DURATIONS OF TRADE IN THE PHILIPPINE STOCK MARKET: AN APPLICATION OF THE MARKOV-SWITCHING MULTI-FRACTAL DURATION (MSMD) MODEL

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ABSTRACT

This study examined the durations of trade in the Philippine Stock Market using the Markov Switching Multi-Fractal Duration (MSMD) Model using tick data from 20 frequently traded stocks in the Philippine Stock Market. Results revealed that higher duration results to lower trading intensity because of low information of traders about the stocks during the period. The lesser attention paid to the stock, the more likely that trade will not happen.

The higher trading intensity is a result of shorter trade durations, this means that the interval from one trading transaction to another is smaller. The higher the trading intensity implies higher price impact of trades and faster price adjustment to new trade-related information. Information flow affects intensities but it does not trigger trading automatically because investors have limited attention, and they need to allocate attention to process all kinds of information before making a trading decision.

Keywords: Markov Switching Multi-Fractal Duration (MSMD) Model, Philippine Stock Market, Trade Durations

EXECUTIVE SUMMARY

This study examined the durations of trade in the Philippine Stock Exchange (PSE) using the Markov Switching Multi-Fractal Duration (MSMD) Model using top twenty (20) randomly selected active firms listed in the PSE. Tick-by-tick intra-day trading of the equities in the PSE were used, from May 2 to 31, 2013, from 9:00 – 3:30pm (where the PSEI has recorded its 31st all-time high index). This study considered only the bullish period and not the regular period, to limit the immense data in the estimation.

To study the durations of transaction volumes in the stock market, this paper used the model of inter-trade durations introduced by Chen, Diebold and Schorfheid (2012). This model is closely-linked to the pioneering “multi-fractal" return volatility model of Mandelbrot, Fisher, and Calvet (1997), Calvet and Fisher (2001) and Calvet and Fisher (2004) as discussed and

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extended in Calvet and Fisher (2008). The model which is called the Markov-switching multi-fractal duration (MSMD) model, captures high persistence in duration clustering and it will intrinsically capture long memory while maintaining covariance stationarity.

Empirical exploration suggested MSMD's superiority relative to leading competitor model of durations. MSMD is a parameter-driven long memory model of conditional intensity dynamics, with the long memory driven by structural Markov switching components (Chen *et al.*, 2012). This study of inter-trade durations is an important and natural measure of market liquidity, and its variability is related to risk. The exploration on the MSMD model in the Philippine Stock Market is expected to capture the key features of the financial market inter-trade durations. This would help traders to be informed and be guided in investing in the stock market. A vibrant stock exchange will improve the financial market and this in turn will have a positive impact to the economy.

The following are the summary of findings:

1. In May 2–31, 2013 period in the PSE, GLO achieved the highest maximum duration of 48.52 minutes. All stocks have a minimum duration of .0167 minute. Among the top 20 stocks considered, MEG got the highest number of trade transactions of 15,467. Among the top 20 stock considered, GLO has the lowest trade transactions of 2,302 and has the longest trade duration mean of 2.41 minutes. GLO has a lower trading intensity (among the top 20 stock considered) during this period because it has a longer duration to its next trade transaction.

2. Trade will not happen if investors have lesser interest on the stock. If the number of trading transactions are higher, there is a strong indication on the presence of informed traders in a particular stock during the period. These increased trading volume pronounces an environment of informed trading, which can enhance trading activity if informed traders are further attracted by opportunities to make use of their private information.

3. In terms of the results of the MSMD parameters, k has an increasing level of intensity resulting to $m_{0's}$ (high state) decreasing value. On the other hand, the transition from high state to low state ($2 - m_0$) entails higher probability and this is supported by the rate at which the persistence changes across k intensity components, denoted by b. This means that the increasing trading intensity (k) results to higher probability to which the transition from high state to low state is persistent.

4. There is a higher chance that the occurrence of a high state is decreasing, low state is increasing and the extent of persistence to be decreasing, because of the higher the probability, denoted by γ_k.

5. The probability that there will be a consistent transition from high state to low state in MEG is increasing but at a lower rate compared to GLO because of the increased level of intensities. Traders who are well-informed are willing to invest on a stock that do not have a high risk of going down or up (abruptly) and assures them of better profit. MEG appeared to be the most desirable stock during the period because of its low closing price of PhP 4.00 and this has resulted to enormous volume of stocks amounting to 1.7 billion.

6. The interval from one trading transaction to another is smaller if there is a higher trading intensity as a result of shorter trade durations. A higher trading intensity results to higher price impact of trades and faster price adjustment to new trade-related information. The information flow affects intensities but it does not trigger trading automatically because investors have limited attention, they need to allocate attention to process all kinds of information before making a trading decision. The stronger directionality of trades, there is predominance of trades of similar size and the same direction (buy or sell).

INTRODUCTION

Financial markets are complicated systems since they combine the interactions of thousands of individuals and institutions and generate at every instant the prices to buy and sell, and claim uncertain cash flows in the future. An organized and regulated financial market, where securities (bonds, notes, shares) are bought and sold at prices governed by the forces of demand and supply, called the stock exchange market (Refran, 2013).

Stock exchanges basically serve as primary markets where corporations, governments, municipalities, and other incorporated bodies can raise capital by channeling savings of the investors into productive ventures. They also act as secondary markets, where investors can also sell their securities to other investors for cash, thus reducing the risk of investment and maintaining liquidity in the system. The stock exchange market imposes stringent rules, listing statutory requirements that are binding on all listed and trading parties (www.pse.com.ph).

One of the oldest stock exchanges in Asia is the Philippine Stock Exchange (PSE). It is the national stock exchange of the Philippines, having been in continuous operation since its inception in 1927. It is a private non-profit and non-stock organization created to provide and maintain a fair, efficient, transparent and orderly market for the purchase and sale of securities such as stocks, warrants, bonds, options and others (Philippine Stock Exchange, Inc.).

The main role of PSE is to bring together companies which aim to raise capital through the issue of new securities. Through the listing of their share in the stock exchange, companies can have easier access to funds. The PSE facilitates the selling and buying of the issued stocks and warrants. It provides a suitable market for the trading of securities to individuals and organizations seeking to invest their saving or excess funds through the purchase of securities. Raising new capital through an additional public offering is easier and less expensive when the company is already listed in the Exchange (Philippine Stock Exchange, Inc.). The PSE plays a vital role in the financing of productive enterprises that use the funds for growth and expansion of new jobs. Consequently, essential to the growth of the Philippine economy.

As of February 6, 2013, the Philippine Stock Exchange (PSE) has 344 listed companies with a total market capitalization of US$ 255.1 billion with 134 trading participants registered (www.pse.com.ph). Figure 1 presents the stock market highlights from 2008 to 2013. The year 2008 has been a very difficult year for the country. There were soaring commodity and fuel prices and the worst financial crisis since the Great Depression has left world markets reeling (SEPO, 2009). The is also the year when the country was plagued with political events such as the GSIS-Meralco bribery case, Philippine National Broadband Network controversy (also referred to as the NBN/ZTE deal) and the Euro Generals scandal. These events in 2008 have discouraged investors leading to a declining trend throughout the year, with a 48% decrease in the PSEi.

