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Regime-Switching Market Risk: Evidence from the Philippines

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This paper presents an alternative approach in measuring time variation in market risk. Using equity returns in the Philippines, we employ a Markov-switching model to estimate market risk that varies with occasional and discrete shifts in states. Results show that the technique is a productive alternative in evaluating the market risk of firms in the Philippines. Shifts in the market risk seem to be related to market developments, which can have a permanent or transient change in the volatilities of security returns relative to that of the market.

Keywords: Markov-switching, time-varying betas, market risk, CAPM

1 Introduction

Market risk, as measured by beta, is increasingly used not only to explain the cross section of security returns but also to understand the behavior of other financial and economic variables (e.g., firm performance) and to predict events (e.g., bank failure). Computed as the ratio of the covariance between the security return and market return to the variance of the market return, the beta is based on the Capital Asset Pricing Model (CAPM) which asserts that the return on a security is composed of the risk-free rate and a rate that compensates an investor for bearing the market risk.

Implicit in the conventional computation of beta is the assumption that it is fixed over time. A fairly new stream of research has evolved that provides empirical evidence that the beta varies over time (see Fabozzi & Francis, 1978 or Faff & Brooks, 1997). Complemented by developments in empirical research methods, this stream of research has grown and implications on the cross section of security returns have been derived. In the Philippines, time variation in the beta of stocks listed in the Philippine Stock Exchange (PSE) has been recently analyzed using different techniques (see Yu, 2004; Dela Cruz, 2007; Saquido, 2007).

The existing literature on time-varying market risk provides alternative approaches in estimating beta in each period (usually one month). While these approaches can establish trends in market risks of securities, it presents a practical difficulty in identifying the appropriate estimate of market risk due to the high frequency of changes. Besides, the variation in market risk in each period may not be significantly different from the conventionally estimated market risk.

This paper is an alternative approach in measuring time variation in market risk. Using equity prices in the Philippines, we employ a Markov-switching model to estimate market risk that varies with occasional and discrete shifts in states. Thus, the estimate of the market risk remains the same unless there is a change in the state. This limits the frequency of changes in the estimate of market risk and provides a more practical approach for purposes such as computing the cost of capital and valuation of assets.

The paper is organized as follows: Section two provides an empirical framework in the estimation of the Markov-switching market risk, Section three presents the results and analysis, and Section four concludes.

2 Framework

2.1 The CAPM with time varying betas

The CAPM model traditionally used to estimate betas and/or to determine under- or overvaluation of firm *i*'s stock is of the form:

$$r_{it} = \alpha_i + \beta_i r_{mt} + u_{it} \quad ; \quad i = 1, \dots, n \tag{1}$$

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where $r_{it} = R_{it} - R_f$ is the stock's excess return and $r_{mt} = R_{mt} - R_f$ is the excess market return.

In this model, the beta is time invariant. However, beta may change considering that "the relative risk of a firm's cash flow is likely to vary over the business cycles" (Jagannathan & Wang, 1996). Besides, market risk should be altered by changes in the firm such as expansion or consolidation in operational scope as well as organizational improvements that evolve as firms adapt to different economic environments. At the industry level, the market risk may also change with changes in technology that result in the introduction, obsolescence, and evolution of products and services.

Beta instability can be determined empirically in a number of ways. Premised on the assumption that market volatility drives the heteroskedasticity in stock returns, Schwert and Seguin (1990) derived an estimate of market risk that varies with the estimated aggregate volatility. Jagannathan and Wang (1996) developed a model that allows beta to change by adding a time-varying market risk premium. Brooks, Faff, and McKenzie (1998) showed the superiority of the Kalman filter algorithm in in-sample and out-of-sample forecasting accuracy of market risk of Australian industrial stocks. More recently, Yamada (2005) used the multi-scale beta estimation approach of Japanese industrial stocks based on the wavelet analysis proposed by Gencay, Sekcuk and Whitcher (2002).

