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Indonesian stock market: Do bear and bull matter?

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Abstract

In this paper we attempt to investigate the foreign shock and domestic shock on determining the period of the bull and the bear of Indonesian Stock market. In particular, we investigate the impact of oil market, global stock market, money market, exchange rate market, and output market as explanatory variables in determining the period of bear and bull of stock market. The markets that perform well to predict the period of bull and bear period of Indonesian Stock Market are world oil market, Malaysia Stock Market, Singapore Stock Market, US Stock market and foreign exchange market.

Keywords: Oil price shock, Bull and bear period, Stock market, Markov Switching VAR.

Mercado de valores de Indonesia: Importan los osos y los toros?

Resumen

En este documento intentamos investigar el shock extranjero y el shock doméstico al determinar el período del toro y el oso del

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mercado de valores de Indonesia. In particular, investigamos el impacto del mercado petrolero, el mercado bursátil global, el mercado monetario, el mercado de tipo de cambio y el mercado de salida como variables explicativas para determinar el período bajista y alcista del mercado bursátil. Los mercados que funcionan bien para predecir el período Del toro y el oso Del mercado de valores de Indonesia son el mercado mundial Del petróleo, el mercado de valores de Malasia, el mercado de valores de Singapur, el mercado de valores de EE. UU. Y el mercado de divisas.

Palabras clave: Precio del petróleo choque, Período alcista y bajista, Mercado de valores, Markov Switching VAR.

1. INTRODUCTION

The past experience of 1997/98 economic crisis and 2008 financial crisis gave us lesson that the crisis could happen any time and the sources of crisis may come from internal and external factors. The 1997/98 Indonesian Economic crisis was triggered by sudden capital flight as well as the banking crisis which led to currency crisis. To avoid the worst scenario, the Indonesian central bank attempted to rise the interest rate. The banking sectors collapsed when 16 commercial banks were closed and this led to lower the investor’s confidence on how the Indonesian government managed the economy.

The 2008/2009 global economic crisis was triggered by 2007 financial crisis in the US and spread worldwide. This crisis is characterized by the crash of financial market, the fall of purchasing power, the decline of asset holder’s welfare, the decrease of economic activity and this led to the slowdown of economic growth. Meanwhile, the research on the many financial studies have investigated financial contagion and its causes from the perspective of currency crisis (KAMINSKY, and REINHART, 2000; KAMINSKY, 2003), banking crisis (AHARONY and SWARY, 1996;) debt crisis (COLE and TIMOTHY, 1996; REINHART, CARMEN and ROGOFF, 2010), bond market (EVRENSEL and KUTAN, 2008) as well as the stock market crisis (SEE E.G., CHIANG, et.al. 2007; FLAVINET.al., 2008, KHAN and PARK, 2009).

Stock market crisis or crash is a sudden dramatic decline of stock prices across a significant cross-section of a stock market, resulting in a significant loss of paper wealth, driven by panic selling. Stock market crashes are triggered typically by loss of investor confidence after an unexpected event, and are exacerbated by fear (www.businessdictionary.com). They are usually preceded by a period of prolonged and high inflation, economic and/or political uncertainty, or hysteric speculative activity. In addition, the studies investigating the cause of stock market contagion also evidenced the existence of the role of economic fundamentals. Our research attempts to accommodate this liiterature gap. Our model takes into account the external factors both the contagion of the regional stock markets and the effect of oil market and the internal factors from the fundamental macroeconomic variables.

In this paper, we attempt to investigate the foreign shock and domestic shock on determining the period of the bull and the bear of Indonesian Stock market. In particular, we investigate the impact of global and domestic market as explanatory variables on stock price and this can be treated as a measure of domestic financial market risk. To our best knowledge, the study that investigate these relationships is new. We decompose the global explanatory variables into two markets namely oil market and global and regional stock market. Meanwhile, we use money market (money supply), exchange rate market, and output market as domestic macroeconomic variables in determining the period of bear and bull market. We attempt to address these issues by adopting a univariate Markov-switching-AR model (HAMILTON, 1989) and developed extensively by Markov Switching-VAR model (KROLZIG, 1997).

