THE RELATIONSHIP BETWEEN STOCK RETURNS AND VOLATILITY IN THE PHILIPPINE STOCK MARKET: A SEMI-PARAMETRIC APPROACH

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Abstract: This paper studied the relationship between stock market returns and conditional volatility (variance) in the Philippine Stock Exchange Composite Index (PSEi). Empirical results in the literature are mixed relating to the sign of the risk-return trade-off. Most asset-pricing models (e.g., Sharpe, 1964; Linter, 1965; Mossin, 1966; Merton, 1973) show a positive relationship of expected returns and volatility which means more risk, more return. More recent studies implicate a negative relationship between returns and volatility such as Black (1976), Cox and Ross (1976), Bekaert and Wu (2000), Whitelaw (2000), Li et al. (2005) and Dimitrios and Theodore (2011). Based on parametric GARCH- in Mean models, Hofileña and Tomaliwan (2013) found a similar existence of a negative yet weak relationship between stock returns and conditional volatility. The insignificant relationship was seen to be caused by the parametric conditional variance modelling, which suffered from misspecification problems and thereby, yielded misleading statistical inferences. So by deviating away from parametric modelling, I applied a flexible semiparametric specification for the conditional variance and found evidence of a significant positive relationship between returns and volatility of the PSEi's weekly Wednesday returns from January 5, 2000 to December 23, 2013. The findings of the study are in line with the recent positive events happening in the stock exchange such as the launching of the country's first Exchange Traded Funds (ETFs).

Keywords: Risk-returns trade-off, Semiparametric GARCH-in Mean model, the Philippines

This paper is an abridged version. The full version is planned by the author to submit to other journals for publication.

1. INTRODUCTION

It is well-known in financial It is well-known in financial research that stock return volatility is highly persistent. At the same time, existing literature cannot find a definite relationship between asset returns and its variance, which is used as a proxy for risk. As Li et al. (2005) pointed out, the relationship, whether it is positive or negative, has been controversial. Theoretically, asset pricing models (Sharpe, 1964; Linter, 1965; Mossin, 1966; Merton, 1973, 1980) link returns of an asset to its own variance or to the covariance between the returns of other stocks and the market portfolio.

As summarized by Baillie and DeGennarro (1990), most asset-pricing models (e.g., Sharpe, 1964; Linter, 1965; Mossin, 1966; Merton, 1973) show a positive relationship of expected returns and volatility. Yet, there are also many empirical studies that implicates a negative relationship between returns and volatility such as Black (1976), Cox and Ross (1976), Bekaert and Wu (2000), Whitelaw (2000), Li et al. (2005) and Dimitrios and Theodore (2011). For example, Li et al. (2005) found a significant negative relationship between expected returns and volatility in 6 out of the 12 largest int'l stock markets. Bekaert and Wu (2000) explain that returns and conditional volatility are negatively correlated in the equity market.

As mentioned earlier, numerous studies have been made in the literature with a focus on stock volatility among developed countries.. Only in the last decade or so had studies been made on developing countries such as Aggarwal et al. (1999), Bekaert and Wu (2000), Kassimatis (2002), Goudarzi, H. (2011) and N'dri (2007). Furthermore, if volatility is present during a crisis then it should be noted that this event does not only impact developed markets but emerging markets as well. In line with this, Guinigundo (2010) reported that by end-December 2008, the benchmark Philippine Stock Exchange Index (PSEi) had declined by 48.3%, year-on-year. Thus, this study aims to investigate the relation between stock returns and its volatility in the Philippines. To model the stock market volatility and its return, I applied a flexible semiparametric GARCH- in Mean specification for the conditional variance.

2. METHODOLOGY

Semiparametric GARCH-M specification

The semiparametric GARCH-in Mean model will be estimated by

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \delta_t^2 + u_t \equiv x_t\alpha + u_t$$

(Eq. 1)

where y_t is the stock market returns,

$$x_t = (1,\ y_{t-1},\ \sigma_t^2),$$

$$\alpha = (\alpha_0, \alpha_1, \delta),$$

σ_t^2 =var($y_t\,|\,\Omega_{t-1}$) is the conditional variance of y_t conditional on information set available at *t*-1. The error term is a martingale difference process, i.e., E($u_t\,|\,\Omega_{t-1}$)=0. The study is testing the null hypothesis of H_0: $\delta = 0$ *versus* $H_1 : \delta \neq 0$. The null hypothesis says that the conditional variance does not affect return y_t. The null hypothesis says that the conditional variance does not affect return y_t. So if H_0 is rejected, a positive δ implies that the expected stock return and volatility are positively related while a negative δ implies that they are negatively related.

