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Does the Choice of the Time Series Model Affect Stochastic Profit Testing Results?

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This research aims to fill the gap in Stochastic Profit Testing studies. The central research question of this paper is: does the choice of time series model affect the Stochastic Profit Testing (SPT) result? The financial model of this research was built through SPT by using the Monte Carlo method. The target population for the study was any conventional (not sharia) individual Unit Link product from a life insurance company in Indonesia with regular premium payments denominated in Rupiah currency. This research used simple random sampling as part of probability sampling techniques. From the population consisting of 34 companies, 20 samples were drawn. Data were taken from the Indonesian Financial Service Authority (OJK). The data used was from the time period between 1 January 2014 - 30 June 2019. The time series model tested were GARCH, EGARCH, GJRGARCH, TGARCH, APARCH, CGARCH, NAGARCH and ARFIMA-EGARCH. These are the most popular time series model to predict equity return. The equity index data comes from monthly Jakarta Composite Index from 1 April 1983 to 31 December 2019. Based on the results obtained it was found that the choice of time series models did not significantly change the Profit Margin of the product generated by the Stochastic Profit Testing except for the ARFIMA model. Therefore, the company does not have be too worried about the robustness of their SPT model as long as they choose a popular time series to model the equity return.

Key words: *Stochastic Profit Testing, Unit Linked, GARCH models.*

Introduction

Unit lLnked is a life insurance product in which the policyholder pays an annual or monthly premium and it provides a life insurance cover to the policyholder along with investment options. Some of the premium paid goes to secure the cost of insurance of the insured and the rest of the money is invested on the policyholder's behalf in specific mutual funds. These form the policyholder's fund. In this paper, the mutual fund is assumed to be 100% in equity. Regular charges are deducted from the policyholder fund to cover company expenses. On survival to the end of the contract term the benefit is just the policyholder's fund. With death during the term of the policy (usually the whole life), the beneficiary will receive the sum assured and the policyholder's fund.

Unit Linked product is usually designed or priced through Profit Testing (PT) technique. PT is defined in the "Encyclopedia of Actuarial Science" as "the process of assessing the profitability of an insurance contract in advance of it being written". The first paper on profit testing was by Anderson (1959) in the United States, while the first major paper in the United Kingdom was from Smart (1977). In fact, Unit linked is one of the drivers of development of the profit testing technique. D'Arcy and Lee (1989) uses profit testing to determine the optimal premium for Variable Universal Life (Unit Linked) which is maximised after tax return. Dixon (1990) discusses profit testing in relation to developing the Unit Linked product.

The modern development of PT is increasingly done on a simulated stochastic basis which introduced Stochastic Profit Testing (SPT). Valkenburg (1996) discussed the stochastic profit testing model, which incorporates management dynamic decisions. In recent years, D'Agostino (2014) uses SPT to evaluate Unit Linked contracts by means of Monte Carlo Simulation. The SPT is built within the Solvency II EU Directive. Le Courtois uses SPT introduced in Dickson, Hardy, and Waters (2013) to examine variable annuities and found that it is little sensitive to the choice of the investment return models.

Unit Linked products involves uncertainty in investment return on the policyholder fund. If we just use traditional profit testing which is deterministic, it does not reflect the reality of the uncertainty in investment return in most cases. The Profitability of Unit Linked products is modelled more appropriately as a random variable rather than a single deterministic number. This is best modelled by SPT. The most common way to generate stochastic equity return is using Monte Carlo simulation.

Return is strongly correlated to its volatility. In the literature, there are two branches of volatility forecasting. They are time series forecasting and Option Implied Volatilities (Xiao & Aydemir, 2007). Time series methods utilise historical data to forecast future volatility, while Option Implied Volatilities utilise traded option price to estimate volatility (Poon & Granger, 2003). In the time series branches, there are three big classifications: models based on historical volatility, such as Historical Average Method; models based on autoregressive conditional heteroskedasticity (ARCH) type; and Stochastic Volatility (Wei, 2012). Among the three classifications, the ARCH type is the most widely used. Banumathy (2015) also states that time series is the widely used model to forecast stock market volatility. However, to forecast stock market volatility well, having a reliable forecasting model is essential. Past studies fail to arrive at a common conclusion in terms of best suited time series forecasting models for a specific stock market (Adebayo & Sivasamy, 2014; Lim & Sek, 2013; Ladokhin, 2009; Febrian, 2006), which may be due to the variation in their selected data samples and study periods (Wilhelmsson, 2006).

