International Journal of
Financial Studies

MDPI

Article

Back to the Future Betas: Empirical Asset Pricing of US and Southeast Asian Markets

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Academic Editor: Nicholas Apergis
Received: 7 October 2015; Accepted: 12 July 2016; Published: 20 July 2016

Abstract: The study adds an empirical outlook on the predicting power of using data from the future to predict future returns. The crux of the traditional Capital Asset Pricing Model (CAPM) methodology is using historical data in the calculation of the beta coefficient. This study instead uses a battery of Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) models, of differing lag and parameter terms, to forecast the variance of the market used in the denominator of the beta formula. The covariance of the portfolio and market returns are assumed to remain constant in the time-varying beta calculations. The data spans from 3 January 2005 to 29 December 2014. One ten-year, two five-year, and three three-year sample periods were used, for robustness, with ten different portfolios. Out of sample forecasts, mean absolute error (MAE) and mean squared forecast error (MSE) were used to compare the forecasting ability of the ex-ante GARCH models, Artificial Neural Network, and the standard market ex-post model. Find that the time-varying MGARCH and SGARCH beta performed better with out-of-sample testing than the other ex-ante models. Although the simplest approach, constant ex-post beta, performed as well or better within this empirical study.

Keywords: CAPM; empirical; GARCH; ex-ante beta; artificial neural network; time-varying beta

JEL: B23; C22; C52; C53; G12; G15

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1. Introduction

The Capital Asset Pricing Model (CAPM) gained notoriety due to William Sharpe's published work in 1964. Since then many applied tests supported the CAPM, including research by Black, Jensen, and Scholes (1972) [1] in which their research found a positive relationship between returns and betas. The drawback discovery they found was that the current model suffered from a flat security market line (SML). Since then papers have increased that find evidence against the original model. Fama and Macbeth (1973) [2] results show that there is a relationship between beta and returns, though the beta is not constant from one five-year period to the next. Testing the CAPM poses challenges to researchers in application of the theory.

First, the CAPM makes predictions about the expected return of an asset, an essentially unobservable variable. There is no database storing the returns the investors expect when they trade securities. Therefore, it must be assumed that investors have rational expectations. This means that though investors may make mistakes periodically, in large samples their nonsystematic errors are reduced and they become correct on average. Thus, realized historical returns can be used as a proxy for expected returns.

Second challenge is due to the fact that CAPM is a one-period ahead model, with duration of the period unknown. It does not address how investor expectations may change from period to period. In addition, the beta is treated as a constant though in actuality it changes over time as firms evolve, alter capital structures and investments, and/or change management.

Although the aforementioned challenges exist, the CAPM has no equal in calculating the cost of equity and asset prices, Graham and Harvey (2001) [3] found that 75%, of the 392 US CFOs interviewed almost always or always use the CAPM. This is up from only 30% in the 1980s. Currently in developing markets, such as Brazil, it is closer to 30% of the CFOs utilize CAPM to determine the market required return on their stock. With the CAPM widespread use on the rise, this research seeks to uncover the most accessible and accurate way to estimate beta between the ex-ante and ex-post methods. This study estimates beta within the US and ASEAN community within the recent 10-year period (2005 to 2014).

The capital asset pricing model (CAPM) allows analysts the ability to obtain discount factors, cost of capital, managing risk, portfolio management measurement, event study analysis, and used as the benchmark in testing of asset pricing theories. The CAPM beta coefficients can also be used to measure the amount of risk relative to the market and in linear form the R^2 from the regression model can be used to estimate the amount of systematic risk. The beta is thus a factor that explains the returns of assets. Another important function the beta serves is as an indicator for corporate managers to judge how the market views the riskiness of potential projects to make capital management decisions. Investors are able to indirectly respond to management by the selling if they dislike and buying when they approve of management's choices, in aggregate. Board of directors and managers then try to maximize shareholder wealth by making decisions based on the net present value of an endeavor. The key input to that process other than the cash flows is the required return, which depends on the individual project and the risk that goes with it. Managers must understand how investors assess that risk and what risk premium they demand. Surmising the required return and net present value for every possible project under consideration requires a vast amount of resources and time. The CAPM remains a simple and straightforward approach to deduce this required return, also referred to as cost of capital, and use historical data to capture investors' behavior toward required returns and their betas.

The ex-ante approach attempts to use future values of variance, rather than historical; to get better time-varying beta estimates to calculate expected returns more accurately. Pricing models and VaR measures often require forecasts for weeks or even months into the future. Less is known about this long-term forecast window and this study seeks to fill this gap with empirical data across a wide variety of markets, in-sample lengths, and four different ex-ante beta models (SGARCH, EGARCH, MGARCH, and ANN). GARCH models are the most applied in practice with the two most popular being the MGARCH and EGARCH. While not as commonly used the ex-ante ANN model is also examined to compare how well this machine learning model performs with the CAPM. The results in this study extend those of Reeves and Wu (2010) [4] who found that, in long-term forecasting, the constant beta model outperforms forecasts of time-varying AR beta models, and "dominates" the Fama-Macbeth model. Their research used individual stocks in the US, UK, and Australia.

