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Time-varying Industrial Portfolio Betas under the Regime-switching Model: Evidence from the Stock Exchange of Thailand

Suthawan Prukumpai *

Department of Accounting, Faculty of Business Administration, Kasetsart University

Bangkok 10900, Thailand Email: fbusswp@ku.ac.th

Applications of beta are crucial in determining equity pricing and portfolio strategy. The conditional Capital Asset Pricing Model (CAPM) theory suggests that systematic risk factor (henceforth “beta”) is changing over time. Therefore, this paper investigates the time-varying beta behavior in the Stock Exchange of Thailand using the two-regime Markov-switching model. The monthly returns of eight industrial portfolios from July 2005 to September 2014 were used in this study. In comparison, the results from the unconditional CAPM beta and three-year rolling regression show that betas are unstable over time. In addition, the linearity LR tests confirmed non-linearity in all of the industrial portfolio returns, suggesting that betas are time-varying. The empirical results from the Markov-switching model showed that the conditional betas could be classified into two regimes: low beta one and high beta one. Overall, the results confirmed that the systematic risk of industrial portfolios is time-varying and regime-dependent. Therefore, the performance of asset allocation and risk management strategies could be improved if investors considered the regime-switching behavior of industrial portfolio returns in the portfolio construction instead of the traditional approach with constant beta.

Keywords: Conditional-CAPM, Markov-Switching Model, Stock Exchange of Thailand

JEL Classification: C58, G10, G12

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Introduction

A substantial number of empirical studies have revealed that the unconditional Capital Asset Pricing Model (henceforth referred to as CAPM) is unable to explain the cross-section of average returns on stocks (e.g. Jensen, 1968; Dybvig and Ross, 1985; Fama and French, 1992; Jagannathan and Wang, 1996). Specifically, unconditional CAPM or static CAPM cannot explain why small firms outperform large firms (e.g. Banz, 1981); why firms with a high book-to-market ratio outperform those with low book-to-market ratio (e.g. Fama and French, 1992); and why stocks with high prior returns during the previous year continue to outperform those with low prior returns (e.g. Carhart, 1997).

The significance of non-beta variables triggered the validity of the single factor Capital Asset Pricing Model. In addition to such problems, the stability assumption of risk measure is weakening. Over the past few decades, a number of studies have empirically examined the performance of the static CAPM; however, the results reported in those studies supported the view that it is possible for beta to change over time (e.g. Fabozzi and Francis, 1978; Bos and Newbold, 1984) and that this is tied to some exogenous macroeconomic factors (e.g. Jagannathan and Wang, 1996; Faff and Brooks, 1998). Specifically, Adrian and Franzoni (2005) emphasize the necessity to include the time-varying beta into the model to capture investor characteristics. Following this criticism, several time-varying beta models (e.g. Campbell and Vuolteenaho (2004); Fama and French (2005); Petkova and Zhang (2005); Lewellen and Nagel (2006); Ang and Chen (2007)) have been proposed to calculate the true underlying beta of an asset. Those models are referred to the conditional CAPM where the betas are conditional to set of information. In particular, Jagannathan and Wang (1996) clearly explained that the relative risk of a firm's cash flow is likely to vary over the business cycle. For instance, firms with high financial leverage are relatively more distressed to the others during a recession, causing their stock betas to rise. Hence, betas and expected returns will in general depend on the nature of the information available at any given point in time and vary over time.

There have been several approaches to addressing the issue of time-varying betas. First, Bollerslev, Engle and Wooldridge (1988) proposed the Multivariate GARCH (M-GARCH) model to generate a time-varying series of conditional variances and co-variances. This method was empirically applied to measure time-varying beta in numerous studies, e.g. Faff and Brooks (1998), Faff et al. (2000), and Mergner and Bulla (2008).

Second, the state-space model has been applied to estimate changes in the beta (slope) parameter. Particularly, the state space model allows unobserved variables to be incorporated into the estimated observable model. The Kalman filter technique was used to compute the beta based on an initial set of prior series of conditional beta from a single index model². Several studies applied this technique to estimate time-varying betas, e.g. Groenewold and Fraser (1999), Choudhry and Wu (2008), and Adrian and Franzoni (2009). Rather than the first two approaches, which allow betas to continuously change over time, the third approach, the regime-switching model, treats beta to be constant over a particular period and changes to other values during other periods. Moreover, regime-switching model does not require choosing a prior threshold of state variable that makes beta changing. Instead, the regime switching is based on probability and determined by data. Using the Markov Switching model, Huang (2000) found two different regimes of beta coefficients. This approach was also successfully applied in Chen and Huang (2007), Mergner and Bulla (2008), and Yu et al. (2010).