Before discussing further, it is better to briefly consider a simple semiparametric GARCH model (σ_t^2 =var($y_t\,|\,\mathrm{I}_{t-1}$), var($u_t\,|\,I_{t-1}$)) to just grasp the overall picture. From Li. et al (2005), they have stated the semiparametric GARCH model which they consider as having not to suffer from the "curse of dimensionality" problem as in Pagan–Ullah's specification as:

$$\sigma_t^2 = m(u_{t-1}) + \gamma\sigma_{t-1}^2 \quad \textbf{(Eq. 2)}$$

where $m(\cdot)$ is unspecified. From its mean equation $y_t = \alpha_0 + \alpha_1 y_{t-1} + \delta\sigma_t^2 + u_t$, a more general form of Eq. (2) is

$\mathrm{var}(y_t\,|\,\mathrm{I}_{t-1}) = \sigma_t^2 = g(y_{t-1}, y_{t-2}) + \gamma\sigma_{t-1}^2$ **(Eq. 3)**

When $g(y_{t-1}, y_{t-2}) = m\,(y_{t-1} - \alpha_0 - \alpha_1 y_{t-1}) = m(u_{t-1})$, Eq. 3 goes back to Eq. 2 but Eq. 3 allows the conditional variance to have general interactions between y_{t-s}, y_{t-s-1} (s=1, . . . , ∞). Denoting z_{t-1}= (y_{t-1}, y_{t-s-1}) and substituting (Eq.3) recursively yields the nonparametric component of the whole semiparametric GARCH model:

$\sigma_t^2 = g(z_{t-1}) + \gamma g(z_{t-2}) + \gamma^2 g(z_{t-3}) + \cdots + \gamma^{d-1} g(z_{t-d}) + \ldots$ **(Eq.4)**

The nonparametric specification considered by Pagan and Ullah (1988) suggest to use a truncated fixed r-lag specification to approximate σ_t^2 i.e., using $\mathrm{var}(y_t\,|\,y_{t-1}, \ldots, y_{t-r})$ to approximate $\mathrm{var}(y_t\,|\,\Omega_{t-1})$, and they suggested to estimate $\mathrm{var}(y_t\,|\,y_{t-1}, \ldots, y_{t-r})$ by the nonparametric kernel method. This approach can only allow a small number of lags (say r =2 or 3) to be used in practice because it suffers the "curse of dimensionality" problem if r is large. Therefore, this approach is difficult to capture the highly persistent nature of the variance process.

Given that $0 < \gamma < 1$, Eq.4 can be approximate by a finite lag model if d is sufficiently large:

$\sigma_t^2 \cong g(z_{t-1}) + \gamma g(z_{t-2}) + \gamma^2 g(z_{t-3}) + \cdots + \gamma^{d-1} g(z_{t-d})$ **(Eq.5)**

Eq. 5 is a restricted additive model with the restriction that the different additive functions are proportional to each other. Therefore, for a fixed value of *d*, Eq.5 is one dimensional nonparametric model because there is only one univariate $g(\cdot)$ function that needs to be estimated. This model can allow many lagged y_{t-s}'s to be included at the right-hand side of Eq. 5. Unlike a purely nonparametric model with *d*-lagged valued regressors (e.g., Pagan and Ullah, 1988), the additive model Eq.5 does not suffer from the "curse of dimensionality" problem.