This paper is structured as follows: Section 2 provides an overview of the data before discussing the methodology for time-varying GARCH and Artificial Neural Network models, as well as constant beta models. Section 3 reveals the main results. Section 4 finally draws the main conclusions.

2. Data and Methodology

The capital asset pricing model (CAPM) defines the relationship between risk and return.

$$E\left(R_i\right) = R_f + \beta_i \left(R_m - R_f\right) \quad (1)$$

In Equation (1), $E(R_i)$ is the expected return investors require for asset i, R_f is the risk-free rate of return and R_m is the market portfolio return, both using the rolling period returns in the ex-ante forecasts.

Historical betas, Equation (2), are estimated from the stock's characteristic line by running a linear regression between past returns on the stock and past returns on some market index, ex-post data.

$$\frac{Cov\left(R_i, R_m\right)}{Var\left(R_m\right)} \quad (2)$$

In the SGARCH and EGARCH approach the covariance, in Equation (2), is assumed to remain constant and the models forecast future value of volatility to be used for the market variance. Given differing values from the forecast allows for a time-varying ex-ante beta. This study also models the multivariate-GARCH to forecast the covariance-variance in the beta. A theoretical limitation exists within the MGARCH model, in that in order to correctly use a consistent and valid covariance matrix it must be positive-definite (non-singular). The data presented in this study uses portfolios (one variable) with 10 years of weekly observations, it is not singular. The covariance is always positive-semidefinite because it is Gramian, see Hull (2012) [5] for the proof. Nonetheless, the MGARCH model is widely applied in forecasting asset prices. The most widely used model of conditional covariance and correlations in financial management is the dynamic conditional correlation (DCC) as used by Caporin and McAleer (2011) [6] with portfolio analysis. In support of the use for the SGARCH and EGARCH models it is assumed that the relationship between the portfolio and market returns remain unchanging during the short, five week, forecast period. For applications with a constant relationship see Gibbons and Ferson (1985) [7] and Ferson, Kandel, and Stambaugh (1987) [8]. They have examined the conditional CAPM by allowing time variation in expected returns, but assuming the covariance of asset returns to be constant over time, as is done in this study.

In research by Ederington and Guan (2010) [9], they analyze how to improve long-term volatility forecasts. One suggestion is the use of a varying weight for beta in GARCH for long-term 10 to 20 day forecasts. For the index fund used in their report, there was no statistical significance between using and not using a varying weight beta parameter at the two horizons for both the EGARCH and SGARCH models. In the case of the SGARCH model at the 10-day forecast, using the varying parameter actually had a negative effect. Due to their results, for the purpose of this study and simplicity in implementation, the varying weight in their study is not used. Instead to account for the importance older observations play as the forecast horizon increase, weekly returns are used. Volatility has a mean reversion tendency, which can lead to serious estimation error in longer period forecasts, as GARCH has a short memory and the $t + 1$ is often assumed to continue through to the end. The weights on current volatility relative to weights on volatility three months ago receive the same weighting in forecasting volatility a month into the future as it does for tomorrow. To avoid this problem weekly data is used to forecast out one month. This increases the weights on older observations to better match the forecast horizon $t + 1$ as suggested by Ederington and Guan (2010) [9].

2.1. Data

Empirically, this market portfolio has a proxy used in its place, most commonly the S&P500. The beta and market premium calculations use this proxy, so when researchers accept or reject the predictions it is unclear if it is due to their proxies used or the CAPM. In this study, each ASEAN country uses their market index exchange to represent the market return possible. Each country only has the one stock exchange market for publicly traded capital, each exchange is all inclusive of all securities available and thus is the most accurate proxy for the market return. For the five US sectors, which are traded on a variety of US exchanges, the Wilshire 5000 index is used to represent the market return. The Wilshire 5000 index is easy to obtain and includes over 3000 more companies than the S&P500. All of which are headquartered in the US (Over-The-Counter, penny, American Depositary Receipts, Limited partnerships, and stocks of extremely small companies are excluded). The index currently includes over 22 trillion dollars of US capital, about three trillion more than the S&P500.

Another problem confronting empirical studies is the risk-free rate. Naturally it is known that no investment is truly risk free and that the proxies for such an asset vary over time. This is a 10-year sample study and it is assumed that the investors will be a buy-and-holder and invest for a period of 10 years; hence the weekly returns of the 10-year US Treasury bond is then used in all calculations when a risk-free rate is required. At times the return is negative, with there being no true risk-free asset case in point, thus lowering the average rate.