In the Philippines, there are a handful of empirical inquiries on the time variation of beta. Yu (2004) employed the approach of Schwert and Seguin to derive time-varying beta of portfolios of stocks in the Philippines. Dela Cruz (2007) used bivariate BEKK-GARCH model to compute for the market return's time-varying variance and its covariance with stocks to estimate time-varying betas. Saquido (2007) estimated wavelet betas in the empirical test of the CAPM.

In this study, we assume that the parameters of the CAPM above vary according to a first order Markov switching process. Hence, the model to be estimated is a modification of equation (1):

$$r_{it} = \alpha_i(s_t) + \beta_i(s_t) r_{mt} + u_{it}(s_t) \quad ; \quad i = 1, \dots, n \tag{2}$$

The specification above accounts for regime-dependent heterocesdasticity as can be seen from the third term of equation (2). This MS regression is a special case of MS VAR system developed by Krolzig (1997). This study makes use of his MSVAR code that runs on Ox Console version 3.4 program. The next sub-section briefly discusses the MS model.

2.2 Markov switching methods

Hamilton's (1989) seminal article introduced Markov-switching to help overcome the limitations of traditional time series tools that could not account for nonlinearities in macroeconomic time series. Hamilton's original MS model is basically an extension of the linear univariate AR model and is of the form:

$$y_t = \mu_{s_t} + \phi_1\left(y_{t-1} - \mu_{s_{t-1}}\right) + \cdots + \phi_k\left(y_{t-k} - \mu_{s_{t-k}}\right) + \varepsilon_t \tag{3}$$

where the ϕ_ks are the k autoregression parameters and ε_t is a white noise process. μ_{s_t} is the mean of y_t when state s_t occurs. The state is assumed to be the outcome of an unobserved first-order M-state Markov process (i.e., $s_t = 1, \ldots, M$). Its evolution can be described by transition probabilities, $\Pr(s_t = j | s_{t-1} = i) = p_{ij}$, where $\sum_{j=1}^{M} p_{ij} = 1$ and which can be conveniently arranged into a matrix:

$$\mathrm{P} = \begin{bmatrix} p_{11} & \cdots & p_{M1} \\ \vdots & \ddots & \vdots \\ p_{1M} & \cdots & p_{MM} \end{bmatrix} \tag{4}$$

Each element of the transition probability matrix, **P**, shows the probability that state i is followed by state j. The process is assumed to depend on past values of y_t and s_t but only through s_{t-1}. Note that since only y_t is observed but not the state, a way must be found to form optimal inferences about the current state based on the observed values of y_t. Given the number of states, Hamilton (1989, 1994) shows how to estimate the parameters of the model and the transition probabilities governing the motion of the variable of interest. He provides a recursive method for drawing probabilistic inferences about the state of y_t (the value of s_t) given the history of y_t.

Extensions of the original model have been done by Krolzig (1997, 2000) in a number of articles. One can re-specify the model to include strongly exogenous variable. Hence, the probability of being in a particular state is:

$$p\left(y_t \middle| y_{t-1}, \dots, y_{t-j}, x_t, s_t\right) = \begin{cases} f\left(y_t \middle| y_{t-1}, \dots, y_{t-j}, x_t; \Omega_1\right) & \text{if} \quad s_t = 1 \\ f\left(y_t \middle| y_{t-1}, \dots, y_{t-j}, x_t; \Omega_M\right) & \text{if} \quad s_t = M \end{cases} \tag{5}$$

Ω_M is the parameter vector and x_t is a vector of strongly exogenous variables. Krolzig's extension allows for a system of equations to be driven by the Markov process, hence y_t is a vector and the system becomes a Markov-switching VAR system. The model in this study is a special case of the MS-VAR and is simply an MS regression model defined as follows:

$$y_t = \begin{cases} x_t\beta_1 + u_t;\;\; u_t|s_t \sim NID(0, \Sigma_1) \text{ if } s_t = 1 \\ \vdots \\ x_t\beta_M + u_t;\;\; u_t|s_t \sim NID(0, \Sigma_M) \text{ if } s_t = M \end{cases} \tag{6}$$

See Krolzig (1997, 2000) for a fuller discussion of VAR systems with MS processes and the special cases covered by the method.[1] More detailed technical discussions of Markov-regime switching methods can be found in Kim and Nelson (1999). This book discusses MS implementations using state-space techniques that include extensions of Kalman filtering methods.