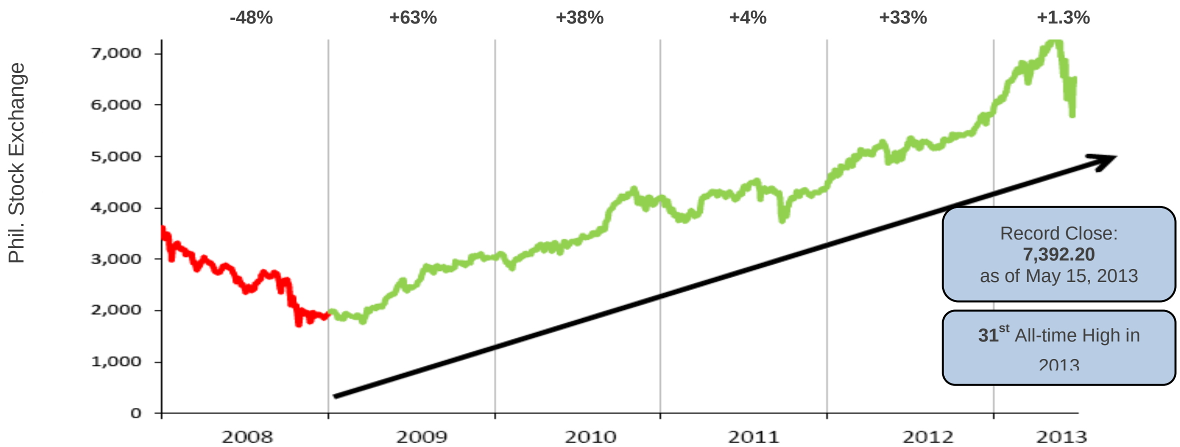

Figure 1. Stock Market Highlights from 2008 to 2013 (as of December, 2013).
Source: www.pse.com.ph

The stock market recovered in 2009 and 2010, with increase stock returns of 63% and 38%, respectively. The best performing sectors in the PSEi during those years were mining and oil with an index that rose by about 234%, followed by the industrial sector, whose index rose by 116%. Foreign investors also renewed their interest as they bought Php 14.9 billion worth of local stocks (SEPO, 2010).

From 1986 until 2013, PSEi averaged 2,203 index points reaching an all time high in May 2013. A record low of 130 Index points in February 1986, during the EDSA Revolution, affected the investors' interest to trade in the stock market. The PSEi, which has a 13.3% record increase in July 16, 2013, ranked fourth among selected Asia indices (see Figure 2). This is the period after the peaceful May 2013 election. The orderly conduct of the election might have boosted the confidence of investors to trade in the stock market.

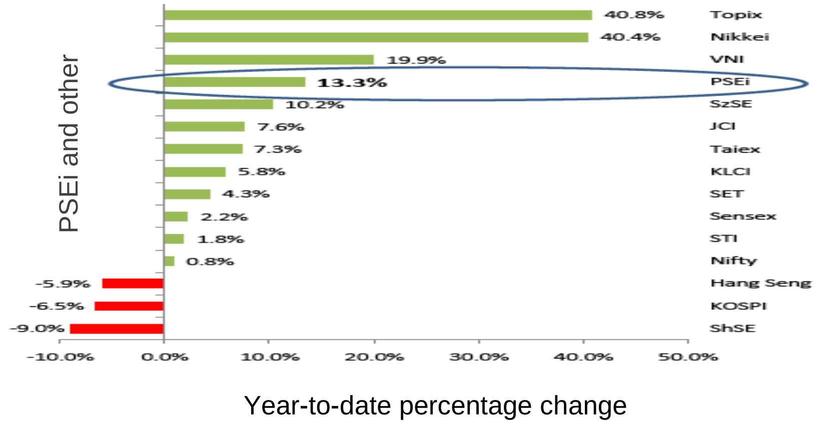

Figure 2. PSEi vs. selected Asian Indices. Year-to-date change

Figure 2 presents the year-to-date change of the PSEi and how it outperformed other Asian indices. It can be seen that the PSEi is gaining recognition from international financial critiques and this is a good sign of a booming economy. As of July 2013, the stock market made a 13% increase for the first two quarters. It has also recorded the 31st all-time high with a record close of 7,392.20 last May 15, 2013. The PSEi registered all-time highs in several occasions, generating profits for most investors, but it ended to a meager year-to-date increase of 1.3%. Midway through the year, the Quantitative Easing (QE) tapering issue emerged, where the U.S. Federal Reserve announced it is winding down its bond-buying program which provided stimulus to the U.S. economy in the past years. As a result, the Philippine stock market tanked due to fears that foreign investments which poured into the local markets would be siphoned back to the U.S. From a high of 7,392.20 in May 2013, the PSEi closed at 5,889.83 on the last trading day (December 27, 2013) of the year – a 20% decline from its peak (www.pinoymoneytalk.com).

Even though 2013 ended with only a 1.3% increase from 2012, the PSE still recorded all-time highs which are milestones brought about by the investment upgrade from Fitch Ratings (BBB-Stable Investment Grade), Standard and Poor's (BBB-Stable Investment Grade) and Moody's (Ba1-Stable). This rating system helped investors in determining the risk associated with investing in a country, specific company, investing instrument or market. Ratings can be assigned to short-term and long-term debt obligations as well as securities, loans, preferred stock and insurance companies. Long-term credit ratings tend to be more indicative of the country's investment surroundings and/or its ability to honor its debt responsibilities (www.investopedia.com). Because of these recent investment upgrades, the Philippine Stock Exchange (PSE) was given the Marquee Award, for being the Best Stock Exchange in Southeast Asia in the 7th Annual Alpha Southeast Asia Best Solution and Deal Awards for 2013 (www.pse.com.ph). According to the World Federation of exchanges, the PSEi is consistently included among the best performing indices in the world since 2010. Further, it topped the "Bloomberg Riskless Return Ranking" among ASEAN indices in 2012 (www.bloomberg.com) and identified by CNN Money as the fifth hottest stock market in the world last April 2013 (www.cnn.com).

One of the main indices monitored in the credit ratings is the PSE Composite Index or PSEi, which is a major stock market index tracking the performance of the most representative companies listed on The Philippine Stock Exchange. It is a free-float, capitalization-weighted index. The selection of companies in the PSEi is based on a specific set of criteria. There are also six additional sector-based indices called the All Shares Index, a much broader index. The remaining six indices are sector indices based on a company's main source of revenue (Table

1). Although listed in an index, companies are listed on the PSE under the First Board, Second Board or the Small and Medium Enterprises Board based on market capitalization.

Table 1. The eight PSE constituent indices.

Indices	Ticker Symbol
PSE All Shares Index	All
PSE Composite Index	PSEi
PSE Financials Index	FIN
PSE Holding Firms Index	HDG
PSE Industrial Index	IND
PSE Mining and Oil Index	M-O
PSE Property Index	PRO
PSE Services Index	SVC
PSE-Exclusive Index	Eei

Source: www.pse.com.ph

Movements in the stock market can have a profound economic impact on the economy. If there is a collapse in share prices, it has the potential to cause widespread economic disruption (Pettinger, 2013). In 2012, our country has encountered all sorts of problems. The country was plagued with various political problems such as corruption scandals and impeachment trials of our country's highest officials. Moreover, the country experienced a paralyzing fiscal crisis that threatened our credit standing (Sy, 2013).

The stock market did not drop despite all the negative news and events which may have precipitated a correction. The market overcame global headwinds such as the US government shutdown and debt ceiling problems. Moreover, our stock market continued to rise despite local adversities such as the MILF insurgency, super typhoons, a strong earthquake and the pork barrel scandal. All these events failed to break our stock market's strong upward trajectory (Sy, 2013).