The five countries that are in the ASEAN trade bloc with at least 50 publicly listed corporations with historical prices back to 2005 have been selected to represent ASEAN. They include Indonesia, Malaysia, Philippines, Singapore, and Thailand. The other exchanges of ASEAN member states were not included because their exchanges lacked enough publicly traded companies or were too young and did not span back to 2005. In addition to the five Southeast Asian portfolios, five sectors have been selected to represent the US market. Each ASEAN country and each US sector has a random sample of 50 individual stocks for a total of 250 stocks for ASEAN and 250 stocks for the US, 500 total.

Weekly adjusted closing prices are used for the 500 stocks, 6 indexes and the US 10-year Treasury bond in this research. The stocks were randomly selected by taking the total list in random order and dividing by 50, then selecting every *i*th company on the list. The list excludes those companies that were recently listed and historical pricing did not span back far enough. The complete list of securities used by each portfolio, graphs modeling the market (R_m) volatilities, and graphs of portfolio returns with ANN forecasts are available in the supplementary materials. The data consists of the weekly adjusted close and percent changes from 3 January 2005 to 29 December 2014. Weekly data is used, instead of daily or monthly, as it is the best measure. The value of an asset remains unknown until a sale is made. Over one-third of US companies listed on exchanges are not traded daily. The ASEAN markets being far less liquid, therefore giving an inappropriate amount of zero percent returns and skewing the results if daily data is used. On the other extreme is monthly data, which is also not used, as it provides too few data points for the results to be meaningful (only 120 observations per index) and would smooth out the volatility in the price changes too much for the GARCH models to be effective.

Each of the ten replicating portfolios have the 50 randomly selected stocks. The most obvious and accurate way would be to use several industry and country specific stock indexes. However, due to lack of information, portfolios were created from 50 randomly selected stocks. This approach is justified by the fact that companies within a sector share characteristics such as business cycles, tariffs, country risk, technological development, and raw material availability. This method is also commonly performed in CAPM studies and also benefits from the law of large numbers. The average correlation between the 10 portfolio returns and its market index returns is 0.85, indicating well diversified portfolios. Portfolios rather than individual stocks are used as test assets to overcome the errors-in-variables, data snooping and information loss issues. The former problem is due to the sensitivities to risk factors specified by the asset pricing models which are estimated from data that contains sampling errors. Since factor sensitivities for portfolios are estimated more precisely than for individual stocks, the factor risk premium estimates will be less biased due to errors-in-variables problems if one uses portfolios and not individual stocks.

2.2. Ex-Ante GARCH Beta and Artificial Neural Network

Stock returns are constantly changing all over the world for a variety of reasons, but a constant across all markets is the negative correlation between stock returns and volatility. The implications of this negative correlation means that shocks that are negative will have a greater impact on price than positive shocks to the market.

The use of historical returns to calculate the future is of concern for many random walk practitioners. Many seek to use future, not historical, data to calculate the future returns. The variances of asset prices are not constant, but are known to change quite considerably through time. Empirical data also may include volatility clustering and outliers in the unconditional distribution. This next section looks at forecasting future returns of the market index and calculating beta based on the forecasted market variance and assumes that the covariance between the portfolios and their market indexes remain constant. The financial data used has heavy tails and a student-*t* distribution was used in the modeling as it improved results. The data was checked for stationarity before any other steps are performed, using four different tests for increased confidence (PP, ADF, KPSS, and ZA).

Various combinations of GARCH models are estimated using different lagged terms in the mean and variance equations. Six different classes of GARCH models were estimated and the best performing model from three different classes (SGARCH, EGARCH, & MGARCH) are presented in the results. First the need was to identify a mean equation by testing for serial dependence. Then used the residuals with Engle's ARCH effects Lagrange-multiplier test and the squared residuals to test for ARCH effects with a Lung-Box test. Both tests indicated strong presence of ARCH effects. Lastly the appropriate model was chosen from information criteria (e.g., AIC, SIC, LB Q-stat. of estimated residuals), likelihood function, and performing in-sample backtests for comparison and then judging forecasts based on errors and out of sample tests from actual data. Best practices when using GARCH models is that one month is considered a long-run forecast and in application GARCH models are not used to forecast a quarter or more into the future. To state again, the out-of-sample used are the last five weeks of 2014.

The data were also subsampled into three- three year samples and two- five year samples and the models were compared again to make sure the results hold within the subsample periods and were not subject to data structural breaks. The three-year interval is of importance because the average career span of a CEO is approximately this length of time. Opponents of CAPM suggest that when management changes so does the risk, thus this three-year period is also examined with the different models. In addition, if there are any forms of structural break (Great Recession), the effect would be encapsulated within the smaller subsamples. The five-year sample period is a frequently used length of time in the pivotal CAPM studies and is thus used as the second interval period.