Research Objectives and Contributions

In securities analyses and company valuations, the accuracy of beta is crucial in determining investment strategies and the pricing of individual equities. A vital feature of the beta is the explanative power it lends to assessing portfolio risks and returns. Given a lack of explanative power, portfolio managers are unable to forecast returns and minimize the risk-to-reward ratios (Klemkosky and Martin, 1975). Once allowing the beta to change over time to represent the dynamic pattern of the investors' required rate of returns, the portfolio is frequently rebalanced to ensure the investors' optimal satisfaction over time. GARCH-type and Kalman filter methods allow betas to change continuously; however, in practice, the more trading activities there are, the higher are the transaction costs. For this reason, the regime-switching model, which assumes betas to be constant during some period then change to other level in other periods, is applied in this paper to estimate conditional beta³ at the industrial portfolio levels. Industrial portfolios were used because of their importance in practical portfolio construction.

² See Hamilton (1994) for details on the estimation algorithm of the Kalman filter technique.

³ Ang and Bekaert (2002) and Guidolin and Timmermann (2007) provide a discussion and empirical evidence supporting the uses of regime-switching models in asset allocation.

Though several researchers have empirically examined the conditional version of CAPM, there are a limited number of studies of this model using emerging data. Recently, the emerging markets have attracted interest from investors because of their high expected returns. Though they provide high expected returns, they carry more risk. Therefore, this study will explain the time-varying behavior of betas, which will provide a better understanding of the nature of systematic risk. This can also improve portfolio construction and risk management, which eventually will benefit the development of the financial markets.

Thai's stock market is ranked among most attractive emerging markets in ASEAN. Using the data from the Stock Exchange of Thailand would benefit not only for Thai investors but also the equity mutual funds. Moreover, the evidence of instability betas from Stock Exchange of Thailand would fill the recent gap in existing line of literatures.

Theoretical Framework and Literature Review

Unconditional and Conditional CAPM

The basic of the CAPM is the extension of portfolio theory with risk-free asset and unlimited short sales. Under the CAPM, not only is the single investor focused on, but all investors are considered to determine the market equilibrium. Therefore, the market price is an equilibrium price. However, a crucial assumption is that all investors have the same beliefs concerning the probability distribution of all assets, i.e. they agree on the expected returns, variances, and covariances. Sharpe (1964) and Lintner (1965) showed that there was a positive relationship between expected returns and risk as follows:

$$E(R_{i,t}) = r_f + \left[\frac{\text{cov}(R_{i,t}, R_{m,t})}{\text{Var}(R_{m,t})} \right] (R_{m,t} - r_f). \quad (1)$$

In equation (1), we see that the expected returns depend linearly on the covariance of the asset with the market portfolio, R_m . Such covariance can be interpreted as a measure of risk for individual assets and hence is called systematic risk or beta, β_i . The intuition of this relationship is that for the risk an investor takes, he or she is compensated by the amount of $(R_{m,t} - r_f)$ per unit of risk, and the total amount $(R_{m,t} - r_f)\beta_i$ is then called the risk premium or the market price of risk. Additionally, the risk-free rate of return may be interpreted as the price for time.

Thus far, we have considered the CAPM in which investors are not able to base their beliefs on the information they receive. In particular, this is the assumption that beliefs are constant over time. This version of CAPM is called the static CAPM since β_i is constant, or the unconditional CAPM since conditional information plays no role in determining expected returns. Empirically, the Black (1972) version of static CAPM is

$$E(R_i) = \gamma_0 + \gamma_1 \beta_i. \quad (2)$$

In a widely-cited study, Fama and French (1992) examined the CAPM relationship given in equation (2) and found that the estimated value of γ_1 was close to zero. They interpreted the “flat” relationship between expected returns and beta as strong evidence against the CAPM. While such a flat relationship may be evidence against the unconditional CAPM, it is not necessarily evidence against the conditional one. In addition, many empirical investigations have given strong support to the idea that beliefs vary over time; of special importance is the beta (Keim and Stambaugh, 1986 and Breen, Glosten, and Jagannathan, 1989). This aspect is taken into account in the conditional CAPM.

Allowing the beta to vary over time can be justified by the reasonable assumption that the relative risk and the expected returns of an asset may vary with the business cycle. Jagannathan and Wang (1996) showed that the expected return depends linearly on the market risk and the risk of a change in the market risk, i.e. it depends on two different betas⁴. Specifically, the conditional CAPM for each asset i in each period t is

$$E(R_{i,t} | I_{t-1}) = \gamma_{0,t-1} + \gamma_{1,t-1} \beta_{i,t-1}, \quad (3)$$

where $\beta_{i,t-1}$ is the conditional beta of asset i defined as

$$\beta_{i,t-1} = \frac{\text{cov}(R_{i,t}, R_{m,t} | I_{t-1})}{\text{Var}(R_{m,t} | I_{t-1})},$$

$\gamma_{0,t-1}$ is the conditional expected return on a zero-beta portfolio or risk-free rate, and $\gamma_{1,t-1}$ is the conditional market risk premium. To explain cross-section variations in the unconditional expected return of each asset, the unconditional expectation was taken on both sides of equation (3) in order to get

$$E(R_{i,t}) = \gamma_0 + \gamma_1 \bar{\beta}_i + \text{cov}(\gamma_{1,t-1}, \beta_{i,t-1}), \quad (4)$$

where $\gamma_0 = E(\gamma_{0,t-1})$, $\gamma_1 = E(\gamma_{1,t-1})$, and $\bar{\beta}_i = E(\beta_{i,t-1})$.

