Will Indonesia be the Next Victim of the Malthusian Population Prophecy?
Empirical Evidence from “Box – Jenkins” ARIMA Approach

Nyoni, Thabani¹ & Bonga, Wellington. G²

¹Department of Economics, University of Zimbabwe, Harare, Zimbabwe; nyonithabani35@gmail.com
²Department of Banking & Finance, Great Zimbabwe University, Masvingo; sirwellas@gmail.com

Abstract:—Employing annual time series data on total population in Indonesia from 1960 to 2017, we model and forecast total population over the next 3 decades using the Box – Jenkins ARIMA technique. Diagnostic tests such as the ADF tests show that Indonesia annual total population is neither I (0) nor I (1) but rather I (2). Based on the AIC, the study presents the ARIMA (3, 2, 0) model. The diagnostic tests also indicate that the presented model is very stable and quite reasonable. The results of the study reveal that total population in Indonesia will continue to sharply rise within the next three decades, for up to approximately 341 million people by 2050. In order to address the threats posed by a spiraling population, policy recommendations have been put forward by the study.

Key Words: ARIMA, Box-Jenkins, Forecasting, Indonesia, Malthusian Theory, Population Growth.

JEL Codes: C53, Q56, R23

I. INTRODUCTION

As the 21st century began, the world’s population was estimated to be almost 6.1 billion people (Tartiyus et al., 2015). Projections by the United Nations place the figure at more than 9.2 billion by the year 2050 before reaching a maximum of 11 billion by 2200. Over 90% of that population will inhabit the developing world (Todaro & Smith, 2006). Indonesia is by far the largest country in Southeast Asia, with a population comprising 40% of the entire population of Southeast Asia (UNFPA, 2010). Indonesia, with a current population of 241 million persons, is an important example for illustrating the Copenhagen Consensus Center’s assessment of high-priority policy area of demography and population dynamics. Indonesia is the forth most populous country in the world and will be eight in the list of countries contributing to population growth by 2050 (Kohler et al., 2015). The official population projections for Indonesia show that considerable population growth will take place over the next 25 years, though the rate of increase will be slowing (UNFPA, 2010). With continuing significant population growth, it will not seem surprising that a target recommended in the Copenhagen Consensus study is to make family planning available to everyone (Kohler et al., 2015).

The problem of population growth is basically not a problem of numbers but that of human welfare as it affects the provision of welfare and development. The consequences of rapidly growing population manifests heavily on species extinction, deforestation, desertification, climate change and the destruction of natural ecosystems on one hand; and unemployment, pressure on housing, transport traffic congestion, pollution and infrastructure security and strain on amenities (Dominic et al., 2016). Will Indonesia be the next victim of the Malthusian population prophecy? This question is arguably lingering in the hearts of many Indonesian demographers and policy makers. At this stage of the research, we will leave it to you to decide! In Indonesia, just like in any other part of the world, population modeling and forecasting is important for policy dialogue, especially given the fact that the fast growth of population during the past decades has frustrated the development efforts in Indonesia and has posed serious threats to natural resources, persistant unemployment and worsening poverty levels. This study endeavors to model and forecast population of Indonesia using the Box-Jenkins ARIMA technique.

II. LITERATURE REVIEW

2.1 Theoretical Literature Review

The Malthus’ population prophecy uncovers the impact of spiraling population on economic growth, of which Malthus (1798), later supported by Solow (1956), argues that population growth is a threat to economic growth and development. Whether this famous population prophecy has been fulfilled is an empirical issue. While Solow’s arguments were basically consistent with the basic Malthusian prophecy, he rather focused on the term “population growth rate” unlike Malthus who prioritized the term “population level”. As time went on Solow and Malthus faced criticism, mainly from Ahlburg (1998) and Becker et al (1999) who thought that population growth was good and actually rubbed the Malthusian population prophecy! Ahlburg’s arguments were hinged on the
technology pushed” and “demand pulled” dimensions while Becker and his colleagues focused on “high labor – a source of real wealth”. This study will let us know where Indonesia is going with regards to the fulfillment of the Malthusian population prophecy.

2.2 Empirical Literature Review

In an Asian study, Zakria & Muhammad (2009) forecasted population using Box-Jenkins ARIMA models, and relied on a data set ranging from 1951 to 2007; and found out that the ARIMA (1, 2, 0) model was the optimal model in Pakistan. Haque et al (2012), in another Asian study, analyzed Bangladesh population projections using the logistic population model with a data set ranging from 1991 to 2006 and found out that the logistic population model has the best fit for population growth in Bangladesh. In Africa, Ayele & Zewdie (2017) analyzed human population size and its pattern in Ethiopia using Box-Jenkins ARIMA models and employing annual data from 1961 to 2009 and concluded that the best model for modeling and forecasting population in Ethiopia was the ARIMA (2, 1, 2) model. In the case of Indonesia, the paper will adopt the Box-Jenkins ARIMA methodology for the data set ranging from 1960 to 2017.