For the SGARCH and EGARCH models the market variances are forecasted five steps ahead then plugged into the beta formula assuming that the covariance between portfolio and market remains constant. The MGARCH (DCC) allows for the forecast of both the covariance, between the portfolio and market returns, and the variance of the market returns. For the MGARCH both the numerator and denominator, in Equation (2), are time-varying. When the statistical software automatically chooses the parameters for the GARCH models it gives fairly low alpha1 and beta1 model parameters. Because only 515 periods are used for each model fitting, the alpha1 and beta1 parameters are unreliable from the software. Through trial and error the research found that using the fixed parameters of alpha1 = 0.01, which determines the size of the instability, and beta1 = 0.87, which determines how quickly the instability dies away; the predictions are more accurate than the computer selected models. Though the information criteria is better with lower parameters, the improved forecast errors trump the automatically selected parameters and for this study the GARCH models are given the same fixed alpha1 and beta1 parameters for consistency.

2.2.1. Standard (S-GARCH)

Because the data is fewer than 1000 observations for each portfolio, the estimation is unlikely to give real information about the parameters in the model specification. The research has tested a variety of alternating parameters, but only the best model is in the results.

Bollerslev (1986) [10] proposes a useful extension, of Engle's (1982) [11] work in creating a non-linear relation to current volatility with past innovations, known as the generalized ARCH (GARCH) model. For a log return series r_t, let $a_t = r_t - \mu_t$ be the innovation at time t. Then a_t follows a GARCH (m, s) model if

$$a_t = \sigma_t \epsilon_t, \qquad \sigma_t^2 = a_0 + \sum_{i=1}^{m} a_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \tag{3}$$

where again $\{\epsilon_t\}$ is a sequence of iid random variables with mean 0 and variance 1.0, $\alpha_0 > 0$, $\alpha_i \geqslant 0$, $\beta_j \geqslant 0$, and $\sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1$. Here it is understood that $\alpha_i = 0$ for $i > m$ and $\beta_j = 0$ for $j > s$. The latter constraint on $\alpha_i + \beta_i$ implies that the unconditional variance of a_t is finite, whereas its conditional variance σ_t^2 evolves over time. Term ϵ_t follows a standardized Student-*t* distribution which is indictive of the fatter tail financial returns data.

Three strengths of using a GARCH model over the cross-sectional model can easily been seen from Equation (3). First, a large a_{t-i}^2 or σ_{t-j}^2 gives rise to a large σ_t^2. This means that a large a_{t-i}^2 tends to be followed by another large a_t^2, generating the eminent behavior of volatility clustering in financial time series.

The tail distribution of a GARCH process has heavier tails than normal distributions, fitting of stock return data. Lastly, the model can describe the volatility evolution with the provided simple parametric function. The forecasted volatility from Equations (3) and (4) become the denominators of Equation (2); which in turn, allows for the time-varying ex-ante beta in Equation (1).

2.2.2. Exponential (E-GARCH)

To overcome some weaknesses of the S-GARCH model in handling financial time series, Nelson (1991) [12] proposes the exponential GARCH (E-GARCH) model. To allow for asymmetric effects between positive and negative asset returns, he considered the weighted improvement

$$g\left(\epsilon_t\right) = \theta\epsilon_t + \gamma\left[\left|\epsilon_t\right| - E\left(\left|\epsilon_t\right|\right)\right], \tag{4}$$

where θ and γ are real constants. Both ϵ_t and $|\epsilon_t| - E(|\epsilon_t|)$ are zero-mean iid sequences with continuous distributions. Therefore, $E[g(\epsilon_t)] = 0$.

An EGARCH (m, s) model can be written as

$$a_t = \sigma_t\epsilon_t, \qquad \ln\left(\sigma_t^2\right) = a_0 + \frac{1 + \beta_1 B + \ldots + \beta_{s-1}B^{s-1}}{1 - a_1 B - \ldots - a_m B^m} g\left(\epsilon_t - 1\right), \tag{5}$$

The unconditional mean of $\ln(\sigma_t^2)$ is α_0 which is the same as with S-GARCH, but the model does differ from S-GARCH in several ways. First, it uses logged conditional variance to diminish the somewhat positive constraint of model coefficients. In addition, the use of $g(\epsilon_t)$ enables the model to respond asymmetrically to positive and negative lagged values of a_t. In addition the E-GARCH model allows the conditional variance to evolve in a non-linear fashion depending on the sign of $a_t - 1$. The EGARCH model has a memory that is longer than the SGARCH and the relative impact on past returns on the forecast does not depend on the horizon. Cao and Tsay (1992) [13] also recommend the use of the EGARCH model, over other volatility models, to obtain multi-step ahead forecasts of financial time series data. See Nelson (1991) [12] for additional properties of the EGARCH model.

2.2.3. Multivariate GARCH (M-GARCH)

The multivariate GARCH model, unlike the other GARCH models, allows investors to forecast the covariance of multiple assets. Most would not argue that assets change correlations with each other over time. Whether this aspect is significant in long-run forecasting will be tested in this study. The dynamic conditional correlation (DCC) method was used and it is the most popular MGARCH method and was found by Engle (2002) [14] to have superior forecast performance empirically over other MGARCH methods.