On the theoretical ground, there are the same consencus about the importance of the influence of the oil price shock on the economy. The oil shock can lead to lower aggregate demand since oil price rise can be considered as a tax imposed from net exporter oil to net importer oil countries. For the net oil importing countries, the increase in oil price could reduce the aggregate supply, then the availability of the energy as one of the main production's input will fall because the firms purchase less energy. Consequently, there is an increase in production cost that causes inflationary pressures and then in turn, it will decrease the output, the real money balance, household welfare, consumption, as well as the stock market as one of the form of liquid asset market. Economic downturns and inflationary pressures will lead to consumer's behavior and slowdowns in overall consumption and investment spending, which then affect the stock market. Hence, the immediate increase in oil prices will lead to economic slowdowns and the pattern of the bull and the bear periods of stock market.

On empirical ground, although there have been relatively numerous studies analyzing the relationship between oil prices and stock market prices, research into the oil price to predict the period of bull and bear of stock price has been increasing in recent years. MILLER and RATTI (2009) finding supports a conjecture of change in the relationship between real oil price and real stock prices in the last decade compared to earlier years, which may suggest the presence of several stock market bubbles and/or oil price bubbles since the turn of the century. Using timevarying transition-probability Markov-switching models, Chen (2010) investigates whether a higher oil price pushes the stock market into bear territory. Empirical evidence suggests that an increase in oil prices leads to a higher probability of a bear market emerging. NAIFAR and DOHAIMAN (2013) found evidence that the relationship between GCC stock market returns and OPEC oil market volatility is regime dependent.

In the framework of the current global economic crisis, an interesting question is whether the regional financial markets are suffering from contagion effects. In the case of US sub-prime mortgage market crisis starting at 2007, the effects of the crisis were automatically reflected in the rest of the world economies. These effects become more severe as the rest of the world is facing economic and financial instability. In this case, the American shock can be seen as the trigger that revealed the other economies’ own financial problems. Hence, it is important for financial investors to understand how financial markets correlate and how country-specific shocks are transmitted to other markets. Several aspects of the interactions among the international stock markets have been studied. LIU (2013) found that extreme downside movement of the S&P 500 and Nikkei 225 are significantly predictive for the likelihood of extreme downside movement in all the investigated Asia-Pacific markets (Autralia, mainland China, Hongkong, South Korea, Singapore, and Taiwan). KHAN and PARK (2009) investigate the herding contagion in the stock markets during the 1997 Asian financial crisis, above and beyond macroeconomic fundamental driven co movements.

Using cross-country time-varying correlation coefficients among the stock prices for the countries of Thailand, Malaysia, Indonesia, Korea, and the Philippines, between crisis and tranquil periods, they find strong evidence of herding contagion between these stock markets. RODRIGUEZ (2007), models dependence with switching-parameter copulas to study financial contagion in five East Asian stock indices during the Asian crisis, and from four Latin American stock indices during the Mexican crisis. They find evidence of changing dependence during periods of turmoil and Structural breaks in tail dependence are a dimension of the contagion phenomenon. MORALES and ANDREOSSO (2012) finds that the US stock markets are not generating contagious effects into the Asian stock markets. However, strong evidence of volatility transmission derived from these economies' interlinkages has been detected. QIAO et.al. (2013) reveal that the correlations among the three markets (US, Australian and New Zealand) are significantly higher in a bear regime than in a bull regime.

More recent evidence on the breakdown in the linkage between the movement of stock market and real economic activity in the US was presented in a series of papers by Binswanger (2000, 2001, 2004), who interpreted the evidence as giving support to the stock-market bubble hypothesis. In relation to these studies, there has long been interest in making reliable predictions for stock markets. The basic idea of their research is the violation of predicting the stock market based on the principle of semi strong market efficiency.

Studies in implementing the switching models of predicting the stock market and macro economy are voluminious. For instance, a study by RAPACH et al. (2005) examines a large set of macro variables and presents evidence that stock returns can be predicted using macro variables under the regime switching. GUIDOLIN and ONO (2006) estimate a number of multivariate regime switching VAR models on a long monthly US data set for eight variables that include excess stock and bond returns, the real T-bill yield, predictors used in the finance literature (default spread and the dividend yield), and three macroeconomic variables (inflation, industrial production growth, and a measure of real money growth). They find evidence that the dynamic linkages between financial markets and the macro economy have been stable over time. CHEN (2008) suggests that among the macro economic variables they have evaluated, yield curve spreads and inflation rates are the most useful predictors of recession in US stock market.

