WORKING PAPER

FORECASTING GROWTH OF THIRD PARTY FUNDS

Ina Nurmalia Kurniati

December, 2015

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Abstract

This research discusses the alternatives for forecasting method of third party funds (TPF) growth as a complement of forecast produced by BAMBI—Banking Model of Bank Indonesia using several methods: holt winter additive exponential smoothing, ARIMA, multivariate regression, and forecast on expectations of the banking sector contained in qualitative survey. The estimation is followed by three types of combined forecasts to increase accuracy and predictive power of the model. The result analysis shows the model offered can describe the behavior of TPF growth. Market players’ expectations in qualitative survey in the Indonesian Banking Survey are also proven to have forecast potential of TPF growth. Based on the combined forecast conducted, the weighted average of combined forecast using regression approach produces the best result. Not only compared to individual forecast, but also to other combined forecast methods. TPF growth in Q4-2015 is expected at 11.19% with probability of 95% would be within confidence interval (8.19%, 14.18%), while for Q4-2016 is predicted at 14.97% with probability of 95% would be within interval (11.98%, 17.7%).

Key words: forecasting and prediction methods, banking, forecasting and simulation

JEL Classification: C53, G21, E47

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I. PREFACE

As an authority who plays role in financial system stability, Bank Indonesia needs to have good forecast on banking main variables, one of which is forecasting bank third party funds. To date, Bank Indonesia has BAMBI (Banking Model of Bank Indonesia) which is used as projection tools of variables in the banking sector. The model is simultaneous, comprehensive, and can accommodate consistency between banking projection and macroeconomic projection produced by the Short Term Forecast for Indonesian Economy (SOFIE)\textsuperscript{2} model. BAMBI produces short-term projection (1–2 years ahead) on several main variables in the banking sector, such as third party funds (TPF), interest rate, loan interest rate, TPF growth, credit growth as well as non-performing loan (NPL) ratio. Nevertheless, a big model such as BAMBI does not necessarily reduce simple model.

This short study discusses several simple forecasting methods using univariate and multivariate models as well as trying to dig expectations of the banking sector contained in qualitative survey on the Indonesian Banking Survey. The analysis is followed with three types of combined forecasts. In general, the analysis conducted provides three positive contributions on literature.

This analysis is the first in comparing several forecasting methods using Indonesian data. Existing literatures generally concentrate on multivariate model to identify determinant of third party funds. For example, Haron and Wan Azmi (2006) identify that the level of bank profits, deposit rate, guaranteed base rate, KL composite index, consumer price index, money supply, and GDP are determinants of deposits in Malaysia. Another contribution is analysis using bank expectations on qualitative questions in the Indonesian Banking Survey. The hypothesis used is expectations of bankers have strong correlations with actual TPF growth. If proven, the analysis will be continued with forecasting using the survey data. The third contribution is combined forecast analysis to increase predictive power and reduces model risk. Timmerman (2006) advises to make combined forecast to diversify deterioration of each method and to avoid difficulties in choosing the best forecast method.

\textsuperscript{2} SOFIE is developed and managed by the Department of Monetary and Economic Policy, Bank Indonesia.
This analysis is formed of 5 sections. After preface, section 2 describes literature study. Section 3 presents the data and methodology used. Then the result and analysis are elaborated in section 4, as well as the evaluation of models and combined forecast used. Lastly in section 5 there is conclusion and recommendation for the next research.
II. LITERATURE STUDY

In literature combined forecast are generally used in forecasting inflation and gross domestic product. To the author’s knowledge there has yet a combined forecast conducted for banking variables, including TPF. In forecasting method there are three big groups: (1) forecast using univariate data which originates from past data; (2) forecast based on other variables which contain expectation value of the variables, such as survey; and (3) forecast based on other determinant variables.

In the first group the method generally used is exponential smoothing, linear regression such as ARIMA dan SARIMA, as well as non-linear univariate or time-varying model. Ang et al. (2007), Canova (2007), and Stock and Watson (2008) used the method in this group as a benchmark with multivariate forecast and/or combined forecast.

One that is commonly used in the second group is survey. Ang et al. (2007) expressed that forecasts from expectations of economic agents in three different quantitative surveys in the United States (Livingston Survey, survey of professional forecaster, and Michigan Survey) produce better predictive power when compared to other forecast method usage. Not only quantitative survey which can be used to make forecast, qualitative survey is also proven to have predictive power. Scheufele (2011) conducted comparison of several methods to quantify qualitative survey data and found out that forecast resulted from qualitative survey data is not far compared to other popular forecast methods for Germany inflation data.