III. MATERIALS & METHODS

3.1 ARIMA Models

ARIMA models are often considered as delivering more accurate forecasts than econometric techniques (Song et al, 2003b). ARIMA models outperform multivariate models in forecasting performance (du Preez & Witt, 2003). Wan (2018), indicated that ARIMA models exploit information embedded in the autocorrelation pattern of the data.

ARIMA is a strict statistical approach and only requires the prior data of a time series to generalize the forecast. Overall performance of ARIMA models is superior to that of the naïve models and smoothing techniques (Goh & Law, 2002).

ARIMA models were developed by Box and Jenkins in the 1970s and their approach of identification, estimation and diagnostics is based on the principle of parsimony (Asteriou & Hall, 2007). The general form of the ARIMA (p, d, q) can be simply represented by a backward shift operator as:

\[ \Phi(B)(1 - B)^d PIND_t = \theta(B)\mu_t \]

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

\[ \Phi(B) = (1 - \Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p) \]
\[ \theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q) \]

and

\[ (1 - B)^d PIND_t = \Delta^d PIND_t \]

Where PIND is the variable population, \( \Phi \) is the parameter estimate of the autoregressive component, \( \theta \) is the parameter estimate of the moving average component, \( \Delta \) is the difference operator, \( d \) is the difference, \( B \) is the backshift operator and \( \mu_t \) is the disturbance term.

3.2 The Box – Jenkins Methodology

The Box-Jenkins methodology refers to a set of procedures for identifying and estimating time series models within the class of ARIMA models (Wan, 2018). The method is appropriate for time series of medium to long length (at least 50 observations). The Box-Jenkins methodology does not assume any particular pattern in the historical data of the series to be forecasted (Adhikari & Agrawal, 2013).

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage.

The process may go on and on until an appropriate model is identified (Nyoni, 2018i). Anderson (1977), supported the procedure by indicating that, if the model is found to be inadequate, then this assessment should indicate promising modifications to the identification, and the cycle is repeated; and so on until the analyst is satisfied.

www.dynamicresearchjournals.org/jef
3.3 Data Collection

This research paper, whose data was gathered from the widely recognized World Bank online database; is based on 57 observations of annual total population (POP, referred to as PINDO in the mathematical formulation above) in Indonesia.

IV. DIAGNOSTIC TESTS & MODEL EVALUATION

4.1 Stationarity Tests: Graphical Analysis

The first step, as with any applied statistical problem, is to get the feel of the data; the series is plotted against time, and visual inspection will indicate whether it is plausible to assume that the process is stationary (Anderson, 1977). Stationarity is a fundamental property underlying almost all time series statistical models (Wan, 2018).

The total population in Indonesia as shown above in figure 2; is sharply trending upwards and is most likely to be non-stationary. Below, we formally test for stationarity.
4.2 The Correlogram in Levels
In order to identify tentative initial choices for p and q, the a. c. f. and p. a. c. f. are calculated, and preferably plotted, for the first K lags (Anderson, 1977).

![ACF and PACF plots for POP](image)

4.3 The ADF Test

<table>
<thead>
<tr>
<th>Table 1: Levels-intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>POP</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2: Levels-trend &amp; intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>POP</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3: Without intercept and trend &amp; intercept</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>POP</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
4.4 The Correlogram (at 1st Differences)
Non-stationary series can be made stationary through differencing (Wan, 2018). The differenced series has \( n-1 \) observations after taking the first difference, \( n - 2 \) observations after taking the second difference, and \( n - d \) observations after taking \( d \) differences.

Figure 4

Table 4: 1st Difference-intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-2.098972</td>
<td>0.2459</td>
<td>-3.560019 ( @1% )</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td>-2.917650 ( @5% )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-2.596689 ( @10% )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: 1st Difference-trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-2.314297</td>
<td>0.4191</td>
<td>-4.140858 ( @1% )</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td>-3.496960 ( @5% )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-3.177579 ( @10% )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: 1st Difference-without intercept and trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-0.979647</td>
<td>0.2890</td>
<td>-2.609324 ( @1% )</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td>-1.947119 ( @5% )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-1.612867 ( @10% )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The total population series, as shown in figures 3 and 4 as well as tables 1 – 6 is neither I (0) nor I (1), thus we test for stationarity once again, this time in second differences.
4.5 The Correlogram in (2\textsuperscript{nd} Differences)