⁴ See Jagannathan and Wang (1996) for conditional CAPM derivation.

According to equation (4), if the covariance between the conditional beta and conditional market risk premium is zero, then it turns out to be the unconditional CAPM. However, in general, they are correlated. For instance, during a bad economy, firms with high financial leverage are in relatively poor shape compared to other firms, causing their stock betas to rise.

Empirical studies of time-varying CAPM

Models with time-varying betas and risk premia have attracted increased attention in recent years (Ferson and Harvey, 1991 and Jagannathan and Wang, 1996). The reasons are the need for modifications of the static CAPM due to the poor empirical performance and the strong empirical evidence of time-varying covariances, variances, and risk premia. By introducing time varying betas and risk premia into the model, Ferson and Harvey (1996) showed that the conditional CAPM performed much better than its unconditional form. In addition, Jensen (1968) and Dybvig and Ross (1985) have documented that the conditional CAPM could hold perfectly period-by-period even though stocks are mispriced by the unconditional CAPM. Therefore, a stock's alpha or pricing error might be zero; that is, the market portfolio might be conditionally mean-variance efficient in every period (Lewellen and Nagel, 2006).

Beside the positive evidence on the conditional CAPM, Lewellen and Nagel (2006) argued that changes in betas and the risk premium are inadequate to explain the asset pricing anomalies like momentum and the value premium. They performed a simple test of conditional CAPM using direct estimates of conditional alpha and beta from a short-window regression. They showed that the conditional CAPM performed nearly as poorly as the unconditional one. The conditional alphas were significant and the conditional betas changed over time but not enough to explain the unconditional alphas, in particular.

While there have been substantive studies on testing the constancy of the beta and the validity of the conditional CAPM, only limited studies on testing the instability of the beta. For example, the multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model has been applied in several studies to model time-varying betas (Giannopoulos, 1995 and Brooks et al., 1998). Under this approach, the betas are indirectly calculated from conditional variance-covariance series.

An alternative way of modeling the time-varying behavior of beta is based on the state space form of the CAPM. Specifically, the Kalman Filter (KF) technique is used to estimate time-varying betas. Under this approach, different models for the dynamic process of conditional betas have been proposed. For instance, Fabozzi and Francis (1978) model beta as a random coefficient, Lie et al. (2000) model time-varying beta as a random walk model, and Bos and Newbold (1984) model beta as a mean-reverting model.

The last approach is the regime-switching model originated by Hamilton (1989, 1990). Although regime-switching regression models have been applied in many areas, the literature related to time-varying betas is relatively limited. Recently, the regime-switching model has gained more attention as an alternative method for testing beta stability. Huang (2000) used the regime-switching model to test the validity of a two-state market model where the parameters are allowed to shift between two different regimes. Huang defined the two-state model as high- and low-risk regimes. Using the monthly returns on the Microsoft Corporation stock and CRSP value-weight index, the results showed that the hypothesis of two states cannot be rejected. Therefore, the regime-switching models could be used to calculate time-varying beta.

Mergner and Bulla (2008) used the GARCH and Stochastic Volatility (SV) conditional betas, Kalman-filter-based and regime-switching approaches, to estimate the time-varying behavior of betas in pan-European economies over the period 1987 to 2005. The results provided strong supportive evidence of time-varying betas. Moreover, the time-varying model exhibited better forecasted returns than those of standard ones. In sum, the Kalman-filter approach is the most accurate method. Evidence from emerging markets provided by Yu et al. (2010) showed that there was time-varying beta in the Philippines Stock Exchange (PSE). Specifically, they used the regime-switching model to model beta behavior and concluded that individual stock reacts to changes in market conditions differently in high- and low-beta regimes. They also noted that shifts in regimes are related to market developments and changes in market volatility.

In sum, a review of the empirical studies provides evidence that the regime-switching model could be a decent candidate to measure the time-varying beta. Although the vast results from these empirical studies provide evidence to support the existence of time-varying betas, there are limited studies on modeling beta behavior over

time, especially using industrial-level data in emerging markets. In particular, the empirical evidence reveals that systematic risk on the industry level is time-variant in Europe, the United Kingdom, the United States, Australia, and New Zealand. However, similar work using Thai data is still missing. Using regime-switching methodology, Khanthavit (2011) estimated expected returns and risks and characterized them according to up and down market conditions. He showed that the performance of portfolio allocation and risk management significantly improved when the Markov switching model was applied. Nevertheless, his study did not cover the time-varying portfolio beta. Therefore, the empirical results in this study will provide additional information about the risk nature of the industrial portfolios in the Stock Exchange of Thailand, which could provide additional guidelines for asset allocation and risk management.

Research methodology

Data Description

This paper aimed to examine the behavior of eight industrial portfolio betas classified by the Stock Exchange of Thailand⁵. Specifically, the value-weighted SET Industry Group Index constructed by the Stock Exchange of Thailand was used to calculate the industrial portfolio returns. Using the Datastream database, the monthly close price of the SET Industry Group Index from July 2005 to September 2014, 111 observations in total were used in this study. The range of the data used depended on the availability of recent definitions of the Industry Group Index. The monthly data were used to average out the noise in the daily and weekly returns. The market return was proxied by the return on the SET index, while the 1-month government bond yield was used as a proxy of the risk-free interest rate.