A 2-step method based on the likelihood function is used with the first step estimates the same model specifications and fixed parameters as the SGARCH model. The second step estimates the correlation. The model is the same model proposed by Engle (2002) [14] and is an extension of Bollerslev's (1990) [15] constant conditional correlation estimator (6) except that the R is time-varying.

$$\mathrm{H_t} = \mathrm{D_t R D_t}, \tag{6}$$

where $\mathrm{D_t} = \mathrm{diag}\{\mathrm{sqrt}(\mathrm{h_{i,t}})\}$ and, R is a time-varying correlation matrix containing the conditional correlations.

2.2.4. Artificial Neural Network (ANN)

Artificial neural networks (ANN) are non-linear, regime-switching forecasting models that are founded on mathematical models of the brain. One advantage of ANN models is that they capture nonlinearities in the system without human intervention, which negates data snooping. They allow complex nonlinear relationships between the forecasted variable and its predictors by creating an intermediate layer containing hidden neurons. The outputs of nodes in one layer become inputs to the next layer. The inputs to each node are combined using a weighted linear combination. The result is then modified by a nonlinear function before being output. The ANN model allows only the intercept to be time-varying and the autoregressive coefficient remains constant. It uses n different logistic functions (nodes). Kuan and White (1994) [16] proved that when using a large n, the model can estimate any first-order model very well. Making it useful for nonlinear relationships with an unknown functional form. Although too many nodes and the model will be over-fit with the noise of the data, thus the value of n is selected using the parsimonious Schwarz's Bayesian Criterion (SBC). Schoeneburg (1990) [17] showed that ANN models with financial data may be applied to short term predictions. Kuan and Liu (1995) [18] used a feed-forward ANN model as is used in this study in forecasting financial time series data. Olson and Mossman (2003) [19] found that ANN networks performed better forecasts with Canadian stock returns than logistic and ordinary least squares (OLS) regression. Lastly, Ghiassi, Saidane, and Zimbra(2005) [20] found that the ANN was more accurate in forecasting time series data than autoregressive integrated moving average (ARIMA) models.

Let the hidden neuron be j, n the sample size, x_i is the value of the ith input node, and b_1, b_2, b_3 and the weights $w_{1,1}, \ldots, w_{1,3}$ are learned from the data then,

$$z_j = b_j + \sum_{i=1}^{n} w_{ij} x_i \tag{7}$$

In the hidden layer, this is then modified using a nonlinear function to give the input for the next layer. This tends to reduce the effect of extreme input values, thus making the network somewhat robust to outliers.

$$s(z) = \frac{1}{1 + e - z} \tag{8}$$

There exists a wide body of literature that conflicts with each other regarding appropriate number of inputs, hidden layers, and nodes in each layer. The methodology in this paper reflects the works of Lane (1993) [21] and Terna (1993) [22].

3. Results

GARCH and Artificial Neural Network

The first major econometric problem is that the data are heteroskedastic and correlated across assets. This is caused because the variances of rates of return are different among assets and the returns of the assets are correlated. The study then turns to the GARCH models in seek of greater performance. It is argued that a standard GARCH model does not apply to emerging markets because of the increased frequency of large shocks, which would have the model predict too much volatility persistence. If the probability of switching out of a high-volatility regime is large, then the high volatility does not need to be very persistent. From the forecast errors in Table 1 below and results in Table 2, the SGARCH model fared worse than the EGARCH model. For both models, their out of sample predictions performed more than double for ASEAN as they did for USA. Making the modeling techniques more reliable in the USA than ASEAN. Unfortunately the predictions have wide confidence bands and are limited in their forecast length, graphs available upon request. Most individual investors would want to know further than five weeks into the future, which is considered a long-run forecast for GARCH models.

Table 1. Entire ten-year sample. Forecast performance measures of out of sample mean squared errors (MSE) and mean absolute errors (MAE).

Forecast Performance		SGARCH	EGARCH
Indonesia	MSE	0.0000403658	0.0000390
	MAE	0.005107957	0.00501
Malaysia	MSE	0.00053395	0.000516112
	MAE	0.018837039	0.018227771
Singapore	MSE	0.00012063	0.000120293
	MAE	0.009907957	0.009892746
Thailand	MSE	0.001319087	0.00132429
	MAE	0.029213832	0.0293356
Philippines	MSE	0.000121112	0.000117586
	MAE	0.009324318	0.009195147
USA	MSE	0.000661214	0.000667447
	MAE	0.019325006	0.01937361

Table 2. Comparison of average results between five-step ahead prediction and actual out of sample values.