Due to the pressure of maintaining a stable stock market index, it is high time to study the movement of stocks and how varied the exchanges are that would encourage or discourage investors to buy or sell stocks every trading day. The high frequency data in the stock market is very volatile because volumes of transactions that enter the market can change in an instant, every minute of each trading day and the interval of each transaction can have short or long durations. A key stylized fact noted in the irregularly-spaced transaction in the stock market is the long memory in durations. Durations are useful for predicting instantaneous volatility and integrated variance over short periods of time (e.g. 1 hour) and so may aid high-frequency volatility trading and risk management (Zikes and Shenai, 2009).

Rationale of the Study

In the last few years, financial market intraday trading data for a number of securities have become available. Several empirical studies have used these data to identify various patterns in trading volume and in the daily behavior of security prices (Admati and Pfleiderer, 1988). The stock market, which has a volatile nature of intraday trading data, is a rarely explored topic in time-series financial econometrics. The need of handling immense data in the stock market and the interest of disengaging the information concealed within it, have been claimed to be a key modern development in all sciences. Duration studies in the financial markets have become one of the most active and productive empirical endeavors in the social sciences. A cynic, or a trained economist, might say that the volume of financial research reflects the high price that market participants are willing to pay, but there are also deep intellectual reasons for the interest in financial market data (Campbell, 2008).

The liquidity of a financial asset on a given day and market depends on how frequently that asset is traded, or equivalently on the times between consecutive transactions, called inter-trade durations, defined as the waiting times between two consecutive transactions in the financial market. The times to trade, which is recorded sequentially in time form time series possesses interesting dynamic properties, such as time varying moments and serial correlation. The duration analysis of financial assets is a relatively new topic of research motivated by the interest in assessing future asset liquidity in the sense of time (Gouriéroux *et al*., 1999).

Multifractal measures were introduced by Mandelbrot in 1972 and have been applied in the physical sciences to describe the distribution of energy and matter, such as turbulent dissipation, stellar matter, and minerals. These measures are new to economics and as far as the literature is concerned, have not yet been explored in the Philippine Stock Market studies. A number of financial econometricians have conducted studies about durations of trade. Popularly employed inter-trade duration models are the autoregressive conditional duration (ACD) (Dufour and Engle, 2000), stochastic conditional duration (SCD) (Zikes and Chenai, 2009) and fractionally integrated autoregressive conditional duration (FIACD) models (Dungey *et al.*, 2008). Only a few have attempted to use other models, such as the Markov-switching multi-fractal duration (MSMD) method in studying trade durations in the stock market (Zikes *et al.*, 2013; Chen *et al.*, 2012). This study used the Markov-switching multi-ftractal inter-trade duration model developed by Chen, Diebold and Schorfheid in 2012. This was applied to the top active stocks in the Philippine Stock Exchange. Studies in the Philippine Stock exchange are rarely explored because of the unavailability of the data. As far as the author knows, this will be one of the few studies that will be conducted in the country to estimate the nature and durations of trade (through time, volume of transactions and prices) in the stock market.

To study the durations of transaction volumes in the stock market, this paper used the model of inter-trade durations introduced by Chen, Diebold and Schorfheid (2012). This model is closely-linked to the pioneering “multi-fractal" return volatility model of Mandelbrot, Fisher, and Calvet (1997), Calvet and Fisher (2001) and Calvet and Fisher (2004) as discussed and extended in Calvet and Fisher (2008). The model which is called the Markov-switching multi-fractal duration (MSMD) model, captures high persistence in duration clustering and it will intrinsically capture long memory while maintaining covariance stationarity.

Empirical exploration suggested MSMD’s superiority relative to leading competitor model of durations. MSMD is a parameter-driven long memory model of conditional intensity dynamics, with the long memory driven by structural Markov switching components (Chen *et al.*, 2012). This study of inter-trade durations is an important and natural measure of market liquidity, and its variability is related to risk. The exploration on the MSMD model in the Philippine Stock Market is expected to capture the key features of the financial market inter-trade durations. This would help traders to be informed and be guided in investing in the stock market. A vibrant stock exchange will improve the financial market and this in turn will have a positive impact to the economy.

Objectives of the study

The general objective of the study is to apply Markov-switching multi-fractal duration (MSMD) model in the Philippine Stock Exchange. Specifically it aims:

1. to present the trend in the top 20 active stocks from May 2 - 31, 2013, 9:30 AM to 3:30 PM;
2. to provide firm-by-firm descriptive statistics of stocks;
3. to estimate the MSMD model parameter vector using maximum likelihood estimation; and

Conceptual framework

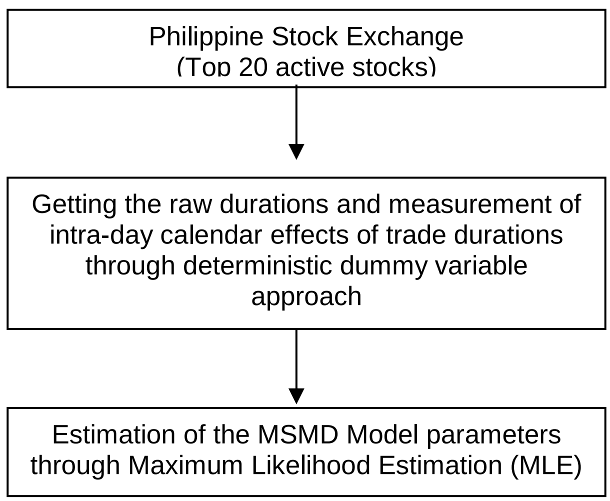

Figure 3. Process flow of MSMD application to PSE's top 20 active stocks.

There are a lot of factors influencing the movements of stocks, but this study will only focus on the application of the MSMD model to the Philippine Stock Exchange's top twenty active stocks through tick-by-tick data of price and volume of transactions. Figure 3 presents the process of applying the MSMD model.

The application process starts with getting the raw durations and transforming it through the incorporation of intra-day calendar effects using the simple deterministic dummy variable approach. After the formation of the adjusted duration series, it will proceed with the estimation of parameters (γ_k, b, m_0) using maximum likelihood estimation (MLE).

Data

The data employed in the study are tick data information of time, price and volume of trades received by the top 20 active stocks every minute of transactions in each trading day. Table 1 presents the security names of the top 20 active stocks in the PSE with their ticker symbols.

Tick data are information used by professional day traders to watch the current price movements at its most detailed level. It shows each individual trade as it occurs, and is usually displayed as a scrolling list. This can be used as part of a larger trading system (such as a confirmation for an indicator trade), or on its own. It provides several pieces of valuable information about each trade, and the market as a whole. It also shows the amount of volume that each trade includes *i.e.* the number of contracts or shares that were traded (www.tickdatamarket.com).

Table 1. Top 20 active stocks in the PSE.

Security Name	**Ticker Symbol**
Aboitiz Power Corporation	AP
Alliance Global Group, Inc.	AGI
Ayala Corporation	AC
Ayala Land, Inc.	ALI
Bank of the Philippines	BPI
BDO Unibank, Inc.	BDO
Cosco Capital, Inc.	COSCO
D&L Industries, Inc.	DNL
Eastwest Banking Corporation	EW
Filinvest Land, Inc.	FLI
Globe Telecom, Inc.	GLO
International Container Terminal	ICT
LT Group, Inc.	LTG
Megaworld Corporation	MEG
Metro Pacific Investments Corporation	MPI
Metropolitan Bank and Trust Co.	MBT
Philippine Long Distance Telephone Co.	TEL
SM Investments Corporation	SM
SM Prime Holdings, Inc.	SMPH
Universal Robina Corporation	URC

Source: www.pse.com.ph

Economic Model

The liquidity of a financial asset on a given day and market depends on how frequently the asset is traded, or equivalently on the times between consecutive transactions, called inter-trade durations.