2. METHODOLOGY

We will first review the MS-VAR class of models and then continue with the estimation process via the EM algorithm. The Markov Switching Vector Autoregressions Model. MS-VAR class of models provide a convenient framework to analyze multivariate representations with changes in regime. They admit various dynamic structures, depending on the value of the state variable, s_t, which controls the switching mechanism between various states. In these models, some or all of the parameters may become varying with regard to the regime prevailing at time t. Besides, business cycles are treated as common regime shifts in the stochastic processes of macroeconomic time series. In other words, both nonlinear and common factor structures of the cyclical processes are represented at the same time.

Consider the MS-VAR process in its most general form:

$$y_t = v(s_t) + A_1(s_t)y_{t-1} + \ldots + A_p(s_t)y_{t-p} + \varepsilon_t \quad (1)$$

Where $y_t = (y_{1t}, ..., y_{nt})$ is an n dimensional time series vector, v is the vector of intercepts, $A_1, \ldots, A_p$ are the matrices containing the autoregressive parameters and ε_t is a white noise vector process such that $\varepsilon_t \mid s_t \sim NID\left(0, \Sigma(s_t)\right)$. The MS-VAR setting also allows for a variety of specifications. KROLZIG (1997) established a common notation to provide simplicity in expressing the models in which various parameters are subject to shifts with the varying state. Table 3 gives an overview of the MS-VAR models.

Table 1: Types of MS-VAR Models (Source: KROLZIG, 1997)

Notation	μ	v	Σ	A_i
MSM(*M*)-VAR(*p*)	varying	-	invariant	invariant
MSMH(*M*)-VAR(*p*)	varying	-	varying	invariant
MSI(*M*)-VAR(*p*)	-	varying	invariant	invariant
MSIH(*M*)-VAR(*p*)	-	varying	varying	invariant
MSIAH(*M*)-VAR(*p*)	-	varying	varying	varying

Note: μ : mean, v : intercept Σ : variance A_i : matrix of autoregressive parameters

In Equation 1 the intercept term is assumed to vary with state beside other parameters. Intercept switch specification is used in cases where the transition to the mean of the other state is assumed to follow a smooth path. An alternative representation is obtained by allowing the mean to vary with the state. This specification is useful in cases where a one-time jump is assumed in the mean after a change in regime. In his seminal paper, HAMILTON (1989) used a univariate two-state mean switch model of order four:

$$y_t - \mu_{s_t} = \phi_1(y_{t-1} - \mu_{s_{t-1}}) + \phi_2(y_{t-2} - \mu_{s_{t-2}}) + \phi_3(y_{t-3} - \mu_{s_{t-3}}) + \phi_4(y_{t-4} - \mu_{s_{t-4}}) + \varepsilon_t \quad (2)$$

where $\varepsilon_t \sim N(0, \Sigma)$ and $s_t = 1,2$

Note that this is just a special form of Equation 1 where only the mean parameter denoted by   is subject to change between regimes. With regard to the classification of KROLZIG (1997), this is an MSM (2)-AR (4) model. The description of the dynamics is complete after defining a probability rule of how the behavior of yt changes from one regime to another. Markov chain is the simplest time series model for a discrete-valued random variable such as the unobserved state variable st. In all MS-VAR specifications it is assumed that the unobserved state st follows a first-order Markov-process. The implication is that the current regime st depends only on the regime one period ago, st-1.

$$P\{s_t = j | s_{t-1} = i,\ s_{t-2} = k, ...\} = P\{s_t = j | s_{t-1} = i\} = p_{ij} \quad (3)$$

Where pij gives the probability that state i will be followed by state j. These transition probabilities can be collected in a (N x N) transition matrix, denoted as P. Each element in the transition matrix pij represents the probability that event i will be followed by event j.

$$P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{N1} \\ p_{12} & p_{22} & \cdots & p_{N2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1N} & p_{2N} & \cdots & p_{NN} \end{bmatrix} \tag{4}$$

$$\sum_{j=1}^{N} p_{ij} = 1 \quad \text{where} \quad i = 1,2,...,N \quad \text{and} \quad 0 \le p_{ij} \le 1 \tag{5}$$