Average Difference between Prediction and Out of Sample	ASEAN	USA	Both Regions
ANN	0.012669	0.003543	0.008106
EGARCH	0.002259	−0.004579	−0.001160
SGARCH	0.002419	−0.001045	0.000687
MGARCH	0.000171	−0.004614	−0.002221

The second major econometric problem is that the CAPM imposes a linear constraint on the returns and betas, assuming they are constant. To address this issue the artificial neural network (ANN) non-linear model is compared with the linear GARCH models in Table 2. The ANN is a regime switching non-linear feed-forward neural network model that was run as a 2-3-1 network with 13 weights and 1000 iterations. The "2" is the number of inputs used, which was determined by testing the data with AR models of varying lags to determine best number of lags. Parsimony, SBC and log-likelihood were used in determination. The "3" is the number of hidden nodes that gives it its non-linear characteristics and finally the "1" represents the number of outputs which were averaged by the 13 weights as the model automatically trains itself and then averages again over the 1000 iterations of the trained model. For more on selecting the number of inputs, nodes, and hidden layers the reader is referred to Lane (1993) [21].

To keep the report manageable the subsample MSE and MAE tables were left out, but are available upon request. The errors within the subsamples indicate that the EGARCH model still fits the true volatility better for the six countries across the three three-year and two five-year subsamples. With the exceptions being Singapore from years 2012–2014 and Philippines from 2006 to 2011. With the results over the entire sample holding within the five subsample periods, the entire sample is used when the out-of-sample forecasts are compared to the actual returns.

The out-of-sample backtest results tell a different story for the five subsamples. Because the GARCH models are built for large volumes of data input, it is of course no surprise within the shortened sub-periods they fared worse than the ANN. With five subsamples and 10 portfolios there were 50 horseraces. The ANN won 24 of the subsample horseraces, with 17 of the 24 wins coming from US portfolios. The GARCH models weekly average of the difference between the prediction and actual return spanned between the minimum being −3.8463% (US Real Estate 2006–2008) and the maximum value at 1.4861% (Malaysia 2012–2014). With the average results of all the three-year subsamples, the SGARCH model outperforms the EGARCH for both US and ASEAN portfolios. As the sample length is increased to five years, the EGARCH outperforms on average, across all 10 portfolios, better than the SGARCH for the ASEAN region only. The average differences across all five US portfolios never ranked EGARCH or MGARCH winners for any of the subsample periods. The remaining of the results report on the entire 10 year sample.

The CAPM GARCH models did outperform the machine learning ANN model, however the average weekly GARCH differences (ranging from −0.46% to 0.24%) multiplied by the five-week period and such a relatively short forecast window are not particularly useful. Graphs of the ANN are available upon request. The MGARCH beta model in the ASEAN region does look promising for the CAPM, with an average difference of 0.0171% per week. The individual portfolio average results are available in Tables A1 and A2 in the appendix. The un-averaged five-step ahead forecast result errors are in Table A5. The ANN forecast improved as the forecast horizon increased for both regions. For the most part the SGARCH and EGARCH forecast worsened as the window to forecast grew longer. The MGARCH model step-by-step forecasts are mixed between the portfolios. The accuracy of the MGARCH results were improving (getting closer to zero) for Indonesia (In), Thailand (Th), Philippines (Ph), Industrial Goods (IG), and Healthcare (HC), but not the other five.

All markets and portfolios spiked in negative volatility between July 2008 and January 2009, except two. Indonesia had two large and somewhat symmetric shocks between July 2009 and July 2010. Secondly, Malaysia's (Mal) largest shock was negative and occurred within January 2007 and July 2007.

The markets and portfolios with the most persistent volatility in the ASEAN region were Indonesia and Malaysia. In the US the Basic Materials portfolio had the highest volatility and forecasted betas. The MGARCH model was the best performing model for these three portfolios. The remaining three ASEAN portfolios did best with the EGARCH model (see Table A1). Overall the SGARCH performance dominated the US region (see Table A2) and the EGARCH did the best within the ASEAN region (see Table A1). Of all ten portfolios, Singapore had the overall best (lowest) predictions (errors) for all models. This could be because Singapore (Sin) was more isolated from the financial crisis in the US.

All predictions are statistically the same except those paired with the ANN and SGARCH models. When comparing the returns of the historical ex-post beta with that of the four ex-ante beta models used, only the ANN forecasts were statistically different from that of the historical beta model. The ANN model was also the worst ranked model on the entire sample (see Table A3).

Standardized Student's t-test reveals that it fails to reject the null of no difference between the out of sample test difference of the 10 portfolios using a time-varying ex-ante GARCH and constant ex-post beta models. The results of the traditional, constant, beta method outperforming a more intricate beta coincide with French's (2015) [23] study on using a non-parametric, time-varying, beta. Nonetheless the t-test does, reject the null, find a difference between the GARCH and ANN model out of sample differences. Looking at the averages in the two regions in Tables 2 and 3, the traditional constant beta model results appear improved for ASEAN over that of the GARCH model and both appear to be equal within the US. In regards to the predictions being under- or over-estimated, the constant model results are reversed to those of the GARCH. ASEAN expected returns less actuals are negative, meaning under-predicted, and US are positive meaning over predicted (−0.29% and 0.23% respectively).

Table 3. Average out of sample difference of the ex-post constant beta model.