Inter-trade durations are defined as the waiting times between two consecutive transactions in the financial market. The times to trade, which is recorded sequentially in time, form time series processes with interesting dynamic properties, such as time varying moments and serial correlation. The duration analysis of financial assets is a relatively new topic of research motivated by the interest in assessing future asset liquidity in the sense of time (Gouriéroux *et al.*, 1999).

The duration between events, or in the case of stock returns, is referred to as trades occurring at period t_i *and* t_{i-1}, represented by this economic model*:*

$$d_i = t_i - t_{i-1},\qquad (1)$$

where:

d_i = duration *i* between trade events
t_i = time period *i* when trade occurred
t_{i-1} = previous time period, *i-1,* when trade occurred

Econometric Model

The Markov-Switching Multi-Fractal Duration (MSMD) Model proposed by Chen, Diebold and Schorfheide (2012), is a new model of durations in terms of a mixture of exponential random variables in which intensity evolves dynamically. This model was derived from the multi-fractal stochastic volatility model of Calvet and Fisher (2008). The sequential derivation of the MSMD Model in this chapter is obtained from Chen, Diebold and Schorfheide in 2012.

Using the mixture of exponentials representation of the MSMD model by using the time deformation function (T_t) and in introducing the model the duration between events is used, this is referred to as trades occurring at period t_i and t_{i-1}:

$$d_i = t_i - t_{i-1}\qquad (1)$$

Let $\tilde{t}_i$ and t_i denote the time of *ith* event in the operational and clock time respectively, $\varepsilon_i = \tilde{t}_i - \tilde{t}_{i-1}$ and $d_i = t_i - t_{i-1}$ are *ith* duration in different time scale. In the operational time scale, the trading process is a homogenous Poisson process, so the distribution of the durations is *iid* exponential. That means
$\epsilon_i \sim$ *iid Exp(1).*

By the definition of T_t, we have:

$$\varepsilon_i = \tilde{t}_i - \tilde{t}_{i-1} = \Lambda(t_{t-1}, t_i) = \int_{t_{t-1}}^{t_i} \lambda(s)ds\qquad (2)$$

Let $\lambda_i = \Lambda(t_{t-1}, t_i)/d_i$ be the mean intensity, then we can write:

$$d_i = \frac{\epsilon}{\lambda_i}\qquad (3)$$

In this model, we assume that the intensities are composed multiplicatively of $\bar{k}$ dynamic components following two-state Markov-switching processes with different degrees of persistence, ranging from very low to very high. This produces the MSMD Model.

These durations are distributed according to this distribution:

$$\epsilon_i \sim iid\ Exp(1),\ i=1,\ldots..,n\qquad (4)$$

$$d_i = \frac{\epsilon}{\lambda_i}$$

where:

i = event *i* or trade *i* in the stock market

Exp(1) = refers to an exponential distribution with intensity parameter 1
λ_i = mean intensities of the durations

Conditional on λ_i , the durations have an *Exp(λ_i)*distribution, and we refer to λ_i's as (mean) intensities. These intensities have evolved in accordance to the Markov-switching multi-fractal process:

$$\lambda_i = \lambda \prod_{k=1}^{\bar{k}} M_{k,i} \tag{5}$$

where:
λ = is a positive constant
k = dynamic components from 1 to $\bar{k}$
$M_{k,i}$ = are positive intensity components independent across k and following the Markov renewal processes

In equation 5, at time *i,* $M_{k,i}$ is either renewed (drawn from a fixed distribution *f(M)* or kept at its value, $k \in \{1,2,3.....,\bar{k}\}$. We write:

$$M_{k,i} = \begin{cases} \text{draw from f(M) with probability (w.p.) } \gamma_k \\ M_{k,i} \qquad \text{with probability (w.p.) } 1 - \gamma_k , \end{cases} \tag{6}$$

where:
f(M) = is the renewal distribution which is identical for all k
k = dynamic components from 1 to $\bar{k}$
M is greater than zero
E(M) equal to 1

The renewal of $M_{k,i}$ corresponds to a new shock of type *k* hitting the system at time *i*, with the draw from the *f(M)* renewal distribution governing the magnitude of the shock. The value of *k* determines the average lifetime and hence, the persistence of an *M* shock. A large *k* corresponds to *M* shocks with short expected lifetime and low persistence. Consider now the renewal distribution *f(M).* We take it as discrete, with two equally likely points of support:

$$M_{k,i} = \begin{cases} m_0 \quad \text{w.p. } ½ \\ 2- m_0 \quad \text{w.p. } ½ , \quad \text{where, } m_0 \in (0, 2]. \end{cases} \tag{7}$$

We refer to the distribution as a binomial measure, which is the simplest example of a multi-fractal model. This distribution differs slightly from a standard 0-1 Bernoulli trial. Note that the condition $m_0 \in$ (0, 2] implies M > 0 a.s. and *E(M)* = 1, as required. By combining (6) and (7) we obtain a two-state Markov process for $M_{k,i}$ that alternates between the states $s_1 = m_0$ and $s_2 = 2-m_0$ with transition probabilities.

$$P_{(\gamma_k)} = \begin{bmatrix} 1-\gamma_k/2 & \gamma_k/2 \\ \gamma_k/2 & 1-\gamma_k/2 \end{bmatrix} \qquad (8)$$

In equation 8, the matrix $\rho_{(\gamma_k)}$ specifies the transition from state s_j to s_i. The largest eigenvalue of $\rho_{(\gamma_k)}$ is equal to one, which implies that the Markov process has an equilibrium distribution. The equilibrium probabilities of states s_1 and s_2 are ½ regardless of γ_k. The second eigenvalue is equal to 1- γ_k and determines the persistence of the Markov Chain.

Finally, to induce parsimony, the following restriction on the sequence $\{\gamma_k\}_{k=1}^{\bar{k}}$ is imposed:

$$\gamma_k = 1-(1-\gamma_{\bar{k}})^{b^{k-\bar{k}}}, \qquad \text{where, } \gamma_{\bar{k}} \in (0,1) \text{ and } b \in (0,\infty) \qquad (9)$$

Two specifications for the distribution of the multipliers have been proposed by Calvet and Fisher (2004) – binomial and log-normal. This study used the binomial multiplier as proposed by Calvet and Fisher (2004), which is the simplest example of multifractal measures. As discussed in Chapter 3 (Digression of the MSMD Model), the binomial measure is a continuous but singular probability measure that has no density and no point mass. In the binomial specification, each multiplier, if at all, is renewed by drawing the values m_0 and $2-m_0$; $m_0 \in (1,2)$, with equal probability, ensuring that the mean is equal to one. The transition matrix associated with each multiplier is thus given by equation 8:

$$P_{(\gamma_k)} = \begin{bmatrix} 1-\gamma_k/2 & \gamma_k/2 \\ \gamma_k/2 & 1-\gamma_k/2 \end{bmatrix} \qquad (8)$$

Although the renewal distribution $f(M_k)$ is the same for all components M_k, the renewal probability, γ_k, differs across k, creating a variety of intensity components ranging from low-frequency components that are renewed infrequently to high-frequency components that are renewed frequently, despite the fact that all renewals are of course stochastic. Small values of k relative to $\bar{k}$ lead to large values of 1-γ_k and therefore produce “low-frequency” or long-run M_k shocks with low renewal probability and hence long expected lifetime and high persistence.