In the third group, TPF growth determinant model which will be used as benchmark is the equation in model developed and used by Bank Indonesia, which is the Indonesia Banking Outlook Model (IBOMo) Quarterly that states TPF growth is positively affected by gross domestic product (GDP) growth and interest rate. The IBOMo system is estimated using two stage least squares, but for this study, since the analysis focus is only on one equation, intervariable relations are estimated using ordinary least squares (OLS). The same relations between TPF growth, GDP growth, and interest rate are also used by “quarterly model” (estimated using OLS) and “annual model” (estimated using weighted least squares) developed by DKMP.
Several forecasting models often have similar accuracy and predictive power which cause forecast makers have difficulties in deciding which is the best model. Therefore, to increase predictive power and reduce risk from several models, forecast makers combine forecast from several methods.

Stock and Watson (2003) express that combined forecast is better than individual forecast. They also state that simple combined forecast, such as median, can reduce instability issue of forecast model they formulate. In line with that, assessment of combined forecast using weighted average conducted by Brave and Fisher (2004) confirms that combined forecast is consistently better than model which is only based on past data.
In this study there are several approaches made for forecasting based on time series data which covers exponential smoothing, autoregressive integrated moving average, multiple regression as well as forecast based on survey data. All the approaches are then arranged in a combined forecast to increase model predictive power. The approach made is illustrated in this following scheme.

![Diagram](image)

**Figure 2. Forecasting Methodology**

### 3.1 Data

TPF data used in this study is the total of savings, current account, and deposits, both in rupiah and foreign currencies of banking in Indonesia. The TPF growth used is the annual growth calculated from quarterly data using the following formula.

\[
g_{TPF_t} = \frac{TPF_t - TPF_{t-4}}{TPF_{t-4}}
\]  

(1)

Note:

- \(g_{TPF_t}\) is TPF growth in quarter \(t\)
- \(TPF_t\) is the nominal value of third party funds during quarter \(t\).
This study tries to utilize information on estimated source of third party funds in the Indonesian Banking Survey conducted by Bank Indonesia. From the population of all commercial banks operating in Indonesia, respondents covered in the Indonesian Banking Survey represent 80% (±40 commercial banks), using the stratified purposive sampling method. Respondents were questioned about the expectation of third party funds whether they would go up, down, or stay in the next quarter. The survey answers were then built as net balance index, which is the difference in percentage of who answered TPF would go up and who answered down as well as ignoring netral response or stay. The net balance index method can be written as follows.

\[
\text{Net Balance Index} = (\% \text{ of who answers up} - \% \text{ of who answers down})
\]  

(2)

Plot on the expected TPF growth with actual TPF growth can be seen on Figure 3 and description of data used in this study can be seen on Table 1.

Source: Bank Indonesia, processed as necessary

Figure 3. Banking Survey – Expected TPF Growth
### Table 1. Data

<table>
<thead>
<tr>
<th>Data</th>
<th>Period and Frequency</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Third party funds</td>
<td>Quarterly (2001 Q3–2015 Q3)</td>
<td>Bank Indonesia</td>
</tr>
<tr>
<td>GDP</td>
<td>Quarterly (2001 Q3–2015 Q3)</td>
<td>BPS</td>
</tr>
<tr>
<td>Deposit rate</td>
<td>Quarterly (2001 Q3–2015 Q3)</td>
<td>Bank Indonesia</td>
</tr>
<tr>
<td>Inflation</td>
<td>Quarterly (2001 Q3–2015 Q3)</td>
<td>BPS</td>
</tr>
</tbody>
</table>

### 3.2 Forecasting Method

#### 3.2.1 Holt-Winters Additive Exponential Smoothing (HWA)

Exponential smoothing is a forecasting procedure which gives a greater weight on the latest data. The Holt-Winters Additive Exponential Smoothing (HWA) method is chosen because it is calculating trend and seasonal pattern from the data. Following Bowerman et al. (2005: Chapter 8), equation on the level, trend, and seasonal factor of a time series data can be stated in the following equations.

\[
\ell_t = \alpha (\pi_t - s_{n_{t-L}}) + (1 - \alpha)(\ell_{t-1} + b_{t-1}), \quad 0 < \alpha < 1
\]  

\[
b_t = \gamma (\ell_t - \ell_{t-1}) + (1 - \gamma)b_{t-1}, \quad 0 < \gamma < 1
\]  

\[
s_{n_t} = \delta (y_t - \ell_t) + (1 - \delta)s_{n_{t-L}}, \quad 0 < \delta < 1
\]  

**Note:**

\(\ell_t, b_t, s_{n_{t-L}}\) is the estimate result of level, trend, and seasonal factor during \(t\).