Econometric Estimation

Unlike volatility-based and state-space approaches, which allow betas to continuously change over time, the regime-switching approach treats beta as a constant

⁵ The eight industry sectors include Agriculture Products and the Food Industry (ARGO), Consumer Products (CONS), Financials (FIN), Industrials (INDUS), Property and Construction (PROP), Resources (RES), Services (SER), and Technology (TECH).

over a particular period and changes to other values in other periods. This property is more suitable for portfolio construction in practice. For this purpose, the focus of this paper was to apply the regime-switching model to conditional beta estimation.

The Markov-switching model (MSM) developed by Hamilton⁶ is usually applied to empirical finance in order to model the possibility of regime-switching. Guidolin (2012) and Ang and Timmermann (2011) summarized the variation of MSMs and their application to research in finance. The uses of MSMs in estimating the conditional CAPM were first suggested by Huang (2000). Specifically, Huang models the behavior of conditional betas to be calculated from two different regimes. Equation (5) presents the two-regime switching model,

$$R_{i,t} = \alpha_{i,s_t} + \beta_{i,s_t} R_{m,t} + \varepsilon_{i,t}, \quad (5)$$

where $R_{i,t}$ is lognormal monthly industrial excess returns while $R_{m,t}$ is lognormal monthly market excess returns.

Notably, s_t could be either state 1 or state 2 of the two regimes CAPM betas, and $\alpha_{i,s_t} = \begin{cases} \alpha_{i,1} & \text{if } s_t = 1 \\ \alpha_{i,2} & \text{if } s_t = 2 \end{cases}$ and $\beta_{i,s_t} = \begin{cases} \beta_{i,1} & \text{if } s_t = 1 \\ \beta_{i,2} & \text{if } s_t = 2 \end{cases}$ denote the conditional alphas and conditional betas in each state, respectively. Alphas represent excess returns after accounted for risk and they are commonly used to evaluate performance of active portfolio management. Moreover, betas characterize the systematic risk of industrial portfolios.

The existence of two regimes in financial market has been documented in previous studies. Ang and Baekert (2002) for example defined the two regime models estimated by the MSM as normal and high volatility bear market regimes. In addition, Khanthavit (2011) found that expected returns and risk of the market and industrial portfolio in Stock Exchange of Thailand could be estimated by the MSM to represent up and down markets. Therefore, this study focuses on the two-regime MSM in estimating time-varying CAPM beta.

In the Markov-switching framework, the different regimes of betas are driven by an unobserved Markov chain. The switching behavior of the beta is governed by a transition probability matrix (Mergner and Bulla, 2008), in particular. Hence, the changing process

⁶ See Hamilton (1994) for the detailed properties of the Markov-switching model.

between the unobservable state variables, s_t , is set to follow the first-order Markov chain process as follows,

$$\begin{aligned} p[s_t = 1|s_{t-1} = 1] &= p \\ p[s_t = 2|s_{t-1} = 1] &= 1 - p \\ p[s_t = 2|s_{t-1} = 2] &= q \\ p[s_t = 1|s_{t-1} = 2] &= 1 - q \end{aligned}$$

where $p[s_t = j|s_{t-1} = i]$ is the probability that state i will be followed by state j . In another way, the transition probability matrix of the two regimes is of the form

$$\begin{bmatrix} p & 1 - p \\ 1 - q & q \end{bmatrix}$$

where p is the probability of staying in the first state from period $t-1$ to period t while $1 - p$ is the probability of switching from the first state to the second state. In addition, q is the probability of staying in the second state from period $t-1$ to period t whereas $1 - q$ is the probability of switching from the second state to the first state.

The estimation of the equation (5) could be performed using the Maximum Likelihood Estimator (MLE). The shift in the regime is explained and is linked to the change in market expectation and the time-varying risk premium under the conditional CAPM framework.

Empirical Results and Analysis

Descriptive Statistics

Table 1 reports the descriptive statistics of the returns on the SET index and the eight industry group indices. The monthly mean returns were small relative to the corresponding standard deviation; however, all of the average returns during the study period were positive with negative skewness. The excess kurtosis was large, indicating fat-tailed distributions. The Jarque-Bera test rejected the normality hypotheses for all of the indices except the TECH. According to Timmermann (2000), the presence of regime-switching in returns could be either positively or negatively skewed and could be fat-tailed. Finally, the results of the ADF test exhibited the stationary property of the returns series in every case.