Once the number of $\bar{k}$ components has been determined, the MSMD model is a fully specified Markov-switching process with $2^{\bar{k}}$ states and the full parameter vector is then:

$$\theta_{\bar{k}} = (\gamma_k, b, m_0)' \qquad (10)$$

where:

$\gamma_{\bar{k}}$ = the renewal probability that controls the persistence of the *k* intensity components directly

b = controls the rate at which the persistence changes across *k* intensity components.

m_0 = the value of the latent intensity component; m_0 in the high state and $2\text{-}m_0$ in the low state

Note that the MSMD model has a $\bar{k}$-dimensional state vector and $2^{\bar{k}}$ states: $M_i = \left(M_{1,i}, M_{2,i} \ldots \ldots M_{\bar{k},i}\right)$. Each latent intensity component takes the value m_0 in the high state and $2\text{-}m_0$ in the low state.

Empirical Analysis of Philippine Stocks

Intra-day calendar effects

Durations display intra-day calendar effects, specifically inter-trade durations have strong diurnal daily pattern, i.e., the average duration is short both at opening time in the morning and at close time in the afternoon, but long at noon time. These characteristics of durations appear to have a daily seasonality. This daily seasonality is documented by many empirical studies (Chen, 2011; Engel, 1997). There are several methods to remove the seasonality. This study adopted the simple deterministic dummy variable approach used by Ghysels *et al.* (2004). The main step is to regress the logarithm of the raw duration on the indicator variables that indicate the time of day. A day is divided into 9 sub-periods. Each sub-period is 30 minutes and Table 2 presents the 9 sub-periods and their corresponding time schedule.

Table 2. Sub-periods of durations.

Sub-periods	Time Schedule
1	9:30 – 10:00 AM
2	10:00 – 10:30 AM
3	10:31 – 11:00 AM
4	11:01 – 11:30 AM
5	11:31 – 12:00 NN
6	1:30 – 2:00 PM
7	2:00 – 2:30 PM
8	2:31 – 3:00 PM
9	3:01 – 3:30 PM

Consider the regression equation:

$$\log d_i = \sum_{k=i}^{9} \alpha_k x_{ki} + \varepsilon_i = \alpha' x_i + \varepsilon_i \qquad (11)$$

where:

x_{ki} =1, if time *i* belongs to the intraday sub-period *k* and 0 otherwise

α = parameter of the regression model

Considering equation (11) the seasonally adjusted series or the adjusted duration series with incorporated calendar effect is defined by:

$$\hat{d}_i = d_i \exp(-\hat{\alpha}' x_i) \tag{12}$$

where:

$\hat{d}_i$ = is the adjusted duration estimate

$\hat{\alpha}$ = denotes the OLS estimator of α

Maximum Likelihood Estimation (MLE)

The likelihood function for a sequence of durations is given by $d_{1:n} = \{d_1, \ldots, d_n\}$, which is governed by MSMD Model. By conditional factorization of the joint density, the likelihood is given by (Chen *et al.*, 2012):

$$p(d_{1:n} | \theta_{\bar{k}}) = p(d_1 | \theta_{\bar{k}}) \prod_{i=2}^{n} p(d_i | d_{1:i-1}, \theta_{\bar{k}}). \tag{13}$$

where:

$d_{1:n}$ = is a sequence of durations , $\{d_1, \ldots, d_n\}$

$\theta_{\bar{k}}$ = is the parameter vector which is given by equation (10) $\theta_{\bar{k}} = (\gamma_k, b, m_0)'$

Conditional on λ_i , each duration *di* simply has an $Exp(\lambda_i)$ distribution with density $p(d_i | \lambda_i) = \exp[-\lambda_i d_i]$, the evaluation of the likelihood would be trivial if the sequence of λ_i were known. But the λ_i 's are not known and must be replaced with estimates from an optimal filter as in Hamilton (1989), the only difference in the MSMD model is, it has $2^{\bar{k}}$ states rather than Hamilton's 2 state.

The potential values of the states as given in equation (9), are *Mk,i* by $s_1 = m_0$ and $s_2 = 2 - m_0$. Using this notation, λ_i can take four values:

$$\lambda_i \in \{\lambda s_1 s_1, \lambda s_1 s_2, \lambda s_2 s_1, \lambda s_2 s_2\}. \tag{14}$$

Given that the states *Mk,i* evolve independently, the matrix of transition probabilities for the mean intensity is simply:

$$\mathrm{P}_{\lambda} = \mathrm{P}(\gamma_1) \otimes \mathrm{P}(\gamma_2) \tag{15}$$

where:

$\otimes$ = denotes the Kronecker product

P_{λ} = is defined in equation (10)

$$P_{(\gamma_k)} = \begin{bmatrix} 1 - \gamma_k / 2 & \gamma_k / 2 \\ \gamma_k / 2 & 1 - \gamma_k / 2 \end{bmatrix}$$

In this notation, the distribution is characterized by λ_i through densities $p(\lambda_i | \cdot)$. After this, the likelihood is evaluated recursively. The first step is to initialize the hidden states with their equilibrium distribution in period *i = 0*. Then starting from $p(\lambda_{i-1} | d_{1:i-1}, \theta_{\bar{k}})$ the *i'th* point likelihood will be obtained by evaluating the conditional distribution:

$p(\lambda_i | d_{1:i-1}, \theta_{\bar{k}})$, which is the forecast of the mean intensity (16)

$p(d_i | d_{1:i-1}, \theta_{\bar{k}})$, which is the forecast of the duration (17)

$p(\lambda_i | d_{1:i}, \theta_{\bar{k}})$, which is for updating (18)

As presented, the parameter vector is given by equation (10) and the number of states is $2^{\bar{k}}$:

$$\theta_{\bar{k}} = (\gamma_k, b, m_0)'$$

Thus, $\bar{k}$ can be seen as a model index by using the notation M_j to denote a MSMD Model with $\bar{k} = j$. As discussed earlier, the $\bar{k}$ will affect the number of hidden states in the MSMD model and it will not change the dimensionality of the parameter vector $\theta_{\bar{k}}$. Even though $\bar{k}$ will be large, the MSMD model remains parsimonious.

Estimation Procedure

The maximum likelihood estimation was done using the OX language by Jorgen Doornik. In the deterministic dummy variable approach, transforming the durations (that will capture the intra-day calendar effects), the Shazam version 11.0 was used.

The steps in the estimation involve:

1. The computation of time interval between consecutive trades, which is defined as inter-trade durations:

   $$d_i = t_i - t_{i-1} \quad (1)$$

2. The computed raw durations are transformed into adjusted duration series. This is done because durations appear to have daily seasonality. The effect of seasonality in durations is removed through simple deterministic dummy variable approach.

   $$\log d_i = \sum_{k=i}^{9} \alpha_k x_{ki} + \varepsilon_i = \alpha' x_i + \varepsilon_i \quad (11)$$

3. The sequence of adjusted durations derived in number 2, is estimated through Maximum Likelihood Estimation and this will yield a parameter vector.

   $$\theta_{\bar{k}} = (\gamma_k, b, m_0)' \quad (10)$$

where:

$\gamma_{\bar{k}}$ = the renewal probability that controls the persistence of the *k* intensity components directly

b = controls the rate at which the persistence changes across *k* intensity components.

m_0 = the value of the latent intensity component; m_0 in the high state and 2-m_0 in the low state

Trend Analysis

Duration is the time interval between two consecutive transactions referring to stock market spaces between trades that vary from time to time within a trading day. Trends are presented through time series duration of trades in minutes. Figure 4 shows the durations of trade with respect to the number of transactions traded by the 20 stocks in the PSE last May 2013. Among the stocks considered, Globe (GLO) appeared to have the highest maximum trade duration of 48.52 minutes and Megaworld Corporation (MEG) has the highest number of trade transactions during the period of May 2013, with a total of 15,467 transactions. The higher duration reflects the low trading intensity of GLO and this can be attributed to the low information of traders regarding the stock during the period. The lesser attention paid to the stock, the more likely that trade will not happen (Chen, 2011). The number of trading transactions of MEG indicates the presence of informed traders in this stock during the period. Increased trading volumes serve as indicators of informed trading, which either may enhance trading activity if informed traders are further attracted by opportunities to exploit their private information (Admati and Pfleiderer, 1988).