Ex-Post Constant β	
ASEAN	−0.0029
US	0.0023

The GARCH models proved to give too inaccurate of predictions for such a short window (five ahead) of forecast period. Though the GARCH models outperformed the artificial neural network within the month time period, they were already as good as or worse than the constant model's out of sample forecast. The GARCH models, aggregated results, under predicted the actual returns for the US and the constant models over predicted, −0.0034 versus 0.0023 average out of sample difference. With the ASEAN portfolios, the traditional constant beta, average out of sample difference is −0.0029 and the GARCH of 0.0016, meaning that the GARCH, in aggregate, over predict and constant models under predict the actual ASEAN data. The findings of such small forecast errors for the MGARCH and SGARCH models are very promising for institutional and retail investors.

4. Conclusions

The beta is the most widely used instrument among financial economists and specialists for risk management and is one of a handful of regression coefficients that people pay money for. This research finds the simple constant beta remains supreme in both US and abroad in the ASEAN community, on the basis of out of sample differences and ease of use. The MGARCH model did best among the most volatile portfolios for both regions and is overall the best for ASEAN. The EGARCH model did well within ASEAN and SGARCH for the US, for predicting returns, on more "stable" volatilities within the respective regions.

The simple constant beta method is the most widely used model by finance practitioners. The users of beta often pay fees to obtain the coefficients. Results in this research conclude there is no reason to suggest a more complicated method that lacks superior performance. Within ASEAN the five-week forecasting return errors range from 0.09% to 6.33% for the ex-ante models. Within the US the return errors are smallest at −0.52% and spread widest at −2.31% for the total five-week forecast with ex-ante models. The constant, historical, beta was 0.29% different from the actual returns in ASEAN and 0.23% for the US. The forecast mean absolute errors, in Table A4, rank the constant beta model king with all ex-ante models underperforming in both regions. Among the ex-ante models the EGARCH (ASEAN) and SGARCH (US) performed the best based on forecast mean absolute errors.

The ex-ante models complicate the implementation and have little practical advantage relative to the constant, ex-post, market model within the sample used. The ex-post market model is able to reduce the variance of returns by removing the portion of return that is related to variation in the market's return. The lack of sensitivity to the choice of model between the original ex-post and newly developed ex-ante GARCH, may be attributed to the fact that the variance of returns is frequently not reduced much by choosing a more sophisticated model. For a proof see Campbell, Lo, and MacKinlay (1997) [24]. It thus appears the original CAPM lives on and is successful in asset price forecasting within the US and ASEAN markets during 2005–2014.

This study thus supports the 30% of CEOs outside the US that currently use the standard CAPM and should give assurance to remaining 70% of practitioners to adopt the CAPM as their preferred pricing tool. The 0.2% difference in monthly accuracy between the, better performing, MGARCH of that of the traditional beta is negligible for the typical investor and non-institutional company. This study empirically demonstrated how the ASEAN countries perform relative to the US markets in terms of fitting volatility for long-term forecasts and the comparison of expected returns to that of actual returns. The usefulness extends to VaR, making market neutral portfolios, and pricing models, which require long-term horizons. Singapore had the overall best (lowest) predictions (errors) for all models. This could be because Singapore was more isolated from the financial crisis in the US. Thus, future research could investigate the spillover effects between the nations, various smoothing kernels in conjunction with time-varying beta, Kalman filtering, or using a multifactor beta model. Finally, one may look at using more ex-post models such as the consumption beta, mean adjusted beta, and market beta models in conjunction with the differing lengths of in-sample periods.

Supplementary Materials: The following are available online at www.mdpi.com/2227-7072/4/3/15/s1, List of 500 securities used in sample, Figure S1: Graphs of the EGARCH models of market volatility and forecasts, Figure S2: Graphs of the Neural Network Auto Regressions.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Average difference between in sample prediction and out of sample returns.

Backtesting	Ind	Mal	Sin	Th	Ph
ANN	0.009711	0.011783	0.006876	0.012530	0.022448
EGARCH	−0.002334	0.009101	−0.000764	0.003377	0.001914
SGARCH	−0.002335	0.009474	−0.001639	0.004679	0.001916
MGARCH	−0.001725	0.007902	−0.001723	−0.005512	0.001916

Indonesia (Ind) and Malaysia (Mal) were the most volatile markets and portfolios with the most persistence. For these two countries the MGARCH was the best performing model. The remaining three did best with the EGARCH model. Singapore had the overall best (lowest) predictions (errors).

Table A2. Average difference between in sample prediction and out of sample returns.

Backtesting	BM	IG	RE	HC	UT
ANN	0.012617	0.003029	0.003431	0.003309	−0.004671
EGARCH	0.004562	−0.006516	−0.005269	−0.004457	−0.011214
SGARCH	0.009430	−0.002865	−0.001322	−0.001004	−0.009467
MGARCH	0.004434	−0.005234	−0.004684	−0.006252	−0.011336

The Basic Materials (BM) portfolio was the riskiest with the highest volatilities and forecasted betas, in the US region. The model that did best for this portfolio was MGARCH with the EGARCH a close second. Though overall the SGARCH performance dominated the US region.