Table 7: 2\textsuperscript{nd} Difference-intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-1.609332</td>
<td>0.4709</td>
<td>-3.560019 @1%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-2.917650 @5%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-2.596689 @10%</td>
<td>Not stationary</td>
</tr>
</tbody>
</table>

Table 8: 2\textsuperscript{nd} Difference-trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-1.791777</td>
<td>0.6947</td>
<td>-4.140858 @1%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.496960 @5%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.177579 @10%</td>
<td>Not stationary</td>
</tr>
</tbody>
</table>

Table 9: 2\textsuperscript{nd} Difference-without intercept and trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>-1.902192</td>
<td>0.0551</td>
<td>-2.609324 @1%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-1.947119 @5%</td>
<td>Not stationary</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-1.612867 @10%</td>
<td>Stationary</td>
</tr>
</tbody>
</table>

Figures 3 – 5 and Tables 1 – 8, indicate that the total population series of Indonesia is not stationary in levels, first differences as well as in second differences. Table 9, however, indicates that the total population series is stationary at 10% level of significance. For simplicity, we assume that the population series is I (2).
4.6 Evaluation of ARIMA models (without a constant)

<table>
<thead>
<tr>
<th>Model</th>
<th>AIC</th>
<th>U</th>
<th>ME</th>
<th>MAE</th>
<th>RMSE</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA (1, 2, 1)</td>
<td>1174.366</td>
<td>0.0022662</td>
<td>-17.553</td>
<td>7057.1</td>
<td>12580</td>
<td>0.0047022</td>
</tr>
<tr>
<td>ARIMA (2, 2, 1)</td>
<td>1134.361</td>
<td>0.0016655</td>
<td>1446.5</td>
<td>5657.1</td>
<td>11222</td>
<td>0.0040046</td>
</tr>
<tr>
<td>ARIMA (3, 2, 1)</td>
<td>1123.644</td>
<td>0.0014689</td>
<td>963.52</td>
<td>5093.9</td>
<td>10969</td>
<td>0.0036546</td>
</tr>
<tr>
<td>ARIMA (4, 2, 1)</td>
<td>1123.936</td>
<td>0.0014683</td>
<td>1339.4</td>
<td>5054.5</td>
<td>10939</td>
<td>0.0036521</td>
</tr>
<tr>
<td>ARIMA (2, 2, 0)</td>
<td>1152.108</td>
<td>0.001973</td>
<td>1596.3</td>
<td>6314.6</td>
<td>11743</td>
<td>0.0044108</td>
</tr>
<tr>
<td>ARIMA (3, 2, 0)</td>
<td>1121.963</td>
<td>0.0014667</td>
<td>908.33</td>
<td>5090.2</td>
<td>10974</td>
<td>0.0036504</td>
</tr>
<tr>
<td>ARIMA (4, 2, 0)</td>
<td>1123.534</td>
<td>0.0014704</td>
<td>991.33</td>
<td>5097.7</td>
<td>10967</td>
<td>0.0036597</td>
</tr>
</tbody>
</table>

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil’s U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). The paper will consider only on the AIC and the Theil’s U in order to choose the optimal model in terms of parsimony (AIC) and forecast accuracy (Theil’s U). Therefore, the ARIMA (3, 2, 0) model is chosen.

4.7 Residual & Stability Tests

Once a model has been tentatively identified, its parameters have to be efficiently estimated, and the resulting fit assessed, mainly by an analysis of residuals, to see whether it can be accepted as a plausible explanation of the series (Anderson, 1977).

4.7.1 ADF Tests of the Residuals of the ARIMA (3, 2, 0) Model

Table 11: Levels-intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\epsilon}_t$</td>
<td>-6.729420</td>
<td>0.0000</td>
<td>-3.562669 @1% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-2.918778 @5% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-2.597285 @10% Stationary</td>
<td></td>
</tr>
</tbody>
</table>

Table 12: Levels-trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\epsilon}_t$</td>
<td>-6.751880</td>
<td>0.0000</td>
<td>-4.144584 @1% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.498692 @5% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-3.178578 @10% Stationary</td>
<td></td>
</tr>
</tbody>
</table>

Table 13: without intercept and trend & intercept

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistic</th>
<th>Probability</th>
<th>Critical Values</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\epsilon}_t$</td>
<td>-6.716367</td>
<td>0.0000</td>
<td>-2.610192 @1% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-1.947248 @5% Stationary</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-1.612797 @10% Stationary</td>
<td></td>
</tr>
</tbody>
</table>

Tables 11, 12 and 13 show that the residuals of the ARIMA (3, 2, 0) model are stationary.

4.7.2 Stability Test of the ARIMA (3, 2, 0) Model

Figure 6: Inverse Roots
Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it proves that the selected ARIMA (3, 2, 0) model is stable.