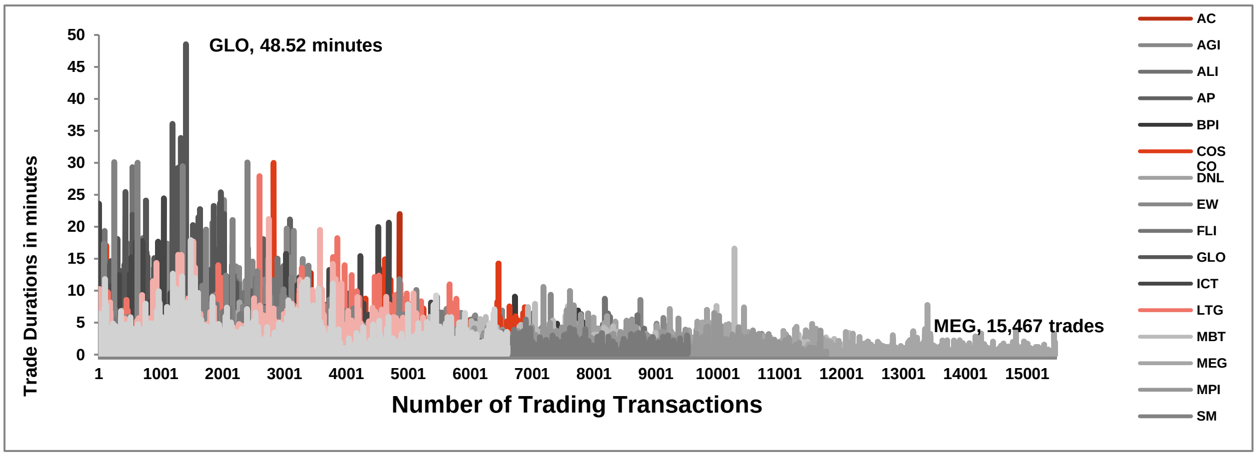

Figure 4. Time series duration of 20 stocks in the PSE, May 2013.
Source: Philippine Stock Exchange, Inc. (PSEi)

The figures of GLO and MEG can be further explained by its trade volume and prices. Figure 5 presents the volume of transactions and box-whisker plots of prices of the 20 stocks in the PSE. Stock prices can be constant or variable in its opening, highest, lowest and closing prices. In the stock market, groups of intermediaries (dealers) are responsible for setting tradeable prices in their stocks. A dealer buys from sellers and sells to buyers on the basis of these prices. The dealer may also be required to provide a well organized/stable market in these shares (Naes and Skjeltorp, 2006). GLO has 1.22 million total volume of transaction and a closing price of PhP 1,451. The longer trade duration of GLO can be explained by its expensive price which resulted to its lower number of transactions. Meanwhile, MEG has the highest volume of transaction, with 1.7 billion given a lower closing price of PhP 4.00. The shorter trade durations and enormous amount of trading transactions of MEG can be explained by its lower price resulting to higher trading volumes. The timing of trades plays an important role in the learning mechanism of market participants in drawing inferences from the trading process (Diamond and Verrecchia, 1987). The actual transaction process of how buyers and sellers find one another and agree on a price can affect price formation and trading volumes in a market (Naes and Skjeltorp, 2006).

The excellent performance of MEG in the stock market can be attributed to its reputation. MEG is a subsidiary of Alliance Global Group, Inc. (AGI) and its main business is real estate particularly in condominium developments in Metro Manila and outside provinces. Due to soaring reputation of the real estate business, investors want to pour more money in this industry resulting to shorter duration of trades which implies higher trading intensity

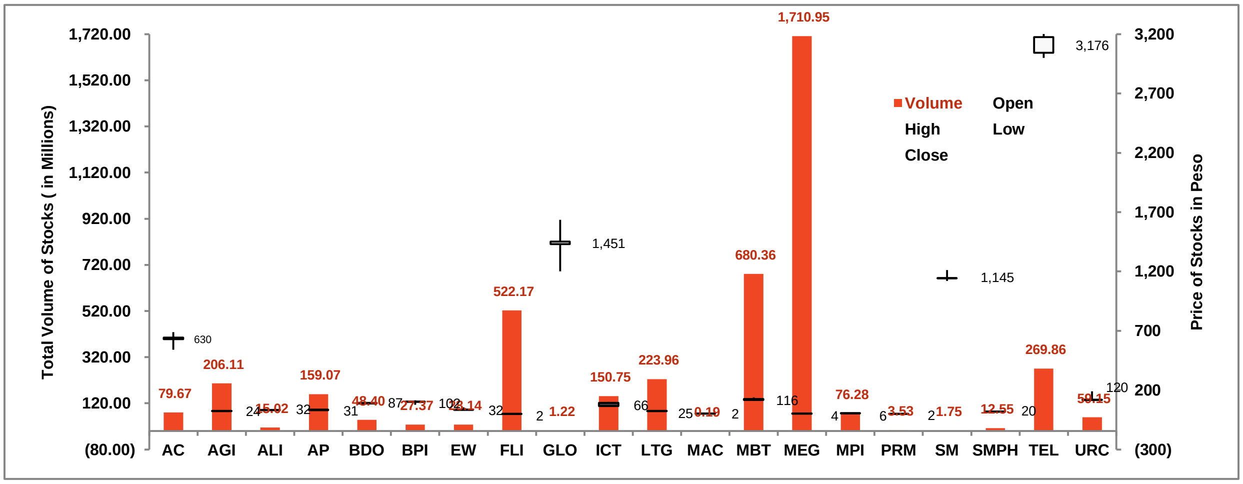

Figure 5. Volume of transactions and box-whisker plots of prices of the 20 stocks in the PSE, May 2013.
Source: Philippine Stock Exchange, Inc. (PSEi)
"Open, High, Low and Close" refers to the opening, highest, lowest and closing prices of each stocks during the period.
*** Labels in the box-whisker plots refer to the closing price of the stock.*

Firm-by-firm Descriptive Statistics

Table 3 shows that descriptive statistics of the twenty frequently traded stocks in the PSE. Presented in the table are the mean, standard deviation, standard deviation, minimum and maximum values, as well as the number of samples (trading transactions) estimated. Among the firms considered, GLO has the highest maximum duration of 48.52 minutes and the minimum duration is common to everyone which is only .0167 minute. The large sample of 15,467 is given by MEG and the lowest sample is 2,302 by GLO. The highest duration mean is 2.41 minutes which is given by GLO. The longer the duration to the next trade transaction reflects a lower trading intensity.

Table 3. Firm-by-firm descriptive statistics of stocks in the PSE.