Li et. al (2005) also suggested to estimate Eq. 5 by the nonparametric series method (say, spline or power series). The advantage of using the series method is that the additive proportional model structure is imposed directly and the estimation is done in one step. To see this, let $\{\emptyset_l(y)\}_{l=0}^{\infty}$denote a series-based function that can be used to approximate any univariate function $m(y)$, a linear combination of the product base function could be use to approximate $g(y_{t-1}, y_{t-2})$, i.e., we approximate (y_{t-1}, y_{t-s-1}) for all s=1, . .., d. by

$$\begin{aligned}\sigma_t^2 \cong\ & \alpha_{00}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_0 y_{t-s}\emptyset_0 y_{t-s-1} + \cdots + \alpha_{0q}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_0 y_{t-s}\emptyset_q y_{t-s-1}\\ & + \alpha_{10}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_1 y_{t-s}\emptyset_0 y_{t-s-1} + \cdots + \alpha_{1q}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_1 y_{t-s}\emptyset_q y_{t-s-1}\\ & + \alpha_{q0}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_q y_{t-s}\emptyset_0 y_{t-s-1} + \cdots + \alpha_{qq}\textstyle\sum_{s=1}^{d}\gamma^{s-1}\,\emptyset_q y_{t-s}\emptyset_q y_{t-s-1}\end{aligned} \quad \textbf{(Eq.6)}$$

There are $(q+1)^2$ parameters: γ and α_{ij} (i and j=0, . .., d). Note that the number of parameters in model Eq.4 does not depend on *d*, the number of lags included in the model. For example, if *q* is fixed, then the number of parameters is also fixed, it does not change as *d* increases. Therefore, we can let *d* -> ∞ as T -> ∞ (with *d*/T -> 0). Asymptotically, it allows an infinite lag structure without having the curse of dimensionality problem (since *q* is independent of *d*).

Getting the number of lag/s (d) and order/s (q)

Picking up all the necessary lags to capture the persistent dynamics without overfitting the model is possible. Therefore, Li et. al (2005) recommend to select the value of d that minimizes the sum of squares of residuals.

The series approximating terms q is selected as follows. Again we use a linear combination of a product base function to approximate $g(y_{t-1}, y_{t-2})$. If we use up to the qth univariate base functions for each component of $x_{t,}$ to approximate $g(x_{t)=}g(y_{t-1}, y_{t-2})$, the number of approximating base function is k =$(q+1)^2$ ($\emptyset_{l1}(y_{t-1})\emptyset_{l2}(y_{t-2})$ for $0 \leq l_1$, $l_2 < q$). One should choose k optimally in balancing the bias square term and the variance term, i.e., minimizing the mean square error. To select k, I would be minimizing some kind of modified AIC criteria which can be computationally simple as proven by Hurvich et al. (1998), Li and Racine (2004), and Racine and Li (2004). They show that a modified AIC criterion performs well in selecting smoothing parameters.

Nonparametric B Spline Estimation

As mentioned by Li et. al (2005), our main equation to be estimated which is Eq. 4 should be done by the nonparametric series method (say, spline or power series). On the statistical software Stata, the nonparametric series method command "npseries" is only at its early stages as it was only uploaded this early 2014 by Boris Kaiser of the Universität Bern at the IDEAS official website[1]. On the other hand, the R program has more established packages using the spline method like "splines" and "crs". Therefore, it was more comfortable to use a program in which codes had already been tested and bugs were fixed.

Regression spline methods are "global" in nature since a single least square procedure leads to the ultimate function estimate over the entire data range (Stone 1994). This "global nature" implies that constructing regression splines will be less computationally burdensome than the kernel-based ones. (Racine, 2014)

Based on Braun (2012) and his detailed notes on B-spline, splines are essentially defined as piecewise polynomials. The properties of splines include a general pth degree spline with a single knot at t. Let P(x) denote an arbitrary pth degree polynomial $P(x) = \left(\beta_0 + \beta_1 x + \cdots + \beta_p x^p\right)$ then

$$S(x) = P(x) + \beta_{p+1}(x-t)^p \quad \textbf{(Eq.7)}$$

takes on the value P(x) for any $x \leq t$, and it takes on the value $P(x)+\beta_{p+1}(x-t)^p$ for any $x > t$ where t is the number of knots. Thus, restricted to each region, the function is a pth degree polynomial. As a whole, this function is a pth degree piecewise polynomial; there are two pieces. In general, we may add k truncated power functions[2] specified by knots at $t1, t2, \ldots, tk$, each multiplied by different coefficients. This would result in $p + k + 1$ degrees of freedom. An important property of splines is their smoothness. Polynomials are very smooth, possessing all derivatives everywhere. Splines possess all derivatives only at points which are not knots. The number of derivatives at a knot depends on the degree of the spline.