3 Data, Results and Analysis

The sample is composed of monthly returns from March 1993 to February 2006 of 22 common stocks of 17 firms which are included in the 30-firm Philippine Stock Exchange (PSE) Index (Phisix), the market index of the Philippines. The sample was chosen based on the availability of end-of-the-month stock price data from Datastream. The stock returns were computed using the lognormal monthly return formula. The excess returns were calculated using the 91-day treasury bill rate.

Table 1.

	AIC	HQ	SC	Linearity test (LR)	Chi(3)	Chi(5)	Davis
ABS-CBN	7.40	7.46	7.56	19.43	0.00	0.00	0.00
Ayala Corp	6.63	6.69	6.79	27.64	0.00	0.00	0.00
Ayala Land	6.67	6.73	6.83	15.11	0.00	0.01	0.03
Belle Resources	8.29	8.36	8.45	38.98	0.00	0.00	0.00
Bank of the Phil Islands	6.90	6.96	7.06	44.53	0.00	0.00	0.00
FPH	7.51	7.57	7.67	36.26	0.00	0.00	0.00
Globe Telecom	7.42	7.49	7.58	53.59	0.00	0.00	0.00
ICTSI	7.69	7.76	7.85	65.49	0.00	0.00	0.00
Jollibee Food Corp.	6.95	7.01	7.11	14.89	0.00	0.01	0.03
Lepanto Mining A	7.92	7.99	8.08	30.78	0.00	0.00	0.00
Lepanto Mining B	8.20	8.27	8.36	44.77	0.00	0.00	0.00
Manila Mining A	8.68	8.74	8.84	35.89	0.00	0.00	0.00
Manila Mining B	8.66	8.72	8.82	30.16	0.00	0.00	0.00
Meralco A	7.13	7.19	7.29	55.73	0.00	0.00	0.00
Meralco B	7.37	7.44	7.53	61.51	0.00	0.00	0.00
Metro Pacific	8.31	8.38	8.47	41.10	0.00	0.00	0.00
Metrobank	6.94	7.00	7.10	38.84	0.00	0.00	0.00
Philex Mining A	8.26	8.33	8.42	68.09	0.00	0.00	0.00
Philex Mining B	8.44	8.51	8.60	39.50	0.00	0.00	0.00

[1] When there is only one state (the ordinary VAR system), one can express the mean-adjusted form of Equation (1) to its intercept form similar to that of equation (6) and the dynamics would not change. This would no longer be true when there is more than one state. The former would generate a smooth transition from one state to the other while the latter would produce a once and for all jump (Krolzig, 1997).

Table 1.

	AIC	HQ	SC	Linearity test (LR)	Chi(3)	Chi(5)	Davis
PLDT	7.08	7.15	7.24	7.80	0.05	0.17	0.40
San Miguel A	6.37	6.44	6.54	52.83	0.00	0.00	0.00
San Miguel B	6.81	6.88	6.97	35.05	0.00	0.00	0.00

Table 1 shows a summary of key statistics. The table shows that, in all cases, there is a strong statistical support for non-linearity in the market model (i.e., the parameters of the model vary over time). This is shown in the LR linearity test on the null hypothesis of linear relationship between the security return and the market return. Table 2 presents the parameter estimates and the transition probabilities for the 22 PSE-listed firms. The table shows that most of the parameter estimates are statistically significant.