V. FINDINGS

5.1 Descriptive Statistics

<table>
<thead>
<tr>
<th>Description</th>
<th>Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>174990000</td>
</tr>
<tr>
<td>Median</td>
<td>176620000</td>
</tr>
<tr>
<td>Minimum</td>
<td>87793000</td>
</tr>
<tr>
<td>Maximum</td>
<td>263990000</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>53416000</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.013986</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>-1.2420</td>
</tr>
</tbody>
</table>

As shown above, the mean is positive, i.e. 174990000. The wide gap between the minimum (i.e. 87793000) and the maximum (i.e. 263990000) is consistent with the reality that the Indonesian POP series is sharply trending upwards. This simply means that Indonesian population is spiraling and apparently posing a threat to the Indonesian economy.

The skewness is -0.013986 and the most striking characteristic is that it is negative, indicating that the POP series is negatively skewed and non-symmetric. Nyoni & Bonga (2017h) emphasize that the rule of thumb for kurtosis is that it must be approximately 3 for normally distributed variables but in this paper, excess kurtosis is -1.2420; showing that the POP series is not normally distributed.

5.2 Results Presentation

<table>
<thead>
<tr>
<th>ARIMA (3, 2, 0) Model:</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ \Delta^2 POP_{t-1} = 2.37683\Delta^2 POP_{t-1} - 2.07349\Delta^2 POP_{t-2} + 0.68225\Delta^2 POP_{t-3} \ldots \ldots \ldots \ldots ] [5]</td>
</tr>
<tr>
<td>P: (0.0000) (0.0000) (0.0000)</td>
</tr>
<tr>
<td>S. E: (0.100440) (0.188854) (0.101150)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>z</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR (1)</td>
<td>2.37683</td>
<td>0.100440</td>
<td>23.66</td>
<td>0.0000***</td>
</tr>
<tr>
<td>AR (2)</td>
<td>-2.07349</td>
<td>0.188854</td>
<td>-10.98</td>
<td>0.0000***</td>
</tr>
<tr>
<td>AR (3)</td>
<td>0.682225</td>
<td>0.101150</td>
<td>6.745</td>
<td>0.0000***</td>
</tr>
</tbody>
</table>

The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively

5.3 Interpretation of Results

All the coefficients of the AR components are statistically significant at 1% level of significance. The coefficients of the AR (1) and the AR (3) components are positive while the coefficients of the AR (2) component is negative. The overall high statistical significance of the coefficients of the AR components indicate that previous period total population is quite relevant in explaining future total population in Indonesia.
Figure 7: Forecast Graph

Figure 8: Predicted Total Population

Figure 7 (with a forecast range from 2018 – 2050) and Figure 8, clearly indicate that Indonesia population is indeed set to continue rising sharply, at least for the next 3 decades. With a 95% confidence interval of 309001000 to 373408000 and a projected total population of 341205000 by 2050, the chosen ARIMA (3, 2, 0) model is consistent with the population projections by the UN (2015) which forecasted that Indonesia’s population will be approximately 322,237,000 by 2050.

While the forecasts clearly warn of a fulfillment of the Malthusian population prophecy, Kohler et al (2015), in line with Ahlburg (1998) and Becker et al (1999); argue that as long as the country can capitalize on the fact that there will be a large fraction of the population of working age over coming decades – what is known as the demographic dividend – Indonesia has much to gain from a population which will continue to grow until mid-century.
VI. POLICY IMPLICATIONS
The study has managed to apply the ARIMA forecasting procedure, and observed and analysed the model results including the forecasts. The study came up with the following policy implications;

a) The government of Indonesia should enforce consistent family planning practices.

b) The government of Indonesia ought to promote the smaller family size norm.

c) Sex education must be delivered in order to control fertility in Indonesia,

d) Among other socially acceptable measures to control population growth.

VII. CONCLUSION
The ARIMA (3, 2, 0) model is an acceptable and most parsimonious model to forecast the population of Indonesia for the next 3 decades. The model predicts that by 2050, Indonesia’s population would be approximately, 341 million; unless and until drastic population control measures are implemented in Indonesia. This clearly proves that population growth is a real threat to the future of Indonesia especially considering the fact that Indonesia is currently experiencing high levels of unemployment and poverty is still rampant. It can be deduced from the forecasts that Indonesia is likely to fulfill the Malthusian population prophecy anytime soon. Kohler et al (2015) maintain that Indonesia’s population will continue to grow for the next few decades but, properly managed, this can create both economic growth and better welfare. In order to overturn the fulfillment of this prophecy, the Indonesia government is expected to implement the above mentioned main policy recommendations. These results are particularity critical for the government of Indonesia, especially when it comes to planning for the future.

REFERENCES