Eq. 7 and the aforementioned properties pertains to splines but what if t represent any piecewise polynomial of degree p? This gives rise to

[1] IDEAS is a RePEc service hosted by the Research Division of the Federal Reserve Bank of St. Louis.

[2] As a function of x, $(x-t)^p$ takes on the value 0 to the left of t, and it takes on the value $(x-t)^p$ to the right of t.

$$S(x) = \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_p x^p + \beta_{p+1}(x - t_1)^p + \cdots + \beta_{p+k}(x - t_k)^p \quad \textbf{(Eq.8)}$$

Eq.8 says that any piecewise polynomial can be expressed as a linear combination of truncated power functions and polynomials of degree *p*. By adding a noise term to Eq.8, a spline regression model can be obtained relating a response $y = S(x) + u$ to the predictor *x*. Least-squares can be used to estimate the coefficients. Moreover, Eq. 8 looks like the same specific model to be modelled at Eq. 4 except that the y becomes $\sigma_t^2$and the whole S(x) function is the right hand portion of Eq. 4.

Sampling Design and Data Collection Method

The raw data comprised of the Philippine Stock Exchange Composite Index (PSEi)'s weekly closing prices from January 5, 2000 and December 23, 2013. This reflects returns of the exchange in the 21st century. The weekly closing prices were taken on Wednesdays. If a particular date falls on a holiday, the closing price of the previous day was taken. Being a snapshot of the market's overall condition, the PSEi is composed of the 30 largest and most active common stocks listed at the exchange based on their free float-adjusted market capitalization. (PSE, 2011) All data in the study were obtained from the Philippine Stock Exchange (PSE) and had a total of 728 observations.

Despite daily return data being preferred to weekly or monthly return data, daily data are deemed to contain 'too much noise' and are affected by the day-of-the-week effect. On the other hand, monthly data are not an option since they are also affected by the month-of-the-year effect. (Roca, 1999) Ramchand and Susmel(1998), Aggarwal et al. (1999), and Tay and Zhu (2000) were among the large number of studies that have employed weekly data instead of daily or monthly data in order to provide a sufficient number of observations required without the noise of daily data.

As such, the weekly return series is generated from the following equation:

$$y_t = (100)*(\ln(P_t)-\ln(P_{t-1})) \quad \textbf{(Eq.9)}$$

where ln is the natural logarithm operator; t represents time in weeks; y_t is the return for period t; Pt is the index closing price for period t. Each return series is therefore expressed as a percentage. Modeling an index in this manner is typical in the literature (Nelson, 1991).

3. RESULTS AND DISCUSSION

Pre-testing

Table 1. Descriptive Statistics and Normality Test of Return Series Data for PSEi

Statistics	Variable: Return
Mean	.1531351
Median	.1239516
Maximum	13.79998
Minimum	-16.16304
Standard Deviation	3.147188
Skewness	-.1173559
Kurtosis	5.632395***

*Note: *** indicates significance at the 0.001 level.*

Table 1 depicts the results of the normality test and the descriptive statistics for the weekly returns. Under assumptions of normality, skewness and kurtosis have asymptotic distributions of N(0) and N(3) respectively (Xu, 1999). Empirical distributions of weekly returns differ significantly from a normal distribution. There was an indication of negative skewness (Skw= -.1173559) which indicates that the index declines occur more often than it increases but was statistically insignicant. The kurtosis coefficient was positive, having a relatively high value for the return series (Kurt = 5.632395) this points out, that the distribution of returns is leptokurtic. This kind of distribution is naturally inherent in financial time series data. The weekly return series being negatively skewed implies that the distribution is not symmetric. Further graphical representation like the histogram and kernel density could be found in Figure 2 and 3 respectively.

Getting the Number of Lags(d)

Getting the number of lags involves minimizing the sum of squared residuals. Based on Princeton University (2014) and Stata manual, vector autoregression (VAR) could be used to include lagged values of the dependent variable as independant variables. Therefore, using the "varsoc" command, it generated the n order to determine how many lags to use, several selection criteria can be used. The most common are the Akaike Information Criterion (AIC) where it chooses lag length j to minimize: $\log(SSR(j)/n) + (j + 1)C(n)/n$, where $SSR(j)$ is the sum or squared residuals for the VAR with j lags and n is the number of observations. Based on Table 2, it shows the chosen AIC among the many lags is lag number 9 and it is significant.