Table 2. MS Regression Estimates, 1993:3 – 2006:2

	Low Beta Regime				High Beta Regime				Transition Probability	
	α	t-value	β	t-value	α	t-value	β	t-value	p_{11}	p_{22}
ABS-CBN	1.15	1.33	0.76	7.56	–2.84	–1.83	1.62	6.04	0.97	0.97
Ayala Corp	–0.21	–0.35	1.03	10.96	2.60	1.40	1.93	9.49	0.86	0.63
Ayala Land	0.56	0.92	1.31	14.35	–0.09	–0.08	1.38	10.67	0.91	0.88
Belle Resources	–3.09	–2.12	1.22	3.92	4.68	0.94	2.05	1.93	0.80	0.52
Bank of the PI.	3.61	1.60	0.30	1.07	0.50	0.86	1.27	16.45	0.97	1.00
FPH	–0.65	–0.72	0.97	10.49	5.10	1.23	2.73	2.17	0.88	0.45
Globe Telecom	–1.02	–1.38	0.78	5.05	4.63	0.93	1.77	3.11	0.93	0.68
ICTSI	0.48	0.60	0.80	7.07	1.20	0.46	2.16	7.48	0.98	0.97
Jollibee Food Corp.	0.37	0.45	0.43	2.22	0.95	0.81	1.19	5.63	0.59	0.70
Lepanto Mining A	5.79	0.85	–0.01	–0.02	–1.98	–2.02	0.53	4.52	0.44	0.82
Lepanto Mining B	–1.66	–1.72	0.62	4.85	2.94	0.82	0.21	0.43	0.95	0.89
Manila Mining A	31.90	1.73	0.36	0.44	–6.33	–4.28	0.96	5.81	0.13	0.87
Manila Mining B	24.82	2.58	–1.76	–2.01	–4.62	–3.13	1.11	6.04	0.30	0.90
Meralco A	–1.59	–2.70	0.72	8.29	–1.42	–0.42	1.61	3.92	0.96	0.83
Meralco B	–0.75	–1.09	1.01	12.22	–1.82	–0.55	2.28	3.06	0.99	0.96
Metro Pacific	–2.79	–2.67	1.23	8.89	0.78	0.32	2.35	7.54	0.83	0.85
Metrobank	27.34	4.33	–0.59	–1.44	–0.35	–0.59	1.08	13.55	0.38	0.98
Philex Mining A	–1.34	–1.41	0.53	4.13	3.79	0.83	1.49	2.86	0.90	0.78
Philex Mining B	–3.72	–2.70	0.83	4.48	7.97	1.72	1.40	2.19	0.63	0.21
PLDT	2.31	2.18	0.70	6.03	–3.14	–1.97	1.23	7.25	0.94	0.90
San Miguel A	–1.20	–3.31	0.29	4.64	1.67	1.37	0.43	3.30	0.93	0.90
San Miguel B	–0.15	–0.28	0.54	5.77	0.43	0.26	0.89	5.50	0.98	0.95

Figures 1 to 3 show the graphs of the smoothed probabilities of a low beta regime. The shaded area covers the Asian crisis from July 1997 to December 1998. It is seen from these diagrams that, in most cases, there is a fairly high frequency of changes in the market risk of common stocks in the Philippines from low beta regimes to high beta regimes. This is expected as most of the changes in market risk of firms can be attributed to short-term changes in the relative risk of their cash flows.

What is notable in the figures are those cases where there seems to be a permanent change in the market risk of the firm. These are the firms whose graphs of smoothed probabilities have predominantly shifted to values that are either close to one or to zero. The former indicates that the market risk of the firm has gone down; the latter indicates the reverse. Examples of stocks that exhibited these cases are those of ABS-CBN, one of the leading broadcasting companies, Bank of the

Philippine Islands, one of the largest banks in the country, and the B shares of San Miguel Corporation, the largest food and beverage conglomerate in the Philippines. These firms have seen significant growth since the 1990's and their organizational evolution must have altered the relative co-variability of their returns to the market.