Stock	Mean	Standard Deviation	Coefficient of Variation	Standard Error	Min	Max	N
AC	0.9430	1.36	1.45	0.0176	0.0167	22.00	5,970
AGI	0.5269	0.79	1.49	0.0076	0.0167	16.70	10,723
ALI	0.5822	0.75	1.28	0.0076	0.0167	9.87	9,681

AP	1.5159	2.01	1.32	0.0331	0.0167	21.13	3,670
BDO	0.3877	0.51	1.32	0.0042	0.0167	6.37	14,554
BPI	0.7090	0.90	1.27	0.0101	0.0167	9.35	7,908
COSCO	0.5989	1.15	1.92	0.0122	0.0167	30.02	8,911
DNL	0.4824	0.62	1.28	0.0057	0.0167	7.40	11,631
EW	1.6296	2.21	1.36	0.0380	0.0167	24.18	3,401
FLI	1.7332	2.39	1.38	0.0422	0.0167	29.30	3,212
GLO	2.4132	3.63	1.51	0.0757	0.0167	45.52	2,302
ICT	1.0049	1.77	1.76	0.0238	0.0167	24.45	5,569
LTG	0.9641	1.54	1.60	0.0202	0.0167	27.92	5,832
MBT	0.4656	0.65	1.40	0.0059	0.0167	16.62	12,135
MEG	0.3645	0.56	1.53	0.0045	0.0167	9.22	15,467
MPI	0.4788	0.66	1.39	0.0061	0.0167	10.63	11,755
SM	0.9933	1.64	1.65	0.0221	0.0167	30.08	5,504
SMPH	0.5615	0.73	1.29	0.0074	0.0167	7.87	9,518
TEL	1.0654	1.56	1.46	0.0215	0.0167	21.20	5,251
URC	0.8478	1.23	1.45	0.0152	0.0167	17.92	6,604

*Coefficient of Variation = standard deviation/mean

GLO revealed to be low-performing in all descriptive indicators considered in the May 2013 period. The performance of GLO in the period considered is not reflective of the whole year performance of the stock in the year 2013 as a whole, because GLO is known to be a major provider of telecommunications services in the Philippines and owned by Ayala Corporation. It is one of the major brands in the Philippines and the purveyor of the Filipino digital lifestyle (www.globe.com.ph). Its low performance in May 2013 can be considered as a "bearish" period in the stock market, which is normal because not all periods are "bullish" trades.

Estimation Results of the MSMD Parameter

Table 4 presents the results the MLE estimation of the three parameters b, m_0 and γ_k. The estimation procedure was done using the Ox Console Software by Jorgen Doornik. The parameters were first adjusted for seasonality, before they were estimated. The k level of intensity specified in the model are k = 2,4,6. The starting values used the default set by the previous author who used the MSMD model (Zikes *et al.*, 2013). The k values reflect the level of trading intensity in the PSE. The value of k corresponds to shocks (random trading information) with short expected lifetime and low persistence. Traders in the stock market receive random information about firms which distorts the trading intensity, and the trading process evolves on some operational or economic time scale that differs from the calendar or clock time (Chen, 2011).

On the other hand, the value of m_0 pertains to the value obtained from the two-state Markov process for $M_{k,i}$, that alternates between states $s_1 = m_0$ (high state) and $s_2=2-m_0$ (low state), with transition probabilities that specifies the transition from s_1 to s_2. The value of γ_k is the renewal probability in the transition that controls the persistence of the *k* intensity components directly. This is supported by the value of *b* which controls the rate at which the persistence changes across *k* intensity components.

In the general trend of the parameter values, the increasing level of *k* intensity results to a decreasing trend in the value of m_0 (high state). The probability that there will be a transition from high state to low state ($2 - m_0$) is increasing and this is supported by the rate at which the persistence changes across *k* intensity components, denoted by *b* (Table 4). This means that the increasing trading intensity (*k*) results to higher probability to which the transition from high state to low state is persistent. To further explain the transition, Figure 6, 7, 8 and 9 presents the trend of parameter values of m_0, b and γ_k across the assumed *k* trading intensities, respectively. The higher the probability, denoted by $\gamma_{k,}$ the higher is the chance that the occurrence of high state is decreasing and the occurrence of low state to be increasing while the extent of persistence is decreasing.

The higher trading intensity is a result of shorter trade durations, this means that the interval from one trading transaction to another is smaller. The higher the trading intensity implies higher price impact of trades and faster price adjustment to new trade-related information. Information flow affects intensities but it does not trigger trading automatically because investors have limited attention, they need to allocate attention to process all kinds of information before making a trading decision (Chen, 2011). The stronger directionality of trades, there is predominance of trades of similar size and the same direction (buy or sell). The central assumption is that timing of trades is not only driven by the occurrence of information but also reflects the individual decisions of traders (Naes and Skjeltorp, 2006).

Table 4. Parameter Estimates of the MSMD Model.

	k=2			**k=4**			**k=6**		
Stock	**m_0**	**b**	**γ_k**	**m_0**	**b**	**γ_k**	**m_0**	**b**	**γ_k**
AP	1.6841	100	0.50846	1.4823	33.970	0.9990	1.435	12.9	0.9990
AGI	1.6315	100	0.2470	1.4700	13.074	0.4010	1.374	6.62	0.5700
AC	1.6410	100	0.3306	1.4728	14.430	0.5591	1.3815	9.32	0.9950
ALI	1.6500	100	0.30644	1.4600	13.386	0.3980	1.379	8.51	0.4760
BDO	1.6027	100	0.05575	1.4259	39.899	0.12247	1.322	21.108	0.1738
BPI	1.6240	100	0.22341	1.4528	27.062	0.29859	1.3721	14.588	0.3850
COSCO	1.7254	26.364	0.07128	1.5446	7.8825	0.13324	1.4509	5.6252	0.18190
DNL	1.6062	100	0.06974	1.4337	45.800	0.14403	1.3351	11.649	0.18458
EW	1.6838	100	0.35898	1.4820	19.276	0.47371	1.3976	15.477	0.625394
FLI	1.7143	100	0.21127	1.5340	9.1160	0.32678	1.4401	4.7879	0.46114
GLO	1.7811	100	0.58893	1.5586	35.443	0.9990	1.4792	6.3512	0.9990
ICT	1.7256	24.37	0.30884	1.5723	11.534	0.5373	1.5152	7.6756	0.66411
LTG	1.7477	100	0.34769	1.5598	9.8619	0.64678	1.4841	5.7998	0.84334
MBT	1.6295	100	0.22555	1.4267	25.479	0.25503	1.3624	9.8822	0.39602

MEG	1.6503	100	0.10227	1.4833	15.752	0.10946	1.3907	9.9926	0.13819
MPI	1.6694	100	0.25054	1.4874	18.039	0.30365	1.3924	9.56	0.45242
SM	1.6861	88.896	0.50110	1.5575	17.483	0.55679	1.4387	8.2508	0.99346

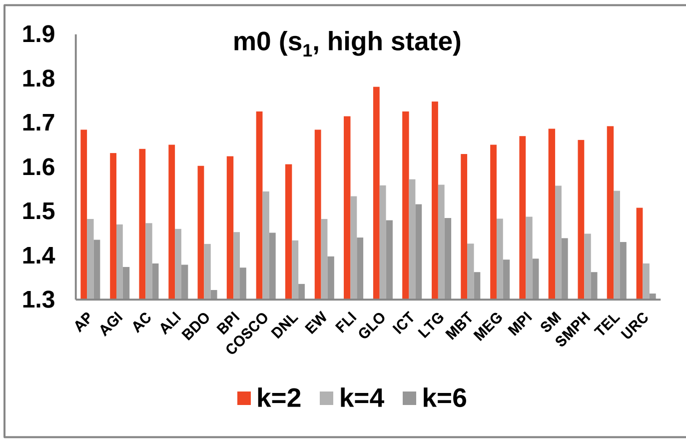

Figure 6. Values of parameter m_0 for each stock at different level of intensities.