Table 1 Descriptive Statistics

Statistics	SET	CONS	FIN	ARGO	INDUS	PROP	RES	SER	TECH
Mean	0.008	0.006	0.009	0.014	0.004	0.007	0.004	0.013	0.007
STDEV	0.066	0.035	0.072	0.061	0.094	0.077	0.080	0.063	0.061
SKEW	-1.073	-0.575	-0.940	-1.004	-1.229	-0.752	-0.565	-1.625	-0.064
KURT	6.037	5.103	4.611	5.868	7.566	5.185	5.400	9.455	3.138
JB Test	63.387***	26.346***	28.086***	56.177***	123.227***	32.248***	32.247***	239.352***	0.161
ADF test	-4.631***	-3.879***	-7.897***	-4.217***	-2.998**	-4.399***	-4.246***	-4.395***	-8.901***

***, ** Significance at a 99% and 95% confidence level, respectively.

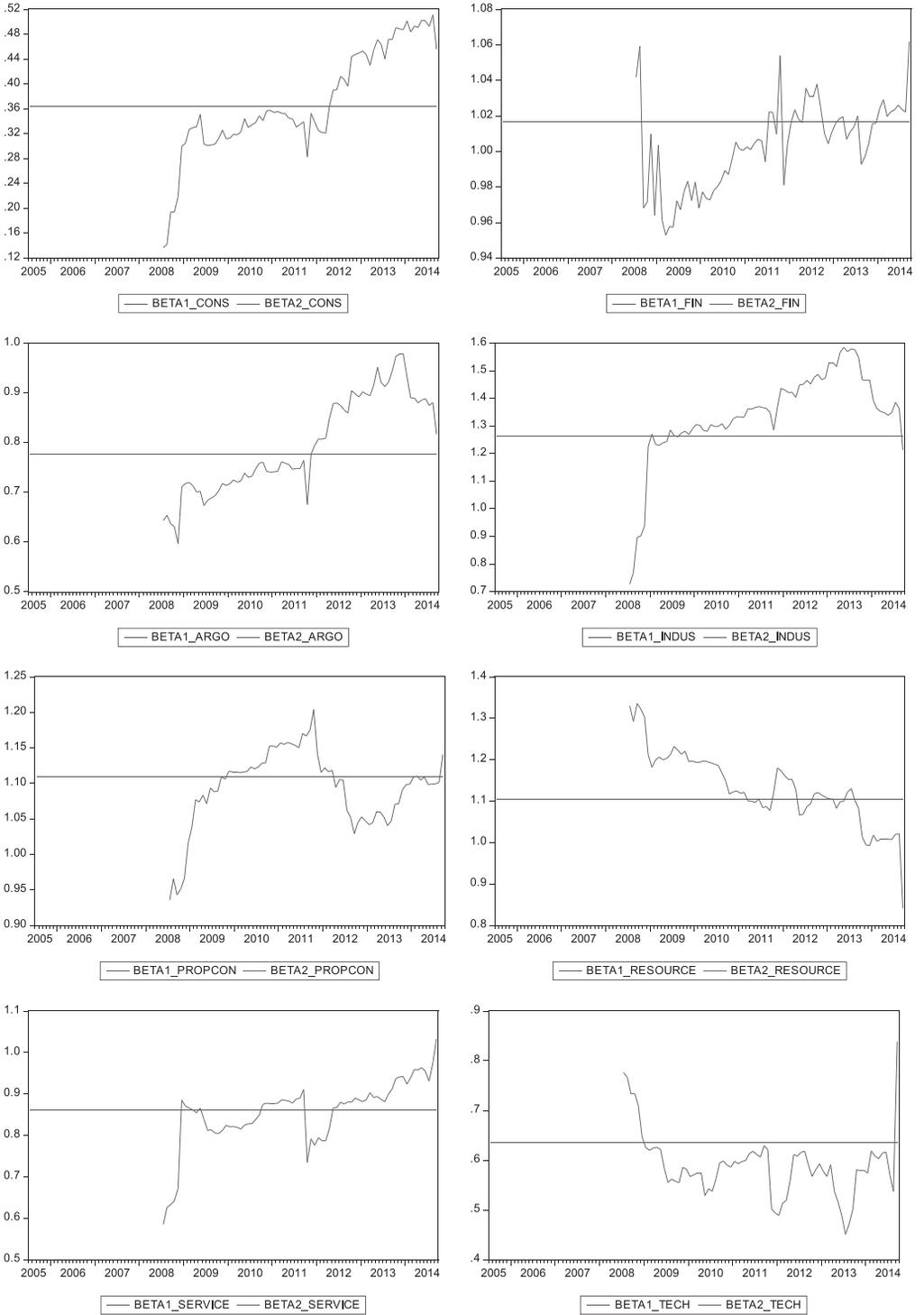


Figure 1 The Three-year Rolling Betas for the Industry Group Index

The Stability of Beta

The stability of beta was firstly addressed using the rolling regression. Figure 1 compares the estimation results of the unconditional CAPM betas using all of the sample data (July 2005 – September 2014) with those of the rolling regression using a three-year rolling window. In the rolling regression, the beta coefficient in the standard CAPM market model was estimated using the last 36 observations. The length of the estimation period was consistent with Campbell and Vuolteenaho (2004), which represented a suitable time period to capture the characteristics of the beta in each regime⁷. The results from the rolling regression were computed to provide an indicator of the possibility of the time-varying betas.