\(L\) is the number of seasons in a year.

The determination of HWA method initial value can be made by regressing half population of the data. Intercept obtained from regression line is the initial value \(\ell_0\), while the slope becomes the initial value \(b_0\). Optimal value from smoothing parameter \(\alpha, \gamma, \text{ and } \delta\) is obtained from the estimate which minimizes the sum squared of error (SSE) value.

Point forecast and 95% prediction interval from HWA method can be formulated as follows.

\[
\hat{\pi}_{t+h} = \ell_t + \tau b_t + s_{n_{t+h-L}}
\]
\[ \hat{y}_{t+h|t} = z_{(0.025)} s \sqrt{c_h} ; \quad \text{where} \quad c_h = \begin{cases} 1, & h = 1 \\ \frac{1 + \sum_{j=1}^{h-1} \alpha^2 (1 + jy)^2}{1 + \sum_{j=1}^{L} [\alpha (1 + jy) + d_{j,L} (1 - \alpha) \delta]^{2}} & \quad 2 \leq h \leq L \end{cases} \] \tag{7}

Note:

- \( s \) is the standard error during \( t \)
- \( d_{j,L} \) is valued at 1 if \( j \) is the multiple of integers from \( L \) and 0 if it isn’t.

### 3.2.2 Autoregressive Integrated Moving Average (ARIMA)

If assumed that current data is linearly dependent on past data and weighted average of past error, then one of the methods that can be considered is autoregressive integrated moving average (ARIMA) or known as Box-Jenkins model. Specification from ARIMA \((p, d, q)\) model is as follows.

\[ \phi(L)(1 - L)^d X_t = \mu + \theta(L) \varepsilon_t \] \tag{8}

Note:

- \( \phi(L) = 1 - \phi_1 L - \cdots - \phi_p L^p \) is AR term
- \( \theta(L) = 1 + \theta_1 L + \cdots + \theta_q L^q \) is MA term
- \( \mu \) is constant
- \( \varepsilon_t \) is white noise (weak) with variance \( \sigma^2_\varepsilon \)
- \( d \) is degree of declination.

ARIMA \((p, d, q)\) model in equation (8) can be rewritten as.

\[ x_t = \mu + \phi_1 x_{t-1} + \cdots + \phi_p x_{t-p} + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \] \tag{9}

and the one-step-ahead point forecast is as follows.

\[ \hat{x}_{t+1} = \hat{\mu} + \hat{\phi}_1 x_{t} + \cdots + \hat{\phi}_p x_{t-p} + \hat{\theta}_1 \varepsilon_{t} + \cdots + \hat{\theta}_q \varepsilon_{t-q}, \] \tag{10}

The result of equation (8) can be iterated to make dynamic forecast for time \( t + 2, t + 3, \ldots \), \( t + h \) so that point forecast of period \( h \) with ARIMA can be written as follows.

\[ \hat{x}_{t+h} = \hat{\mu} + \hat{\phi}_1 x_{t+h-1} + \cdots + \hat{\phi}_p x_{t+h-p} + \hat{\theta}_1 \varepsilon_{t+h-1} + \cdots + \hat{\theta}_q \varepsilon_{t+h-q}, \] \tag{11}

In this paper ARIMA \((p, d, q)\) model is built following the procedure outlined by Bowerman et al. (2005: Chapter 9–11).
In the identification process, plot from real data is used to identify trend, seasonal components, outlier, and initial value of $p$, $d$, $q$. Then ARIMA model is estimated using maximum likelihood estimator (MLE). The optimal lag length for AR and MA is selected based on Schawrtz Criterion (BIC). After the model is estimated, diagnostic test is made to know model compatibility by analyzing if the residuals are white noise. It can be done by seeing autocorrelation function (ACF) and partial autocorrelation function (PACF) from residuals and the result of Ljung-Box-Pierce Q Statistics (Portmanteau Test). If the model is considered sufficient, then can be followed by forecasting process.