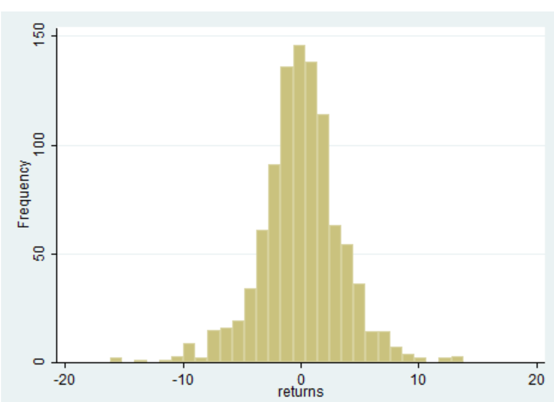

Figure 2. Histogram of Data Distribution

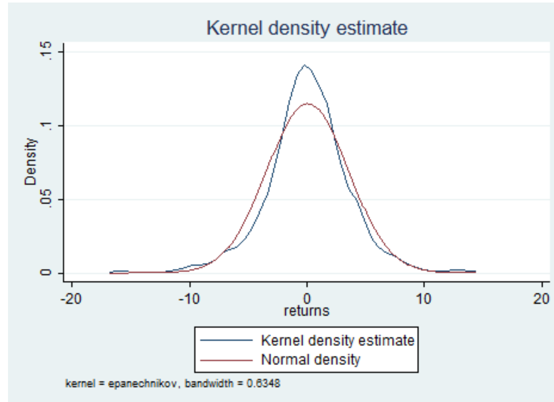

Figure 3. Kernel Density of Data Distribution

Getting the Number of base functions (k)

The series approximation terms q is selected using minimizing the modified AIC. This was developed by Hurvich et al.(1998), Li and Racine (2004), and Racine and Li (2004). Stata is unavailable to estimate nonparametric kernel estimation via least squares cross-validation or thru the modification of the AIC. The R package on modified AIC was made available by Racine back in 2006 so this is what I would be employing since it's more computationally simple.

Table 2. VAR Selection-order criteria

Lags	AIC
0	11.3098
*1**	-23.4941
*2**	-23.5449
*3**	-23.5734
*4**	-23.5887
5	-23.5888
*6**	-23.6204
*7**	-23.6406
*8**	-23.6325
*9**	-23.6459***
*10**	-23.6245
11	-23.6318
12	-23.6264
13	-23.6247
14	-23.6154

15	-23.6171
16	-23.6098
17	-23.6101
18	-23.6045
19	-23.5984
20	-23.5936

*Note:*** AIC chosen by Stata, * indicates significance at the 0.05 level.*

Upon using the R program, I have transferred all data generated by Stata and proceed with nonparametric B-spline function/command of "crs" with the inclusion of cross validation of the modified AIC made by Hurvich, Simonoff, and Tsai (1998). This function can be used to select the degree (which we had because of the lag number) and number of knots (`segments'+one). The number of knots corresponds to the number individual terms in the sequence or series. (Racine, 2014) The knots are automatically generated by the function thru the said cross validation of the modified AIC.

Results of the Nonparametric B-spline Bases Regression Spline

Based on Nonparametric B-spline Bases Regression Spline results, the number of segments is three which totals to four knots including the end points of the knots. The degree, despite the input of nine lags, had been equated to two. All of the results indicated significance at the 0.001 level using a significance test. After having the regression, I have plotted the mean and (asymptotic) error bounds and first partial derivative and (asymptotic) error bounds to know what the b-spline look like and could be found in Figure 4 and 5 respectively. The reason that it is called the mean is because we are looking at the conditional variance equation or Eq. 4 wherein σ_t^2 is the *y* variable for the B-spline bases regression.