Following the above discussion, this paper will use the time series ARCH/GARCH model to generate stochastic equity return. However, there are some models in the ARCH/GARCH family, which scholars use to forecast the equity return. Among the popular ones are GARCH, EGARCH, GJRGARCH, TARCH, APARCH, CGARCH, and NAGARCH. Since the profitability of SPT depends on the choice of ARCH/GARCH models, and in light of the somewhat inconclusive conclusion from past studies on the best time series model, it is natural to ask whether the choice of ARCH/GARCH models will impact the result.

Research Question*: *Does the Choice of Time Series Model Affect Stochastic Profit Testing Result?

This paper contributes to the literature on stochastic profit testing by exploring the relationship between the ARCH/GARCH model to the profitability of the Unit Linked product. The high sample proportion of the primary data that has been collected and processed for the empirical analysis in this study will provide evidence to answer the research question. Finally, with the increasing recommendation to use SPT from regulators and professional bodies in many countries, this study will help to form proper guidance on the use of specific ARCH/GARCH time series.

The scope of this study is life insurance products in Indonesia. The unit analysis is the Unit Linked product developed by a company. The premium payment is a regular one not a single premium. Denominations is restricted to Rupiah currency. The product samples are from the years 2011 to 2019.

Literature Review

Profit Testing

To determine the premium or charges for Unit Linked product, the actuary uses the expected present value of future profits or net present value (NPV) and the profit margin (PM). The NPV of the future cash-flows until time n is defined as:

$$\mathrm{NPV}(n) = \sum_{t=1}^{n} {}_{t-1}p_x^{00}\,\mathrm{Pr}_t v_r^t$$

Where:

${}_{t-1}p_x^{00}$ is the probability that the insured still holds the policy at the beginning of the t^{th} year - so that he or she did not die, surrender, or exit by means of any other type of decrement.

Pr_t is profit for the t^{th} year which corresponds to the period $(t - 1, t]$.
v_r^t is the discount rate corresponding to an interest rate of i_r per year.

The profit margin (PM) is the ratio of the total NPV by the expected present value of premiums (Dickson, et al., 2013) and is expressed as follows:

$$\mathrm{PM} = \frac{\mathrm{NPV}}{\mathrm{EPV\ [Premiums]}} = \frac{\sum_{t=1}^{n} {}_{t-1}p_x^{00}\,\mathrm{Pr}_t v_r^t}{\sum_{t=0}^{n-1} {}_{t}p_x^{00} P_t v_r^t}$$

Where P_t is the premium paid at time t.

Our discussion about profit testing above is called deterministic profit testing. When working on Unit Linked policies that place importance on investment, an actuarial analysis needs to rely on stochastic profit testing rather than deterministic profit testing. This approach gives a fuller picture of the characteristics of the Unit Linked cash flows than the deterministic approaches do. The stochastic analysis is usually done through Monte Carlo simulations. With Monte Carlo simulations, random samples of equity prices are generated for the policies and then determine a probability distribution of the outcomes for each profit measure.

Stochastic Profit Testing (SPT)

Using deterministic profit testing does not reflect the reality of the situation adequately in most cases. The present value of future profit which is expressed in terms of demographic (non-economic) uncertainty only does not contain any information about the uncertainty from investment returns. The profit measure for a Unit Linked contract is modelled more appropriately as a random variable rather than a single number. This is achieved by stochastic profit testing. The most common practical way to do this is with Monte Carlo simulation.

Using Monte Carlo simulation, a large number of outcomes for the investment return on the policyholder's fund is generated. The simulated returns are used in the projected cash flows instead of the constant investment return assumption as in the deterministic case. The profit test proceeds exactly as described in the deterministic approach. However, instead of running it one time, the test is repeated for each simulated investment return outcome. From each repeated run, we get a random sample of outcomes for the contract, which can be used to determine the probability distribution of the profit measure for the contract (Aase & Sandmann, 1995; Zaglauer & Bauer, 2008; Rita & Persson, 2002; Mahayni & Steuten, 2013).

Time Series Model for SPT

More than a dozen studies about the ARCH/GARCH models used to forecast financial return and volatility have been reviewed. These literatures are from the current year, and researchers were from Indonesia and some peer countries. The results were summarized in Table 1.