### 3.2.3 Forecast Using Survey Data

To estimate $E_t(x_{t+h}) = \hat{x}_{t+h|t}$ from third party funds projection in banking survey, qualitative survey data must be converted into quantitative data. This research follows Scheufele (2011) who analyzes Germany qualitative inflation expectation data based on surveys of economic experts. Scheufele conducted unit root test and granger causality test followed by parameter $\hat{\delta}$ estimate with equation as follows.

$$E_t(x_{t+h}) = -\hat{\delta}_t \frac{|a+b|}{a-b}$$

(12)

This writing follows Batchelor (1982) in estimating parameter $\hat{\delta}$ by regressing inflation changes on unscaled estimates $\frac{|a+b|}{a-b}$, which is parameter $\hat{\delta}_t$ constant to time.

### 3.2.4 Multiple Regression

The model used as guide to conduct forecast on TPF growth based on its determinant according to Indonesia Banking Outlook Model (IBOMo) Quarterly
states that TPF growth is positively affected by gross domestic product growth and deposit rate.

\[ gTPF_t = \beta_0 + \beta_1 gGDP_{t-1} + \beta_2 r_t + \epsilon_t \]  

(13)

Note:
\( gGDP_t \) is GDP growth during \( t \)
\( r_t \) is one-month deposit rate during \( t \).

To calculate inflationary impact, GDP growth and deposit used is deposit in real terms.

### 3.3 Model Evaluation

Having a timely, accurate, and reliable forecast is the main factor for policy makers. An accurate model is a model which can minimize expectation of certain loss function. For example \( \hat{x}_{t+h|t} \) states that \( h \)-period ahead is a forecast from \( x_{t+h} \) therefore forecast accuracy evaluation can be calculated by several model accuracy measurements, such as RMSE, MAE, and MAPE as follows.

\[ RMSE = \left( \frac{1}{N} \sum_{h=t+1}^{t+N} \left( \pi_{t+h} - \hat{\pi}_{t+h|t} \right)^2 \right)^{1/2} \]  

(14)

Root mean square error (RMSE) implicitly provides greater weight to the biggest deviation of forecast. This method is used for model which cost of error is the square of the error.

\[ MAE = \frac{1}{N} \sum_{h=t+1}^{t+N} \left| \pi_{t+h} - \hat{\pi}_{t+h|t} \right| \]  

(15)

Mean absolute deviation or mean absolute error (MAE) is used for model which cost of error is proportional with the absolute value of the error.

\[ MAPE = \frac{1}{N} \sum_{h=t+1}^{t+N} \frac{\left| \pi_{t+h} - \hat{\pi}_{t+h|t} \right|}{\pi_{t+h}} \]  

(16)

Mean absolute percentage error (MAPE) is used for model which cost of error is more related with the error percentage compared to error value.

Model with the least RMSE, MAE, or MAPE is the best model.
3.4 Combined Forecasts

According to Watson (2004), for every unbiased forecast $f_i$ with variance $\sigma_i^2$ where $i = 1, \ldots, n$ and for example every forecast does not correlate, combined forecast can be formulated as:

$$f_c = \sum_{i=1}^{n} w_i f_i$$  \hspace{1cm} (17)

with $w_i$ as non-negative weight and

$$\sum_{i=1}^{n} w_i = 1$$  \hspace{1cm} (18)

Mean combined forecast is a case where all weights have the same value,

$$w_1 = w_2 = \cdots = w_n$$  \hspace{1cm} (19)

Optimal weight for uncorrelated forecasts can be calculated with the following formula:

$$w_m = \frac{\sigma_m^{-2}}{\sum_{i=1}^{n} \sigma_i^{-2}}$$  \hspace{1cm} (20)

Weight of forecast $m$ is proportional with its inverse variance. According to Granger and Ramanathan (1984), optimal weight can be calculated by regressing actual value with forecast results using several obstacles: without intercept, coefficient must be non-negative value, and the sum of coefficients is one

$$f_c = \beta_1 f_{1,t} + \beta_2 f_{2,t} + \cdots + \beta_n f_{n,t} + \epsilon_t.$$  \hspace{1cm} (21)

with $\beta_i \geq 0$, and $\sum_{i=1}^{n} \beta_i = 1$. Optimal weight $w_i$ is $\hat{\beta}_i$ for every $i = 1, \ldots, n$. 
IV. ANALYSIS

4.1 Forecasting Analysis

4.1.1 Holt Winter Additive Exponential Smoothing (HWA)

The values of intercept and slope from TPF growth data regression to timing on first half sample is used as initial value of $l_0$ and $b_0$ in HWA approach. The breakdown of regression can be seen on appendix. Prediction obtained from HWA can be seen in the following Figure 5.