As can be seen in Figure 1, over the entire sample, the CONS portfolio had the lowest beta at approximately 0.36, while the INDUS portfolio had the highest beta, 1.25. The results from the constant beta estimation showed that the INDUS, RESOURCE, PROP-CON and FIN portfolios were riskier than the market portfolio. The remaining portfolios (SERVICE, AGRO, TECH, CONS) exhibited relatively low systematic risk (beta less than one). The rolling regressions showed that the industrial portfolio betas changed over time and allowed one to identify particular periods of instability as well as periods of stability. Specifically, the betas were higher than a constant level during some periods while the betas were lower than a constant level in other periods. In other words, the rolling betas exhibited a time-varying pattern. Therefore, the results suggest that the betas time-series may be characterized by two regimes, high beta and low beta.

Markov Switching Regression Estimation

In this section, the two-regime model was employed to classify the low and high beta regimes as suggested in prior studies, e.g. Ang and Baeckart (2002) and Yu et al. (2010). The Markov Switching models for each Industry Group Index return were estimated and the results are reported in Table 2. First, the Likelihood Ratio (LR) test for linearity was considered. The results of the LR tests showed that the null hypotheses (linearity) were

⁷ In each rolling regression, only 1 observation out of 36 ones is new and hence this overlapping may cause the autocorrelation problems in the beta time-series. However, Groenewold and Fraser (2000) investigate this issue by using non-overlapping data and conclude that such approach yields similar results. As a consequence, this issue is not considered in this paper.

rejected in favor of the nonlinear alternative at a 1%, 5% or 10% significance level for every industrial portfolio. These results provided supporting evidence for the time-varying beta in addition to those of the rolling regression estimation in the previous section. Based on the Q-statistics of standardized residuals and squared standardized residuals reported in Table 2, there is no significant evidence of autocorrelation and heteroscedasticity at 5 percent level of significance in every case. Next, the estimated coefficients in the two-regime Markov-Switching Model were considered. In the low beta regime, all of the industry group indices except PROP demonstrated relatively less risk than the market, as the estimated betas were less than one. Moreover, in the high beta regimes, all industry group indices except for CONS, ARGO, and TECH demonstrated relatively higher risk than the market, as the estimated betas were greater than one. Interestingly, the CONS portfolio had the lowest betas in both regimes while INDUS had the largest beta in the high beta regime. Additionally, the betas for PROP were almost the same in both regimes.

Even though FIN exhibited the second largest systematic risk, 1.215, the transition probability of the high beta regime was very low, almost zero. The results suggest that the chance that the beta process will stay at a high beta regime for consecutive months is very low. For other industrial portfolios, the transition probabilities were large and close to 1.00, suggesting the long-swing behavior of the industrial portfolio returns.

Table 2 Empirical Results of the Markov-Switching Regression for Eight Industrial Portfolios

	Low Beta Regime		High Beta Regime		Transition Probability		Expected Duration		LogL	LR Test	Ljung Box test	
	α	β	α	β	p11	p22	Low	High			Q(1)	Q ² (1)
CONS	0.036*** (4.571)	0.251** (2.138)	-0.004 (-1.154)	0.354*** (12.595)	0.8073	0.9510	5.190	20.392	254.6821	13.6471***	0.497 [0.481]	0.380 [0.538]
FIN	0.005 (1.086)	0.940*** (20.257)	-0.007 (-0.972)	1.215*** (12.289)	0.4293	0.0000	1.752	1.000	253.0790	4.7801*	0.218 [0.640]	0.613 [0.434]
ARGO	0.053*** (5.786)	0.583*** (4.239)	0.002 (0.554)	0.778*** (16.426)	0.8503	0.9751	6.680	40.209	223.6090	12.6380**	1.549 [0.213]	0.012 [0.914]
INDUS	0.012* (1.660)	0.973 (7.329)	-0.024*** (-3.393)	1.3896*** (17.520)	0.9283	0.9133	13.940	11.532	192.0091	8.6571**	0.567 [0.451]	0.647 [0.421]
PROP	0.024*** (2.722)	1.079*** (7.586)	-0.007** (-2.404)	1.0848*** (29.544)	0.7497	0.9495	3.995	19.800	254.6861	5.8154*	0.722 [0.395]	0.744 [0.389]
RES	-0.003 (-0.354)	0.479*** (2.633)	-0.003 (-0.712)	1.187*** (22.847)	0.9017	0.9685	10.173	31.724	227.2254	12.3089***	2.529 [0.112]	0.019 [0.892]
SER	0.005* (1.707)	0.688 (17.953)	0.011*** (18.544)	1.1830*** (8.191)	0.7707	0.5820	4.361	2.392	254.4063	17.2750***	0.142 [0.905]	2.174 [0.140]
TECH	0.072*** (3.260)	0.516*** (3.187)	-0.008 (-1.192)	0.628*** (8.909)	0.2109	0.8825	1.267	8.512	190.3908	4.8037*	0.531 [0.466]	0.010 [0.922]

Note: For the estimated alpha and beta, the first line indicates the estimated coefficient while the second line in parenthesis refers to the z-statistics. In addition, p11 and p22 indicate the transition probability of low and high beta regimes, respectively. The LogL denotes the Log-likelihood functions while the LR test denotes the Likelihood Ratio test for linearity. Q(1) and Q2(1) denote Ljung-Box Q-statistics of residuals and squared residuals. Figure in square bracket represents corresponding p-value.

