.08	0.53	**0.51**
33	4.79	7.24	2.80	3.16	0.52	**0.51**
34	4.67	7.60	2.73	3.20	0.51	**0.49**
35	4.54	7.87	2.65	3.20	0.50	**0.48**
36	4.44	8.27	2.59	3.28	0.51	-

Note: forecast horizons = month ahead estimation and bold number is the minimum.
The MSPE of last forecast horizons for VAR model is empty due to data availability for industrial/manufacturing production growth rate, which is only available until October 2016.

Table 6: Output of Diebold-Mariano Test

Model	Jan 2014–Dec 2014		Jan 2014–Dec 2015		Jan 2014–Dec 2016	
	MSPE	Difference	MSPE	Difference	MSPE	Difference
Inflation Target	5.914	1.991	6.417	2.939	4.441	-3.817
Random Walk	3.923		3.478		8.258	
Inflation Target	5.914	2.607	6.417	3.858**	4.441	1.853
One-year MA	3.307		2.559		2.589	
Inflation Target	5.914	2.147***	6.417	3.658***	4.441	1.164
Five-year MA	3.767		2.759		3.277	
Inflation Target	5.914	5.394***	6.417	5.858***	4.441	3.93***
ARMA	0.520		0.559		0.5109	
Inflation Target	5.914	5.312***	6.417	5.84***	4.540	4.06***
VAR	0.6018		0.5769		0.4805	

Note: the null-hypothesis is forecast accuracy is statistically equal; and * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Negative difference means IT model is preferred.
Bartlett kernel is applied to guarantee that variance estimates is positive definite.

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DOI: 10.47291/efi.v62i2.539

casting inflation. Excluding random-walk model, the other backward-looking models also outperform IT model. This article and the study on Brazil by Altug & Çakmaklı draw a similar conclusion whereas the other studies on industrial country mostly endorse a forward-looking approach. One possible reason for this is that developing countries like Indonesia and Brazil are still in "the journey to inflation targeting" thereby it still does not have a full-fledged IT regime (Laurens et al. 2015).

In addition, some economists believe that the single objective of IT in practice may limit monetary policy to quickly respond to a distortion in the economy. Many IT countries thus consent to have some degrees of flexibility by countenancing multiple objectives (Walsh 2014), which is not in accordance with the concept of de jure IT. This de facto flexible IT allowing a country to have either hierarchical objectives or even dual-mandate allegedly may increase uncertainty (Stone 2002) leading to loss in trust of market agents to the target (related to the Kydland-Prescott inflation bias or time-inconsistency problem in monetary policy). This article thus sparks a broader yet essential view for further studies to discuss the stage of the adoption and implementation of flexible IT in comparing forecast power of the two approaches.

Despite the finding of highly persistent inflation rate in Indonesia, empirical result of this article cannot be used directly as a validity to claim that BI's forecast based on forward-looking approach is not reliable. The result should be interpreted with caution. This article only can implicitly give some indications of under-performance of forward-looking approach in Indonesia. Some fundamental reasons of why it happens thereby must be reckoned.

Firstly, it is necessary to investigate the focal motive of IT adoption in Indonesia which presumably can be more political rather than economic since AFC has rendered not only economic but also political reform in 1998. IT regime can be used to support the Government's political agenda in making the role of the CB to be more democratic (Bernanke et al. 1999; Ball & Sheridan 2005). Good coordination between BI and the Government may be beneficial in setting the target, but it can also be a problem when the Government is prone to be overriding. The degree of independence of BI from any fiscal dominance, therefore, must be further scrutinized as it also determines the success of BI in achieving the target (related to Cukierman's notion). Secondly, an increase in uncertainty from the emerged global economic environment, such as political unrest, episodes of economic downturn and fluctuation of commodity prices during the recent period, gives a huge challenge to BI in performing a good forward-looking approach. Even when the approach is able to predict those misfortunes quite well, it still may fail in anchoring public expectation towards the target. The effective forward-looking forecast however will only work if BI has high accountability, which is strongly related to the independence of BI. Lastly, there is still no concrete proof that BI has properly utilized lag and information encompassing in setting the target.

For further studies, in terms of constructing the time-series models, this article recommends to deal the undetected outliers by performing some transformations in the series, so the volatilities can be smoothened. The other ways to overcome this issue are by finding other determinants for inflation, or changing the time period of estimations. This article will end with propounding two policy recommendations. First, BI should consider to reduce the target horizons from three to one-year in order to improve the quality of forward-looking forecast and boost BI's credibility, and second, it still has "homework" to improve the lag and information encompassing properties of its forward-looking approach with regard to volatile administered (energy) and food prices.

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