![TPF Growth Forecast Using Exponential Smoothing](image)

Source: Researcher's Estimate

Figure 5. Holt Winter Additive Exponential Smoothing

Optimal value from smoothing parameter obtained is $\alpha=0.81$, $\gamma=0.00$, and $\delta=0.00$ which indicate high level component with relatively stable trend and seasonal value. It can be seen in Figure 5 that HWA model can predict dynamic behavior of TPF growth and also the level of change. Out-of-sample forecasting shows this method can sufficiently predict TPF growth movement. Overall this method provides SSE of 288,811.
4.1.2 ARIMA (1.0.0)

One requirement of ARIMA model usage is stationarity of data. Graphic analysis on TPF growth data shows potentially data is stationary. ADF formal testing confirms it by rejecting hypothesis that TPF growth has unit root\(^3\). Parameter \(p\), \(d\), and \(q\) are then determined through ACF and PACF graphic analysis. Out of several candidates ARIMA model is selected based on SIC\(^4\) figure.

ARIMA (1.0.0) model is selected as the best model and parameter of this model is estimated. As seen on Table 2, all parameters are proven significant. Testing of residual is conducted to ensure the error formed is random and distributed normally. Testing is conducted using ACF and PACF graphic analysis on residual and Ljung Box Q test. ACF and PACF graphic on residual presented on Figure 6 shows that residual is white noise. Ljung Box Q formal testing indicates that model is considerably good in representing data, and then prediction on TPF growth can be made.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>15.516***</td>
<td>0.8942</td>
</tr>
<tr>
<td>AR(1)</td>
<td>0.6112***</td>
<td>0.1473</td>
</tr>
<tr>
<td>SigmaSQ</td>
<td>4.5347***</td>
<td>1.0884</td>
</tr>
</tbody>
</table>

Portmanteau Q Statistics = 29.28
Prob. > chi\(^2\)(24) = 0.21

Note: Statistical significance at ***1%, **5%, and *10%.

---

\(^3\) Unit Root testing can be seen on appendix.
\(^4\) Complete comparison and selection of ARIMA model can be seen on appendix.
Based on Figure 7 it can be seen that in-sample forecast on ARIMA model can illustrate actual data behavior.

4.1.3 Forecast Using Banking Survey Data

Analysis on correlation of actual TPF growth and expected TPF growth from banking survey is deemed big enough, at 49.35% therefore forecasting analysis can be continued. To convert qualitative survey result from banking survey to TPF growth forecast, a linear regression of TPF growth on weighted net index of expected TPF
growth from banking survey\textsuperscript{5} is made. Forecast result can be seen in the following Figure 8. It can be seen that banking survey is less able to capture magnitude of real data, but still have forecast power going forward.

![TPF Growth Forecast Based on Banking Survey](image)

Source: Researcher’s Estimate

Figure 8. Banking Survey – TPF Growth Projection

4.1.4 Multiple Regression

Regression model obtained based on intervariable relations from IBOMo can be seen on Table 3. Based on the model TPF growth variable is proven to be positively affected by real GDP growth in the previous quarter and deposit rate.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std.Error</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1.202</td>
<td>3.359</td>
<td>0.358</td>
</tr>
<tr>
<td>GGDPRL(-1)</td>
<td>2.356***</td>
<td>0.585</td>
<td>4.025</td>
</tr>
<tr>
<td>REALRDEP1</td>
<td>0.377*</td>
<td>0.222</td>
<td>1.696</td>
</tr>
<tr>
<td>R\textsuperscript{2}</td>
<td>0.382</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob (F stat)</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\textsuperscript{5} Regression result can be seen on Appendix.
Note: Statistical significance in ***1%, **5%, and *10%.

Forecast from the equation models above can be seen on the following Figure 9.

![TPF Growth Forecast](image)

Source: Researcher's Estimate

Figure 9. TPF Growth Forecast – Multiple Regression

### 4.2 Model Evaluation

Previous sections present several forecasting models on TPF growth. In this section there will be performance test from every model to evaluate the accuracy and reliability of each model. Testing is conducted for in-sample and out-of-sample. The following Figure 10 presents recap of every forecasting model presented in the previous sections.

![Individual Forecast](image)

Source: Researcher's Estimate
Figure 10. Out-of-Sample Forecast on TPF Growth

Generally the analyzed forecasting models can capture TPF growth behavior. Formal testing on the forecast accuracy is conducted using RMSE, MAE, and MAPE for out-of-sample period. The test result can be seen on the following Table 4.