Next, the smooth regime probabilities of the high and low regimes in each industrial portfolio are plotted and displayed in Figure 2.

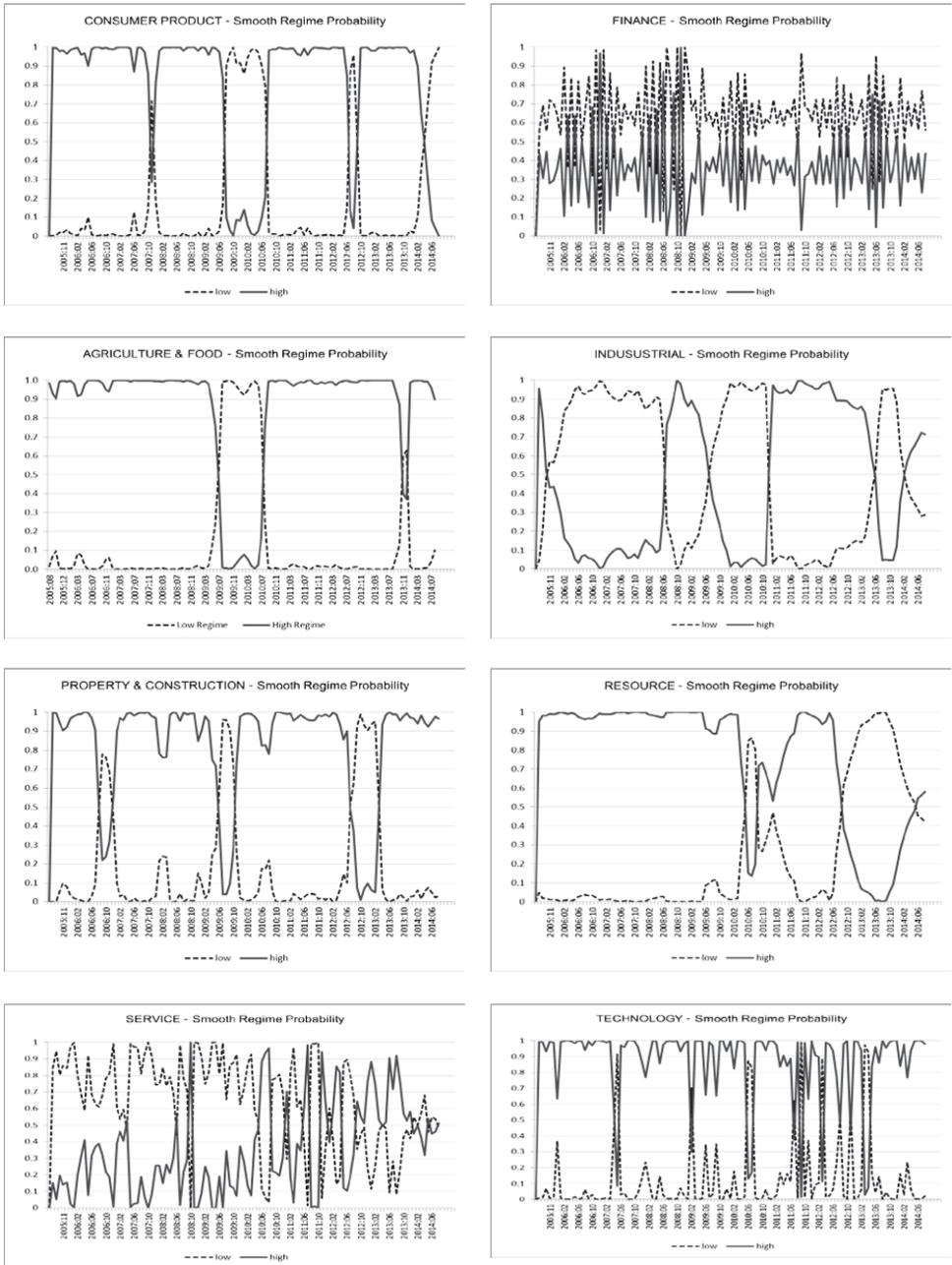


Figure 2 The Smooth Regime Probability of Eight Industrial Portfolios

The results for the transition probabilities can be categorized into three groups. The first group was characterized by a high beta regime in most of the estimation periods; in other words, the betas shifted to a low regime in some particular periods. As can be seen in Table 2, the expected duration, i.e. number of months, to stay in high regime is much longer than that in low regime. This group consisted of (i) Resource, (ii) Agriculture and Food, (iii) Property and Construction, (iv) Consumption, and (v) Technology. For instance, the high beta regime of the resource portfolio covered the period from July, 2005 to February, 2010. From 2010 to 2011 and during the first half of 2013, the betas of the resource portfolio switched from a high regime to low regime and started moving back to a high regime in January, 2014. The expected duration for high-beta regime of resource is approximately 31.724 months while the expected duration for low-beta regime is approximately 10.173 months. Similar patterns were also found for the betas of agriculture and food portfolios. Interestingly, the periods of regime-switching from high to low betas occurred after the global financial crisis. During that time, the Federal Reserve Bank (FED) of the United States applied an unconventional monetary policy, which influenced the risk appetite in the financial market. During the period of the Quantitative Easing (QE) of the monetary policy in the US, investors demonstrated greater tendency to invest in risky assets, i.e. hard commodities (oil, metal) and soft commodities (agricultural products) than during the conventional period. As a result, the systematic risks (betas) for the industry portfolio related to commodity products (resources, agriculture, and food) decreased during the period of the QE policy.