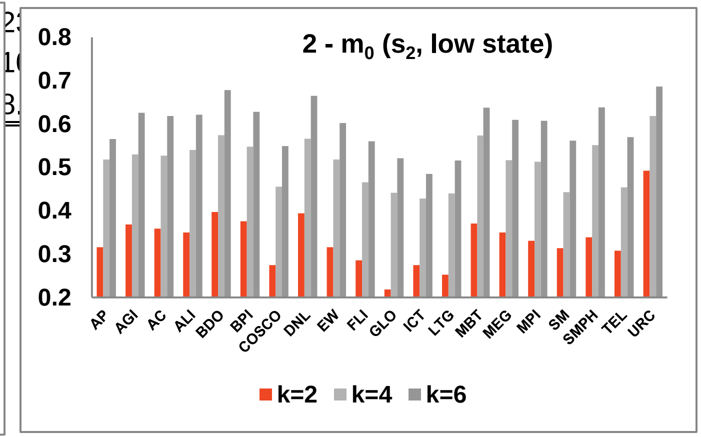

Figure 7. Values of parameter $2\text{-}m_0$ for each stock at different level of intensities.

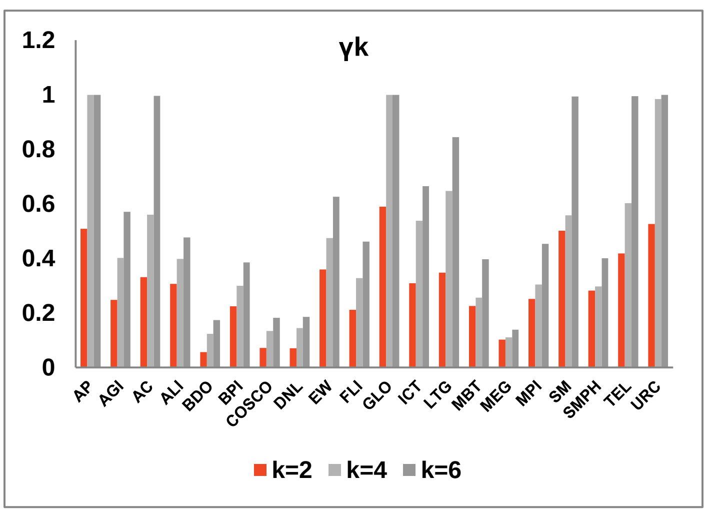

Figure 8. Values of parameter *b* for each stock at different level of intensities.

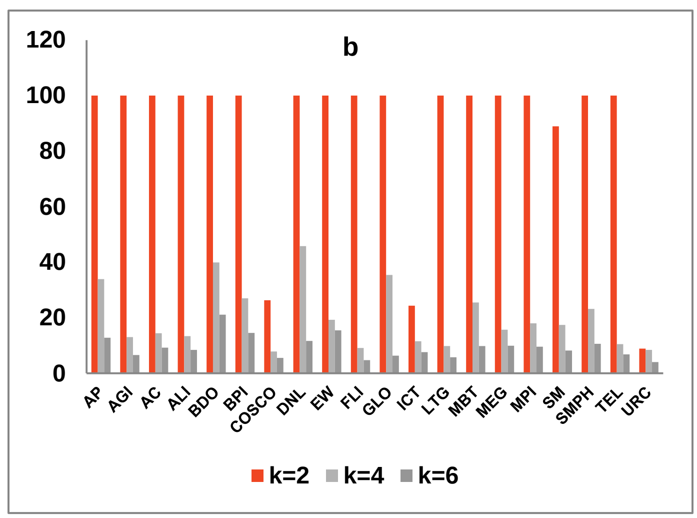

Figure 9. Values of parameter *b* for each stock at different level of intensities.

Summary and Conclusions

This study on the durations of trade in the Philippine Stock Market using the Markov switching multi-fractal duration (MSMD) model has used 20 frequently traded stocks in Philippine Stock Market. The paper has utilized tick data information of trade transactions that enter the stock market in a specified period of time, within each trading day.

The following conclusions were drawn from the results of the study:

1. In May 2–31, 2013 period in the PSE, GLO achieved the highest maximum duration of 48.52 minutes. All stocks have a minimum duration of .0167 minute. Among the top 20 stocks considered, MEG got the highest number of trade transactions of 15,467. The stock who is not performing well during this period is GLO with only 2,302 trade transactions and has the longest trade duration mean of 2.41 minutes. GLO has a lower trading intensity because it has a longer duration to its next trade transaction.

2. Trade will not happen if investors have lesser interest on the stock. If the number of trading transactions are higher, there is a strong indication on the presence of informed traders in a particular stock during the period. These increased trading volume pronounces an environment of informed trading, which can enhance trading activity if informed traders are further attracted by opportunities to exploit their private information.

3. In terms of the results of the MSMD parameters, k has an increasing level of intensity resulting to $m_{0's}$ (high state) decreasing value. On the other hand, the transition from high state to low state ($2 - m_0$) entails higher probability and this is supported by the rate at which the persistence changes across k intensity components, denoted by b. This means that the increasing trading intensity (k) results to higher probability to which the transition from high state to low state is persistent.

4. There is a higher chance that the occurrence of a high state is decreasing, low state is increasing and the extent of persistence to be decreasing, because of the higher the probability, denoted by γ_k.

5. The probability that there will be a consistent transition from high state to low state in MEG is increasing but at a lower rate compared to GLO because of the increased level of intensities. Traders who are well-informed are willing to invest on a stock that do not have a high risk of going down or up abruptly and assures them of better profit. MEG appeared to be the most desirable stock during the period because of its low closing price of PhP 4.00 and this has resulted to enormous volume of stocks amounting to 1.7 billion.

6. The interval from one trading transaction to another is smaller if there is a higher trading intensity as a result of shorter trade durations. A higher trading intensity results to higher price impact of trades and faster price adjustment to new trade-related information. The information flow affects intensities but it does not trigger trading automatically because investors have limited attention, they need to allocate attention to process all kinds of information before making a trading decision. The stronger directionality of trades, there is predominance of trades of similar size and the same direction (buy or sell).

Recommendations

Given the results of the study, the following are recommended:

1. To fully analyze the transition probabilities from low state to high state, out-of-sample forecast and simulation should be done. Furthermore, reliability test of the results should be done to ensure its efficiency. This was not applied in the study due to the lack of program to generate the desired outputs.

2. The risk implied in investing to different stocks should be considered. The analysis on the transition probabilities should be complemented with a gauge in risk measurement. This is to further described the type of investor that would engage in a particular stock *i.e.* risk seeker, risk averse or risk neutral.

Areas for further study

This paper has not yet fully utilized the features of the MSMD model. Future researches can venture on the following studies:

1. To further study the different stocks traded in the PSE, this model can be explored by comparing the high and low trading group of firms using longer time periods.

2. Use of other competing models of MSMD to model the Philippine stock Market *i.e.* Autoregressive Conditional Duration (ACD) and Fractionally Integrated Autoregressive Conditional Duration (FIACD). In financial econometrics studies, ACD model appeared to have a strong evidence of providing duration clustering in analyzing financial transaction data; both deterministic, time-of-day effects and stochastic effects which is an important part of the market microstructure theory (Engle and Russell, 1998). On the other hand, FIACD is a long memory model that effectively incorporates the long memory parameter into short memory ACD model. It has stronger persistence in the conditional mean than ACD resulting to infinite series of coefficients arising from fractional differencing (Jasiak, 1999).

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