Table 1: ARCH/GARCH Model Used by Scholars

Authors	Models Used	Data & Findings
Lim & Sek, 2013	EGARCH, TGARCH	Data: the stock market of Malaysia. GARCH works well in the pre-crisis period and asymmetric GARCH model(s) can be the better model in capturing the volatility of the Malaysian stock market during the crisis and post-crisis periods.
Iltuzer, & Tas, 2013	GARCH, GRJGARCH, APARCH, NAGARCH.	Daily data of 19 emerging stock markets are obtained from Bloomberg databases from 2nd January 1995 to 23th April 2010. NAGARCH is the best model for the 20-day forecast for Argentina and 5-day forecast for KOREA. Different countries have different best suited models.
Gokbulut & Pekkaya, 2014	GARCH, TGARCH, EGARCH, CGARCH and AGARCH.	Data: Turkish financial market. CGARCH and TGARCH appear to be superior for modelling the volatility of financial instruments in Turkey during the years 2002–2014.
Qamruzzaman, 2015	GARCH, EGARCH,	Data: Dhaka Stock Exchange DSE.

	GJR and APARCH	EGARCH, IGARCH, and GJR-GARCH model are the best suited for capturing DSE return volatility.
Omar, & Halim, 2015	GARCH, EGARCH, TGARCH	Data: Daily index return of FBM KLCI (Malaysia) from January 2002 to December 2011. EGARCH model has outperformed the other class of GARCH model and has the best ability in forecasting the volatility.
Yunita, 2015	GARCH (p,q)	Data: LQ45 (Indonesia), HSI (Hongkong), KLSE (Malaysia), and STI (Singapore). Best GARCH model to determine the volatility of LQ45, STI, and HSI is GARCH (1.1) whereas for KLSE is GARCH (3.0).
Triady et al., 2016	GARCH and EGARCH	Data: Jakarta Composite Index (JCI) daily returns from 2001-2012. EGARCH (1,1) model is the best fitting and also best forecasting performance.
Suradi et al., 2016	TGARCH and EGARCH	Data: Closing price JCI from 3 January 2011 until 22 December 2014. TGARCH model is better than EGARCH in predicting JCI.
Lee et al., 2017	EWMA, ARIMA, GARCH	Data: Closing stock index prices from 1st January 1998 to 31st December 2015 from Indonesia, Malaysia, Japan and Hong Kong. GARCH (1, 1) model is found to be the best forecasting model for stock markets in Malaysia, Indonesia, and Japan.
Virginia et al., 2018	GARCH (1,1)	Data: Share price of Adaro energy Tbk, Indonesia, from January 2014 to December 2016. The best model which fits the data is identified as AR(1)-GARCH (1,1).
Chancharat et al., 2018	GARCH (1,1) and EGARCH (1,1)	Data: daily SET (Thailand) data from the 1st January 1992 until 31st December 2016. Using AIC and SIC, it appeared that EGARCH(1,1) is more appropriate than GARCH(1,1).
Sari et al., 2018	GARCH and asymmetric GARCH	Data: Jakarta Stock Exchange Composite Index (JCI), Singapore Strait Times Index (STI), Japan Nikkei 225 Index (NKY) and Hongkong Hang Seng Index (HSI). Asymmetric GARCH is a better estimation for predicting stock return volatility. JCI and HSI are best modelled by APARCH whereas NKY and STI are by TGARCH.

Raneo, & Muthiab, 2018	GARCH (1,1), TARCH (1,1) & EGARCH (1,1)	Data: Indonesia Composite Index from January 2006 – November 2017. EGARCH is slightly better in predicting volatility clustering than GARCH and TARCH.
Widhiarti et al., 2018	GJR-GARCH	Data: Closing prices of IHSG, Bank Indonesia Certificates (SBI), and Business Tendency Index (ITB) from Jan 2011 to Dec 2015. The best GJR-GARCH model in the selected IHSG is the GJRGARCH (1,1) model.
Awalludin et al., 2018	GARCH (1,1)	Data: daily returns of stock prices of Indonesia from July 2007 to September 2015. GARCH (1,1) indicates evidence of volatility clustering in the returns of some Indonesia stock prices.
Nguyen C. & Nguyen M., 2019	GARCH, GARCH-M, EGARCH, TGARCH.	Data: Ho Chi Minh Stock Exchange daily closed price during 1/03/2001–1/03/2019. GARCH (1,1) and EGARCH (1,1) models are the most suitable models to measure both symmetry and asymmetry volatility level of VN-Index.
Singagerda et al., 2019	Multifractal Model of Asset Return (MMAR), GARCH, and EGARCH	Data: ASEAN Market. MMAR is the best model. However, they also document that for the Philippines and Indonesia, the alternative suitable models are GARCH and EGARCH, respectively.
Fakhriyana et al., 2019	ARFIMA-EGARCH (1,1)	Data: Daily Jakarta Composite Index from August 2007 to August 2018. Based on the RMSE value, the best model for forecasting JCI is the ARFIMA-EGARCH model.
Emenogu et al., 2020	GARCH, EGARCH, NAGARCH, IGARCH, TGARCH, etc.	Data: Daily stock returns for Total Nigeria Plc. The results of the estimations indicate that the persistence of the GARCH models are stable except for a few cases in which IGARCH and EGARCH were unstable.
Anggita et al., 2020	ARCH, GARCH, TGARCH, EGARCH	Data: Indonesia stock price index for period 2011-2017. The best volatility model in predicting stock price is the EGARCH (1,1) model.