For a two-state case, we can represent the transition probabilities by a (2×1) vector, $\hat{\xi}_{t|t}$, whose first element is $P\left(s_t = 1 | \psi_t\right)$ where $\psi_t = \{\psi_{t-1}, y_t\}$ and ψ_{t-1} contains past values of yt. If we know the value $\hat{\xi}_{t-1|t-1}$, then it would be straightforward to form a forecast of the regime for t given the information at t-1 and collect the terms for the probabilities of st = 1,2 in a vector denoted by $\hat{\xi}_{t|t-1}$ as follows:

$$\hat{\xi}_{t|t-1} = \begin{bmatrix} P\left(s_t = 1 | \psi_{t-1}\right) \\ P\left(s_t = 2 | \psi_{t-1}\right) \end{bmatrix} \tag{6}$$

We can specify the probability law of the observed variable y_t conditional on st and ψ_{t-1} and collect them in a (2×1) vector ηt:

$$\eta_t = \begin{bmatrix} f(y_t | s_t = 1, \psi_{t-1}) \\ f(y_t | s_t = 2, \psi_{t-1}) \end{bmatrix} \tag{7}$$

The joint probability of yt and st is then given by the product

$$f\left(y_t, s_t = j | \psi_{t-1}\right) = f\left(y_t | s_t = j, \psi_{t-1}\right) P\left(s_t = j | \psi_{t-1}\right) \tag{8}$$

, j=1,2

The conditional density of the tth observation is the sum of these terms over all values of st. For a two-state case:

$$f\left(y_t | \psi_{t-1}\right) = \sum_{s_t=1}^{2} \sum_{s_{t-1}=1}^{2} f\left(y_t | s_t, \psi_{t-1}\right) P\left(s_t | \psi_{t-1}\right) = \eta' \hat{\xi}_{t/t-1} \tag{9}$$

Then, the output $\hat{\xi}_{t|t}$ can be obtained from the input $\hat{\xi}_{t-1|t-1}$ by following the steps described in HAMILTON (1989).

HAMILTON'S (1989) classical algorithm consists of two parts. In the first part, population parameters including the joint probability density of unobserved states are estimated and in the second part, probabilistic inferences about the unobserved states are made by using a nonlinear filter and smoother. Filtered probabilities $P(s_t = j|\psi_t)$ are inferences about s_t conditional on information up to time t and smoothed probabilities $P(s_t = j|\psi_T)$ are inferences about s_t by using all the information available in the sample where $t = 1,2,\ldots T$.

The conventional procedure for estimating the model parameters is to maximize the log-likelihood function and then use these parameters to obtain the filtered and smoothed inferences for the unobserved state variable st. However, this method becomes disadvantageous as the number of parameters to be estimated increases. Generally, in such cases, the Expectation Maximization (EM) algorithm method developed by HAMILTON (1989) is used. This technique starts with the initial estimates of the hidden data and iteratively produces a new joint distribution that increases the probability of observed data. These two steps are referred to as expectation and maximization steps. The EM algorithm has many desirable properties as stated in HAMILTON (1989).

3. RESULTS AND DISCUSSION

As mentioned before, our analysis take into account the impact of foreign factors that decompose into the world oil market (oil) and the world and regional stock market (Dow Jones Stock Market/DJIA, Kuala Lumpur Stock Market/KLSE, Singapore Strait Time/SING, and Thailand/ SETI) and the domestic factors (foreign exchange market/XR, money market/MS, and output/Y) on Indonesian Stock Price (SP). We use monthly data from 2001.1 until 2011.12. Our world oil price data taken from the website www.indexmundi.com. The data of stock price taken from the Indonesian Stock Exchange and the domestic variables are taken from Bank Indonesia. All variables are transformed by taking natural logarithms, in real term and seasonally adjusted.