Figure 1. Smoothed Probabilities of a Low Beta Regime

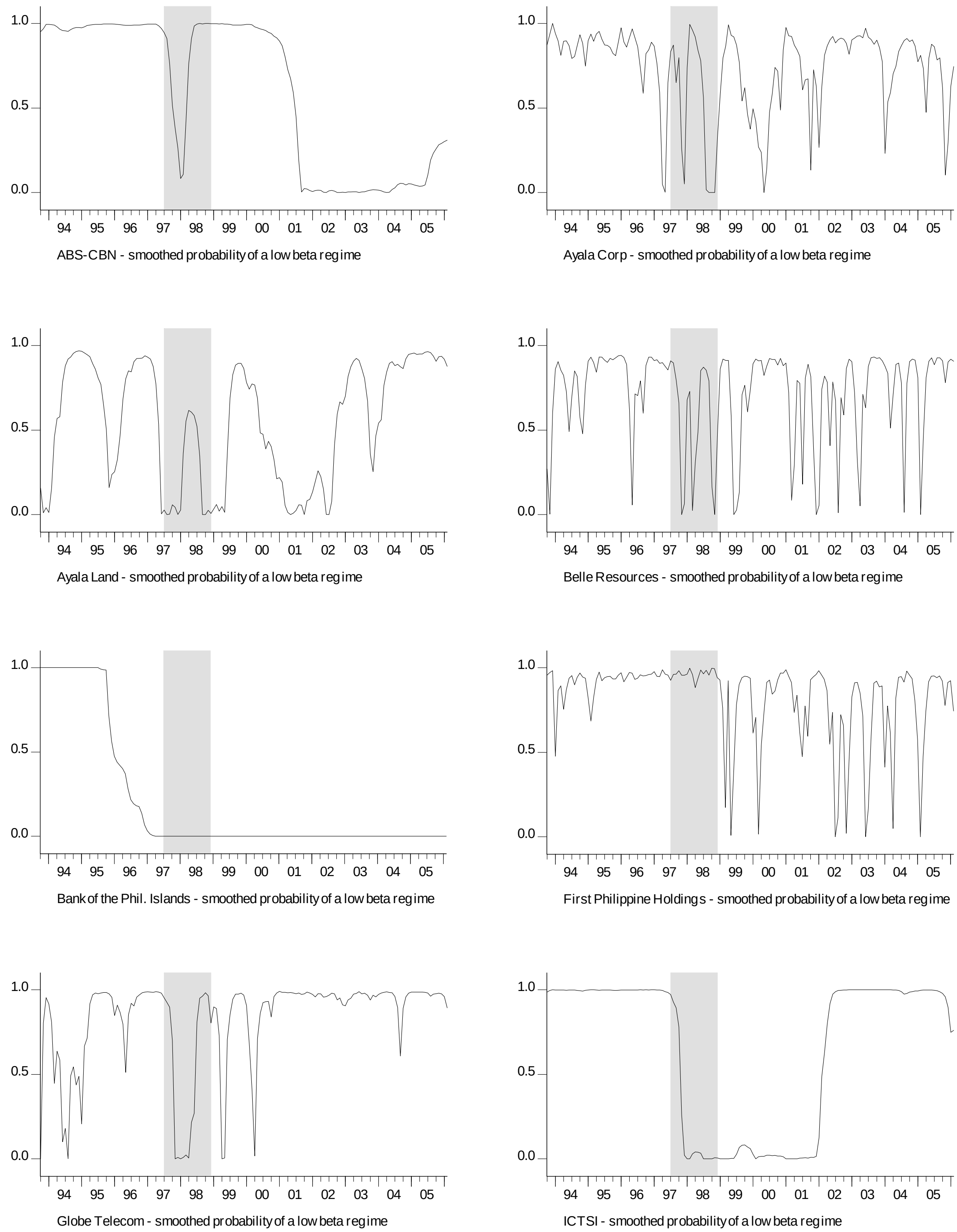


Figure 2. Smoothed Probabilities of a Low Beta Regime

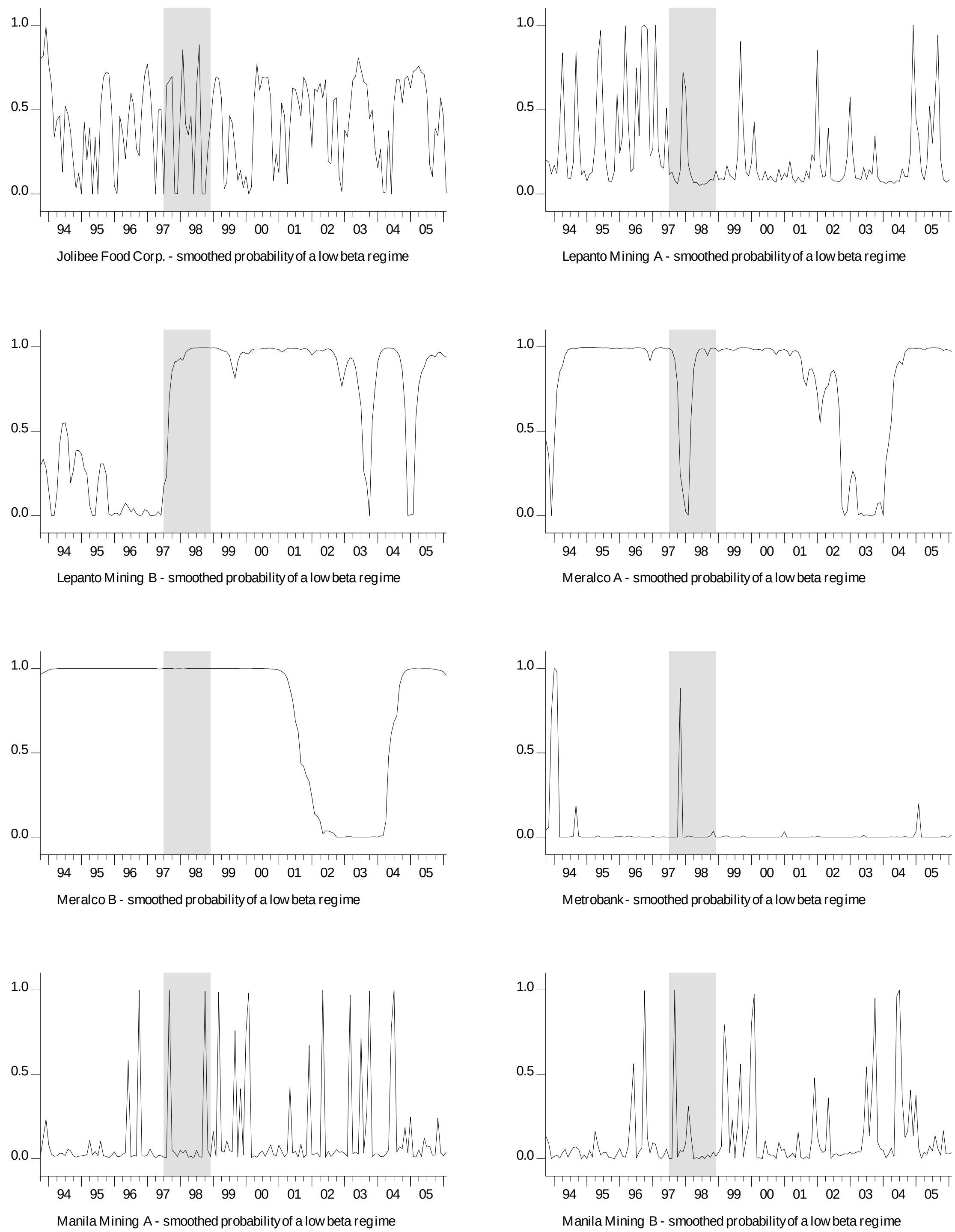
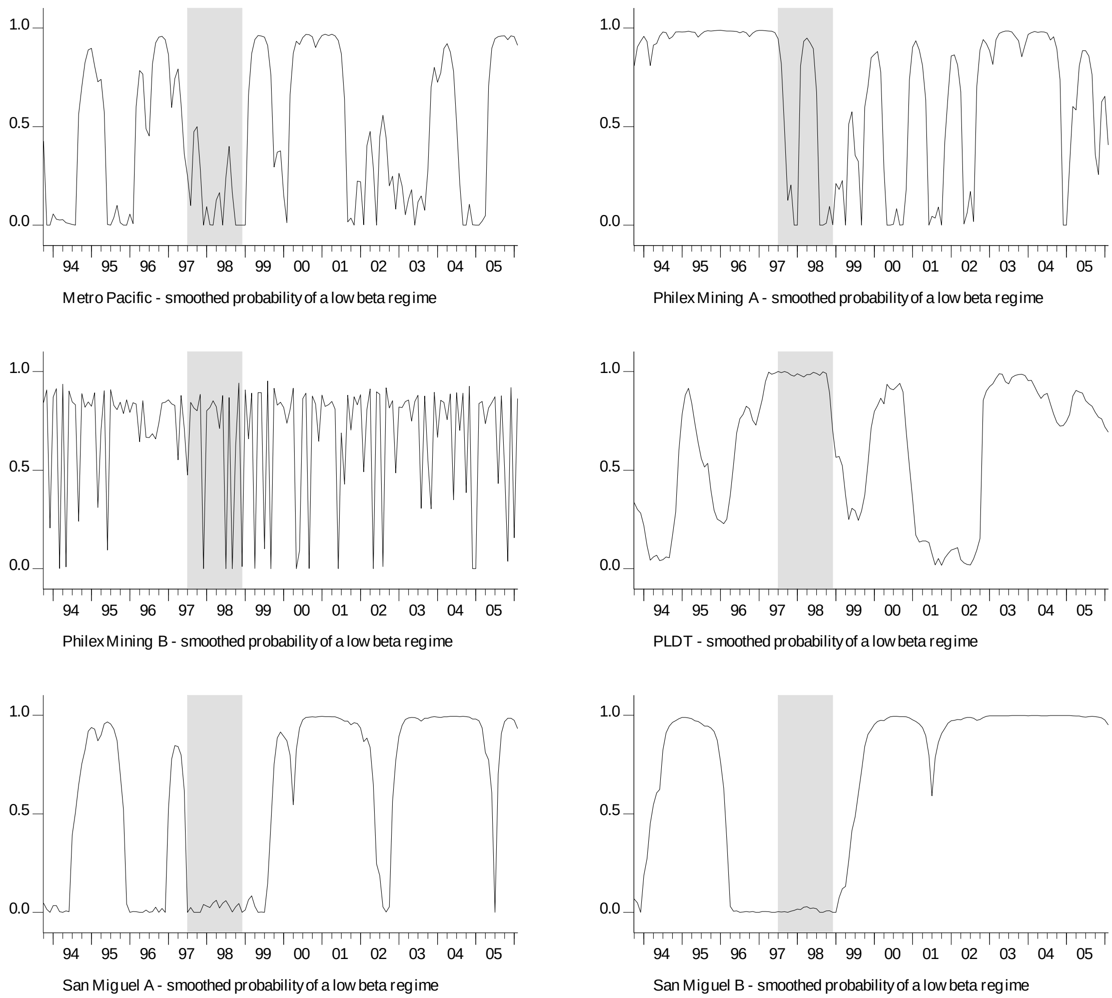


Figure 3. Smoothed Probabilities of a Low Beta Regime



Another notable empirical result refers to those cases where there is a transient change in market risk, albeit significantly longer in duration. These cases include International Container Terminal Services Inc. (ICTSI) which manages container ports and terminals worldwide. In the late 90's, there was a notable drop in probability of a low beta regime, suggesting that the market risk of the firm's common stock has gone up. This coincides with the Asian financial crisis which could have affected the firm, at that time, is extensively involved in the development of international ports. Another case is the stocks of Manila Electric Company (Meralco), the largest power distribution firm in the Philippines. The stocks of Meralco experienced a steep decline in the probability of a low market risk regime starting in 2001. This coincides with the shift in regulatory environment in the Philippine power sector which could have resulted in a temporary increase in the volatility in the returns of the firm.

4 Conclusion

This study demonstrates that time variation in the CAPM can be adequately modeled through Markov switching techniques. Results show that the technique is a productive alternative in evaluating the market risk of firms in the Philippines. Shifts in the market risk seem to be related to market developments which can have a permanent or transient change in the volatilities of security returns relative to that of the market.

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