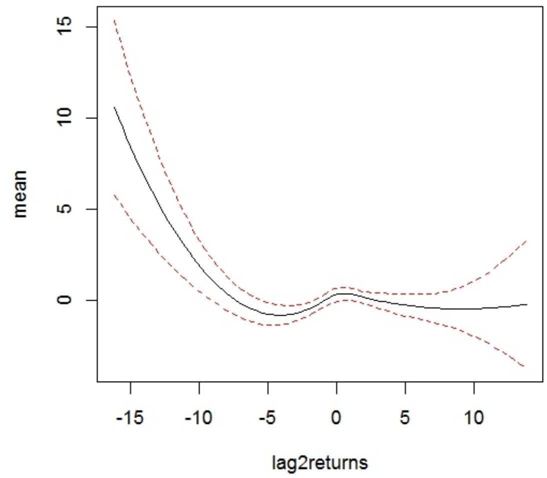

Figure 4. B-spline plot of the mean and (asymptotic) error bounds

The most important part for the regression is to be able to predict the estimated σ_t^2. The numbers predicted will be used on the next step which is the semiparametric regression. There are 725 nonparametrically generated conditional variances to be part of the exogenous variable of Eq. 1.

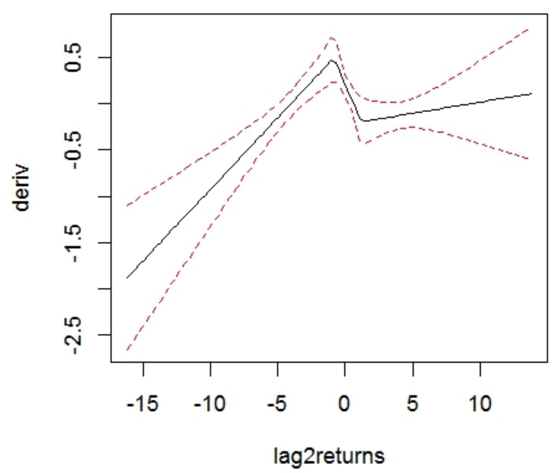

Figure 5. B-spline plot of the first partial derivative and (asymptotic) error bounds

Semiparametric Result Analysis

The study estimated the model stated in Eq. 5 and used a B-spline as the approximating base function. After which, the nonparametrically generated input was ran linearly along with the whole equation stated in Eq. 1. The estimation result is stated in Table 3. From the result, the estimated coefficient of δ is positive and significant in the Philippine stock market. Such finding implies that in the case of the Philippine equities, it still follows a "more risk, more return" outcome in the 21st century despite having a huge volatility during the 2008 financial crisis.

Table 3. Semiparametric GARCH-M estimation results

Coefficient (t-ratio)	Philippine Result
δ (t-ratio)	.9999*** (4.95)

**** indicates significance at the 0.001 level.*

One of the events in the Philippine stock market that might show true to the discovered positive relationship between risk and return would be the first offering of Philippine Exchange Traded Funds (ETFs) to investors last December 2013. (Philippine Daily Inquirer, 2013) If there had been bad performance by the Philippine stock market then there would be no incentive for local participants to buy ETFs especially with the recent financial crisis. Despite huge volatility in previous years, there had been much success with the launching of the said ETFs as its opening indicative NAV with 99.20 per share had ended with 119.5 per share as of January 9, 2015. (Philippine Stock Exchange, 2015). Figure 7 shows you the price of the Philippine ETFs ever since its launching and it showed an increasing trend.

Figure 7. First Metro Philippine Equity Exchange Traded Fund, Inc. Historical Price Chart

4. CONCLUSION

The volatility of PSEi stock returns from January 2000 to December 2013 have been investigated and modelled using a semiparametric GARCH-in Mean. This study found that PSEi returns series exhibit a significant positive relationship between risk and return like many traditional studies. It makes good intuitive sense since if one expects more yields then one should be ready to bear more burden of risk.

To prove such relationship, in the Philippine Stock Market, there had been a recent introduction of the country's first Exchange Traded Fund (ETFs) which is still currently performing well. Such security would not have been pushed thru if investors (whether corporate or individual) do not see any incentive in investing in stock equities if the risk-return relationship in stocks had been negative.

Given the relationship seen in the PSEi, I recommend that policy makers to maintain a well-regulated financial market in order to facilitate a smooth integration of the Philippine market with the global economy. By having this, investors would be given more motivation to invest and we can promote the Philippines as a haven for safe investments.

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