Table 2

	SP	Oil	KLSE	SING	SETI	DJIA	XR	Y	MS
Mean	3.096	1.693	6.887	7.129	6.414	9.259	4.139	2.081	12.359
Variance	0.109	0.056	0.084	0.581	0.136	0.019	0.006	0.001	0.008
Std. Dev.	0.331	0.236	0.289	0.762	0.369	0.140	0.081	0.042	0.092
Max	3.587	2.083	7.365	8.326	7.033	9.541	4.378	2.170	12.573
Min	2.527	1.274	6.350	5.881	5.617	8.862	4.007	1.920	12.227
Skewness	-0.161	-0.151	0.015	-0.161	0.578**	-0.228	0.549**	-0.497**	0.304
Kurtosis	-1.301**	-1.264**	-1.208**	-1.301**	-0.712	-0.286	0.248	1.028**	-1.215**
Jarque-Berra	9.897**	9.300**	8.036**	9.892**	10.140**	1.602	6.973**	11.268**	10.166**

Notes: All variables are taking into natural logarithm. ** represents 5% significant level

We summarizes the basic statistics of all variables in Table 2. From the stock market index, the US stock market has the highest average index in natural logarithm (9.259) compare to Asian stock markets, and followed by Singapore and Kuala Lumpur Stock Market. The SD statistics indicate that the Singapore Stock Market (0.762) is the most volatile market among the five stock market, followed by Thailand (0.369) and Indonesia (0.331). Most variables exhibit significant kurtosis with the Jarque Berra test decisively rejecting normality for all series at the 5% significance level. This indicates that most variables have non normal distribution.

We proceed by testing whether there are indeed the unit root and stationarity for all series. Table 3 reports conventional unit root and statinarity test results for all series. Two alternative tests are employed namely Augmented Dickey Fuller (ADF) test and Phillips Perron (PP) test. All series in both tests are non-stationary but the first order differences are stationary. Thus all series are I(1).

Table 3: Test for Stationarity

Variable	Augmented Dickey-Fuller		Phillips_Perron	
	In Level	In First Difference	In Level	In First Difference
SP	-0.823	-4.543**	-0.554	-8.916**
OIL	-1.072	-4.582**	-0.952	-8.478**
KLSE_CI	-1.570	-4.156**	-0.769	-10.521**
SING_CI	-0.806	-4.519**	-0.549	-8.936**
SETI_CI	-1.966	-4.067**	-1.483	-10.375**
DJIA_CI	-2.520	-3.888**	-1.907	-10.211**
XR	-2.518	-6.565**	-1.404	-9.935**
OUTPUT	-0.359	-8.021**	-3.048*	-31.858**
MS	1.376	-4.882**	1.262	-15.558**

Notes: ** represents 5% significant level. Both tests use constant but no trend in auxilliary regressions

Before estimating the MSVAR model, we specify bivariate linear VAR model between Indonesian Stock prices (SP) with each variable. We employ the Hannan Quinn (HQ) criteria, Akaike Information Criteria (AIC), and Schwarz Bayesian Criteria (SBC) to determine the order of the MSVAR model. The rule of selecting the order is that we employ the most recommended by two or three criterias. If all of these three criterias are different, we chose the smallest order.

4. CONCLUSION

In this paper, we attempt to investigate the foreign shock and domestic shock on determining the period of the bull and the bear of Indonesian Stock market. In particular, we investigate the impact of global and domestic market as explanatory variables on stock price and this can be treated as a measure of domestic financial market risk. We decompose the global explanatory variables into two markets namely oil market and global and regional stock market. Meanwhile, we use money market (money supply), exchange rate market, and output market as domestic macroeconomic variables in determining the period of bear and bull market. We attempt to adress these issues by adopting a univariate Markov-switching-AR model (HAMILTON, 1989) and developed extensively by Markov Switching-VAR model (KROLZIG, 1997).

Our result shows that the bear periods of Indonesian Stock markets are late 2000, late 2002, late 2003, early 2007, early 2008, mid 2010 and early 2011 (7 episodes) and these are associated with serious drop of monthly average rate of Indonesian Stock Price. The longest duration of bear period is the early 2011 episode for 8 months followed by early 2008 episode (6 months) and early 2007 episode (5 months).

Our results also indicate that the probability of regime 1 swith to regime 2 is still high (54.5%) whereas the probability of regime 2 swtich to regime 1 is low (2.4%). These observations further confirm the dominance of regime 2 (bull period) over regime 1 (bear period) in the market, thus the market that perform well to predict the period of bull and bear period of Indonesian Stock Market are world oil market, Malaysia Stock Market, Singapore Stock Market, US Stock market and foreign exchange market.

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