From the table above, GARCH (1,1) and EGARCH (1,1) appear to be the most popular. However, there are other models that are best also in predicting stock price and volatility. They are: CGARCH, TGARCH, GJRGARCH, APARCH, NAGARCH and ARFIMA-EGARCH. This study will use all the ARCH/GARCH family to test the impact on the profitability for the Unit Linked products.

Data and Methodology

Data

The target population for the study was the life insurance company Unit Linked product in Indonesia. The specific target population for the study was any conventional (not sharia) Unit Linked product from life insurance companies with regular premium payments and are denominated in Rupiah currency. The study design used simple random sampling of the probability sampling technique. There are 34 life insurance companies which sell conventional Unit Linked product as of 31 December 2018. A sample of 20 products is selected. Each product represents one life insurance company. Since the authors were interested in investigating the company pricing policy, so one product for each company should be able to represent the policy.

The data comes from the Indonesia Financial Service Authority (OJK). To maintain confidentiality, the data was presented anonymously. Consent had been given to OJK that the data was used for research purpose only. The data collected was product reported to OJK between the period of 1 January 2015 – 31 October 2019.

Data from the monthly Jakarta Composite Index from 1 April 1983 to 31 December 2019 was used as a basis to simulate future returns. Eight ARCH/GARCH time series models were used to generate the future returns.

Methodology

The methodology of this paper used financial modelling. The financial model follows the SPT method developed by Dickson, Hardy and Waters (2013). Monte Carlo method will be used for the stochastic modelling. To improve the validity of the EXCEL model, PROPHET, which is a leading enterprise-wide actuarial modelling system, and was developed by FISTM, the world's largest global provider dedicated to banking and payments technologies, will be used as a checker. However, PROPHET validation is up to the deterministic model.

Profitability of a product is measured by Profit Margin (PM), which is the NPV of Profit Before Tax divided by NPV of Premiums. This study does not include tax in this projection since each company has a different tax situation. Therefore, it is difficult to compare profitability after tax between companies. Different tax situations happen because some companies are still in a loss position; and some sell a combination of non-UL products which have a different taxation rule. By using PM, the effect of premium amount in the calculation is eliminated since it is presented in percentage. Future investment (equity) return on a policyholder's fund is simulated using the time series model.

Modelling ARCH/GARCH family

The literature on the GARCH-family models is extensive. However, for compactness, we restrict our investigation to the eight more popular models based on the literature review, namely, GARCH (Bollerslev, 1986), EGARCH (Nelson, 1991), GJR-GARCH (Glosten et al., 1993), TGARCH (Zakoian, 1994), APARCH (Ding et al., 1993), NAGARCH (Engle and Ng, 1993), CGARCH (Engle and Lee, 1993) and ARFIMA-EGARCH (Granger and Joyeux, 1980). In our analysis, the value of p and q for the lag length parameters were only estimated for (p, q) = (1, 1).

For each of the above GARCH models, ARMA (0,0) was modelled for the mean return. For each of the above models, the monthly return and value of JCI was simulated for the next 240 months. The number of trials per simulation model was 5000. For each of the models, coefficients in the model equation were estimated using the function ugarchfit() in R. Future returns of JCI were simulated using the function ugarchsim().

Empirical Results and Discussions

The fitted models for various volatility models are shown in the following:

1. GARCH (1,1)

$$r_t = 0.006863 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t^2 = 0.0000017 + 0.037194\varepsilon_{t-1}^2 + 0.942017\sigma_{t-1}^2$$

Here, σ_t^2 is the variance for the day t. ε_t is the innovation for the day t.