Table A3. *T*-Test Results (*p*-values) on Forecasting Errors.

Backtesting	MGARCH	EGARCH	SGARCH	ANN
EGARCH	0.276962			
SGARCH	0.019728	0.017125		
ANN	0.000131	0.000134	0.001916	
Historical	0.453870	0.764740	0.684645	0.032509

All predictions are statistically the same except those paired with the ANN and SGARCH model. When comparing the returns of the historical ex-post beta with that of the four ex-ante beta models used, only the ANN forecasts were statistically different from that of the historical beta model. The ANN model was also the worst ranked model on the entire sample.

Table A4. Forecast Mean Absolute Errors.

Backtesting	ASEAN	US	Both Regions
ANN	0.012670	0.005412	0.009041
EGARCH	0.003498	0.006403	0.004951
SGARCH	0.004009	0.004818	0.004413
MGARCH	0.003756	0.006388	0.005072

Using mean absolute errors the SGARCH is still the best ex-ante model in the US, but MGARCH lost its first place rank to EGARCH in the ASEAN region. If doing global asset pricing in both developed and a developing market, the SGARCH may be the simplest and best predicting model.

Table A5. Time-Varying Expected Returns less Actual Returns (five-steps ahead forecast). Results are in ascending order week one (top) through week five (bottom).

	Ind	**Mal**	**Sin**	**Th**	**Ph**
ANN	0.012277	0.045352	0.020035	−0.006136	0.021464
	0.007086	0.033626	0.002833	0.038174	0.036423
	0.018987	−0.005948	0.023660	−0.001880	0.029820
	0.009802	−0.009318	−0.013334	0.018547	0.018969
	0.000404	−0.004801	0.001186	0.013946	0.005563
	BM	**IG**	**RE**	**HC**	**UT**
ANN	0.018118	−0.003697	−0.002279	0.010818	0.002644
	0.072393	0.021044	0.047866	0.011032	0.007952
	−0.058003	−0.022932	−0.025301	−0.012882	−0.025823
	0.007397	0.013013	−0.013224	−0.001718	−0.028426
	0.023183	0.007719	0.010090	0.009295	0.020296
	Ind	**Mal**	**Sin**	**Th**	**Ph**
SGARCH	−0.058300	−0.012726	−0.046311	−0.068665	−0.061285
	0.044858	0.078145	0.042132	0.077188	0.051898
	0.046054	0.031202	0.054228	0.029185	0.053931
	−0.096123	−0.106858	−0.117464	−0.085140	−0.092456
	0.051835	0.057606	0.059219	0.070829	0.057493
	BM	**IG**	**RE**	**HC**	**UT**
SGARCH	−0.015882	−0.047149	−0.042650	−0.032199	−0.049839
	0.111105	0.056820	0.084461	0.049156	0.046977
	−0.032372	0.003294	0.001276	0.015264	0.005696
	−0.089820	−0.086358	−0.111542	−0.099686	−0.126914
	0.074120	0.059071	0.061847	0.062442	0.076744
	Ind	**Mal**	**Sin**	**Th**	**Ph**
EGARCH	−0.058278	0.001485	−0.028147	−0.063444	−0.061168
	0.044842	0.074365	0.034021	0.076141	0.051827
	0.046038	0.021187	0.041884	0.015245	0.053838
	−0.096086	−0.087657	−0.090767	−0.072227	−0.092269
	0.051813	0.036126	0.039189	0.061169	0.057341
	BM	**IG**	**RE**	**HC**	**UT**
EGARCH	−0.040641	−0.065717	−0.062724	−0.049756	−0.058721
	0.111019	0.056755	0.084391	0.049095	0.046946
	−0.031543	0.003915	0.001948	0.015852	0.005994
	−0.090523	−0.086886	−0.112112	−0.100185	−0.127167
	0.074497	0.059354	0.062153	0.062710	0.076880
	Ind	**Mal**	**Sin**	**Th**	**Ph**
MGARCH	−0.063040	−0.010802	−0.061555	−0.037959	−0.065247
	0.038553	0.020330	0.021975	0.053864	0.047100
	0.042742	−0.009484	0.051816	−0.016962	0.053711
	−0.085853	0.012208	−0.092509	−0.022512	−0.087386
	0.058972	0.027257	0.071656	−0.003992	0.061403
	BM	**IG**	**RE**	**HC**	**UT**
MGARCH	−0.026268	−0.043027	−0.048172	−0.046000	−0.040553
	0.044565	0.023744	0.035966	0.049267	0.010714
	−0.050105	−0.011160	0.008391	−0.008303	0.002956
	0.002709	−0.032044	−0.075571	−0.061407	−0.086420
	0.051267	0.036319	0.055968	0.035184	0.056624

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