The second group was characterized by the low beta regime during most of the estimation periods; in other words, the betas shifted to a high beta regime in some particular periods. This group consisted of (i) Finance and (ii) Service where their expected duration to stay in high regime is much shorter than that in low regime as reported in Table 2. In addition, Figure 2 obviously shows that the dotted-blue line, which refers to the transition probability in the low regime of those industries, was large and remained close to 1.00 most of the time. Notably, the transition probability of the low beta regime of the service portfolio is very fluctuate and exhibited a decreasing trend. Interestingly, since mid-2012, there has been a higher chance that the beta would be in a high beta regime than a low beta regime. This can be possibly explained by the political instability problem, which has had a

substantial effect on the tourism sector, which is an important part of the service portfolio in SET. Hence, the systematic risks (betas) of the service sector increased during that period.

The third group consisted of only the industrial portfolio. The expected duration to stay in low and high regime is 13.940 and 11.532 months, respectively. These show that the betas of this portfolio regularly swing between high and low beta regimes. Particularly, from 2006 to mid-2008, the betas stayed at a low regime and then switched to a high regime from 2008 to 2009. In February 2010, the betas moved back to a low regime for one year and then become a high regime in February 2011. The betas again switched to a low regime from the second half of 2013 to the beginning of 2014. Remarkably, during the period of the high beta regime (February 2011 - June 2013), the automobile industry, which is an important part of the industrial portfolio in the SET, was quickly expanded due to the government incentive scheme for first-car buyers⁸. Consequently, the industrial risk could have increased due to the effect of the government policy, which significantly affected the earnings in the automobile industry.

In sum, we found evidence of time-varying betas at industrial portfolio level and each one has different betas pattern. As mentioned in Jagannathan and Wang (1996), firms with high leverage or more capital intensive are more likely to face financial problems than others during high interest rate periods. Therefore, because of the nature of the firms within those industries, leverage effects dominate. In order to understand these complex dynamics, we need a detailed analysis of financing and operating positions of these firms in each industry, but it is far beyond the scope of this paper.

Conclusion and Summary

Despite the considerable empirical evidence that systematic risk is not constant over time, only a few studies have dealt with the modeling of the time-varying behavior of betas at the industrial portfolio level. Previous studies focused on Australia, the United States, and the United Kingdom. In Thailand, the Markov-Switching model was employed to characterize the time-varying behavior at the market level by Khanthavit (2011). This paper contributes to the investigation of the time-varying betas of eight industrial portfolios using

⁸ The tax incentive scheme for first-car buyers lasted from August 2011 to December 2012.

the two-regime Markov-Switching model. In comparison, the results from the unconditional CAPM beta and three-year rolling regression show that betas are unstable over time. In addition, the linearity LR tests confirmed the non-linearity in all of the industrial portfolio returns, suggesting that betas are time-varying. The results of the Markov-Switching model were summarized as follows:

(i) The estimation of the conditional CAPM suggested that the betas were time-varying and could be classified into two regimes: low beta and high beta.

(ii) For Resource, Agriculture and Food, Property and Construction, Consumption, and Technology portfolios, the estimated betas usually stayed in high beta regimes, whereas for Finance and Service portfolios, the estimated betas mostly remained in low beta regimes.

(iii) The estimated betas of the Industrial portfolio regularly switched between high and low beta regimes.

Overall, the results confirmed the time-varying behavior of portfolio betas. The regime switching in some industrial portfolios was found to be related to the major economic policy during those periods. For example, the resource and agriculture products had lower beta regimes during the period of the QE policy where risk appetites are increasing and risk premium in risky asset is less demanded. The important implication of this paper is that the application of the dynamic asset allocation strategy could enhance the benefits from diversification because the systematic risk of industrial portfolios is time-varying and regime-dependent. In other words, the performance of asset allocation and risk management strategies could be improved if investors considered the regime-switching behavior of industrial portfolio returns in portfolio construction. Because asset allocation is the most influence determinant of portfolio risk and return, beta or systematic risk measure would help investors choosing preferred asset classes regarding their risk preference. Long-term strategic asset allocation target should be set as a backbone; however short-term tactical asset allocation by shifting among asset classes should be considered as market conditions change. This information would also benefit to both defensive and aggressive funds in adjusting their asset allocation. However, this study is the first step toward confirming the time-varying and regime-dependent behavior at the industrial portfolio level. The dynamic asset allocation and risk management strategies are left for further research.

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