2. EGARCH (1,1)

$$r_t = 0.008453 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\ln(\sigma_t^2) = -1.598895 + 0.747369 \ln(\sigma_{t-1}^2) + 0.413847(|z_{t-1}| - \mathbb{E}|z_{t-1}|) + 0.107884\, z_{t-1}$$

Where $\mathbb{E}|z_t|$ denotes the expected value of the absolute standard innovation, z_t, and is given by

$$\mathbb{E}|z_t| = \int_{-\infty}^{\infty} |z_t|\, f(z, 0, 1, \dots)\, dz$$

3. GJR-GARCH (1,1)

$$r_t = 0.009186 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t^2 = 0.000021 + 0.013285\varepsilon_{t-1}^2 + 1.000000\sigma_{t-1}^2 - 0.063944 I_{t-1}\varepsilon_{t-1}^2$$

Where

$$I_{t-1} = \begin{cases} 1 if\, \varepsilon_{t-1} \leq 0 \\ 0 if\, \varepsilon_{t-1} > 0 \end{cases}$$

Some of the trials in the simulation using GJR-GARCH (1,1) model gives negative volatility. This is because some of the coefficients in the model is negative. For this reason, it is concluded that GJR-GARCH is not a suitable model in this case and is excluded in the analysis.

4. TGARCH (1,1)

$$r_t = 0.008784 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t = 0.014285 + 0.253922\, \sigma_{t-1}(|z_{t-1}| + 0.144949 z_{t-1}) + 0.472703\sigma_{t-1}$$

5. APARCH (1,1)

$$r_t = 0.006918 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t^{3.486} = 0.000954(|\varepsilon_{t-1}| + 0.526784\varepsilon_{t-1})^{3.486} + 0.963780\sigma_{t-1}^{3.486}$$

6. NAGARCH (1,1)

$$r_t = 0.008239 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t^2 = 0.000020 + 0.008404\sigma_{t-1}^2(|z_{t-1}| + 2.656557)^2 + 0.907323\sigma_{t-1}^2$$

7. CGARCH (1,1)

$$r_t = 0.007289 + a_t, \quad a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\sigma_t^2 = q_t + 0.184968(\varepsilon_{t-1}^2 - q_{t-1}) + 0.522740(\sigma_{t-1}^2 - q_{t-1})$$

$$q_t = 0.999999 q_{t-1} + 0.066554(\varepsilon_{t-1}^2 - \sigma_{t-1}^2)$$

8. ARFIMA-EGARCH (1,1)

$$(1-0.08066B)(1-B)^{0.12019} r_t = 0.10911 + (1-0.04586B)a_t, \; a_t \sim i.i.d.\ N(0, \sigma_t^2)$$

$$\ln(\sigma_t^2) = 0.19870 + 0.19224 \ln(\sigma_{t-1}^2) + 0.06528(|z_{t-1}| - \mathbb{E}|z_{t-1}|) + 0.03201\, z_{t-1}$$

Where the differencing process of d with the backshift operator of B can be written as follows: $Z_t^d = (1 - B)^d Z_t$.

Table 2 compares the mean PM from SPT of the various GARCH models. It also provides the PM under DPT for comparison.

Table 2: PM under DPT and SPT using various GARCH

Product	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2	23.45%	11.68%	23.13%	23.49%	23.45%	23.13%	23.35%	23.22%	24.83%
3	8.65%	6.00%	10.29%	11.96%	12.26%	10.27%	11.27%	10.70%	21.69%
4	15.12%	10.88%	14.41%	15.59%	15.80%	14.40%	15.13%	14.70%	20.78%
5	13.31%	16.10%	9.45%	10.95%	11.22%	9.43%	10.35%	9.82%	20.64%
6	9.30%	11.00%	9.04%	9.36%	9.42%	9.04%	9.24%	9.12%	10.85%
7	21.18%	7.02%	21.40%	21.75%	21.82%	21.40%	21.62%	21.48%	23.12%
8	11.49%	11.00%	10.65%	11.96%	12.18%	10.64%	11.44%	10.97%	19.37%
11	20.06%	11.00%	19.14%	21.43%	21.84%	19.11%	20.52%	19.70%	36.45%
13	11.03%	11.00%	10.23%	11.35%	11.56%	11.82%	10.96%	10.52%	17.30%
14	18.73%	10.00%	18.60%	18.98%	19.06%	18.59%	18.84%	18.69%	20.48%
15	14.64%	11.00%	14.04%	14.96%	15.14%	14.03%	14.60%	14.26%	17.53%
16	13.10%	11.50%	12.77%	13.17%	13.24%	12.77%	13.02%	12.87%	14.70%
18	16.73%	11.16%	15.73%	17.17%	17.42%	17.64%	16.60%	16.08%	25.55%
19	7.01%	11.00%	5.71%	7.74%	8.12%	5.69%	6.93%	6.20%	19.41%
23	16.65%	11.00%	16.10%	16.09%	17.11%	16.09%	16.62%	16.31%	21.43%
24	5.31%	11.00%	5.01%	5.46%	5.55%	5.01%	5.29%	4.79%	7.21%
25	14.98%	11.00%	14.49%	15.25%	15.39%	14.48%	14.95%	14.67%	19.10%
26	13.14%	11.00%	12.56%	13.45%	13.62%	12.55%	13.11%	12.77%	17.73%
27	12.44%	8.14%	13.05%	14.98%	15.24%	13.03%	14.22%	13.47%	26.84%
28	13.92%	11.00%	13.61%	14.10%	14.18%	13.60%	13.91%	13.73%	15.94%
Average	14.01%	10.67%	13.47%	14.46%	14.68%	13.64%	14.10%	13.70%	20.05%
Ratio to DPT			96%	103%	105%	97%	101%	98%	143%