<table>
<thead>
<tr>
<th>Model free: Holt Winters exponential smoothing</th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA(1.0.0)</td>
<td>2.338</td>
<td>2.273</td>
<td>0.175</td>
</tr>
<tr>
<td>Survey forecast: banking survey</td>
<td>2.612</td>
<td>2.330</td>
<td>0.189</td>
</tr>
<tr>
<td>Multiple regression</td>
<td>1.258</td>
<td>0.957</td>
<td>0.068</td>
</tr>
</tbody>
</table>

Based on Table 4 it can be seen that TPF growth forecast using multiple regression resulting the lowest RMSE, MAE, and MAPE compared to other forecast methods.

### 4.3 Combined Forecasts

To increase the performance of forecasting from existing models, this study also utilizes three combined forecast methods: mean, median, and linear regression. The combined forecast approach results in more accurate prediction value because combined forecast diversifies risks on misspecification of conducted individual forecast methods.

On combined forecast using mean approach, weight of ¼ is given to each approach. On combined forecast using regression approach, this study follows the procedure of Granger and Ramanathan (1984) who regress real data with values of individual forecast without using intercept. The coefficient obtained must be non-negative and the sum of coefficients of each method is 1. This is done by applying general to specific procedure by aborting forecasts which produce negative sign so that all estimated coefficients are positive. This RMSE method result shows lower value than forecasts of each individual in the previous sections.

Based on the procedure of combined forecast regression, forecastings selected are multiple regression and HWA with each weighting at 0.35 and 0.65, while ARIMA
(1.0.0) and each survey has respective weight of 0. Accuracy testing on combined forecast is shown on the following Table 5 which indicates that generally combined forecast is still better than individual forecast.

![Combination Forecast](image)

Source: Researcher’s Estimate

Figure 11. Out-of-Sample Forecast on TPF Growth

<table>
<thead>
<tr>
<th></th>
<th>RMSE</th>
<th>MAE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1.626</td>
<td>1.625</td>
<td>0.125</td>
</tr>
<tr>
<td>Median</td>
<td>1.767</td>
<td>1.752</td>
<td>0.134</td>
</tr>
<tr>
<td>Regression</td>
<td><strong>1.150</strong></td>
<td><strong>0.971</strong></td>
<td><strong>0.070</strong></td>
</tr>
</tbody>
</table>

### 4.4 Forecast

Based on out-of-sample estimate, in general, TPF growth showed a declining trend at the end of 2015 and an increase starting from the 1st quarter of 2016. Whole forecast is presented in the following table.
Based on the conducted assessment, the growth of third party funds in Q4-2015 was 11.19% with probability 95% which will be within confidence interval (8.19%, 14.18%), while for Q4-2016 is predicted at 14.97% with probability 95% which will be within interval (11.98%, 17.97%).

Table 7. TPF Growth Forecast

<table>
<thead>
<tr>
<th>Point Forecast</th>
<th>Lower Limit</th>
<th>Upper Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015 Q4</td>
<td>11.19%</td>
<td>8.19%</td>
</tr>
<tr>
<td>2016 Q4</td>
<td>14.97%</td>
<td>11.98%</td>
</tr>
</tbody>
</table>
V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study discusses methods of forecasting third party funds growth in Indonesia using several methods, either univariate, multivariate, or qualitative survey. Univariate model is proven able to forecast behavior of third party funds growth. Expectations of third party funds growth in qualitative survey can also predict third party funds growth for the next quarter. In individual model, multiple regression method produces the lowest RMSE, MAE, and MAPE values if compared to other methods. The result analysis shows that combined forecast increases predictive power of each methodology and method of combined forecast based on regression approach is more accurate than other combined approaches.

Based on the estimation conducted, third party funds growth in December 2015 will be at 11.19% with probability 95% which will be within confidence interval (8.19%, 14.18%), while for Q4-2016 is predicted at 14.97% with probability 95% which will be within interval (11.98%, 17.97%).

5.2 Recommendation

This study forecasts third party funds growth using univariate data, multivariate model, and qualitative survey. Further researches can be made by adding other economic variables which are leading indicators of TPF growth. Assessment can be made using ARMA-X or VAR methods for multivariate analysis, or MSVAR to accommodate nonlinearity.

Related to utilization of banking survey data, if raw data from the survey is available, estimates from TPF growth forecasting can be conducted by referring to Pesaran (1984) by using regression on TPF growth data with fraction of respondents’ replies who answer up and fraction who answer down.
BIBLIOGRAPHY


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