(1) = Deterministic Profit Testing (DPT) - Profit Margin
(2) = DPT - Fixed Future Growth
(3) = Stochastic Profit Testing (SPT) - GARCH
(4) = SPT - EGARCH
(5) = SPT - TGARCH
(6) = SPT - APARCH
(7) = SPT - NAGARCH
(8) = SPT - CGARCH
(9) = SPT - ARFIMA - EGARCH

Generally, the SPT results under various GARCH models except the ARFIMA did not vary significantly from DPT. The difference ranges from -4% to 5%, therefore it was not too significant. If DPT fixed future growth is about 11%, the results are broadly the same as SPT except for ARFIMA. If the fixed future growth is below 11%, the DPT results are lower than SPT (excluding ARFIMA) and vice versa. ARFIMA model produces quite different results compared to DPT (43%) and other GARCH models. Despite this, it is recommended by Fakhriyana et al., 2019 as the best fitted model for JCI. Therefore, the authors will not include it for further discussions.

GARCH generally produces close results to DPT (-4%) despite being on the lower side. GARCH produces a significant different result for product #19 (-19%), despite this product using fixed growth at 11%. On the other hand, it produces a close result to DPT for product #7 (1%) despite this product using 7.02% fixed growth. On average, GARCH produces the lowest result compared to other models. The GARCH result was close to APARCH (-1%) and CGARCH (-2%) and was quite low compared to TGARCH (-8%) and EGARCH (-7%).

EGARCH generally produces close results to DPT (3%) despite being on the higher side. EGARCH also produces quite different results for product #19 (10%). On average, EGARCH produces higher results than other models except to TGARCH. EGARCH was lower than TGARCH (-2%) and higher than other models.

TGARCH results are 5% higher than DPT. The result for product #19 (16%) was also quite different. On average, TGARCH produces the highest results compared to other models. It was 8% higher than APARCH and 7% higher than CGARCH.

APARCH results are 3% lower than DPT. The result for product #19 (-19%) was also quite different. On average, APARCH produces lower results than NAGARCH (-3%) and very close results to CGARCH.

NAGARCH produces the closes result to DPT (1%). NAGARCH also produces a close result (-1%) for product #19. NAGARCH produces 3% higher result than CGARCH.
The generally close result between SPT and DPT provides an incentive to use SPT in pricing instead of DPT. With the DPT, there is a challenge regarding how one chooses a specific deterministic (fixed growth) return, especially if it expands for several years in the future. With the SPT, one could use forecasting from the GARCH model which has undergone extensive research for its credibility.

Conclusion

This study compares the time series models with seven advanced GARCH models, namely, the EGARCH, TGARCH, APARCH, NAGARCH, CGARCH and ARFIMA-EGARCH models. Using a sample of 20 Unit Linked products, each representing one life insurance company in Indonesia; it is found that the choice of time series model does not affect the result of Profit Margin significantly except for ARFIMA-EGARCH. If we compared the SPT to DPT, the variance ranges from -4% to 5%.

Econometric models are still widely used as an Economic Scenario Generator (ESG) to model equity return (Sciety of Actuaries, 2016; Jakhria et al., 2018). This finding has significant practical implications for actuaries who need to project equity return to price Unit Linked product properly or other actuarial works.

As scholars have found that in certain situations and conditions, some variants of GARCH models are more suitable than the others. This study will help actuaries to be more certain that their SPT results will not deviate significantly.

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