



Intertemporal risk–return relationship in the Asian markets around the Asian crisis

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Abstract

This study investigates the risk–return relationship in nine Asian capital markets and the U.S. before, during, and after the Asian financial crisis. Using a state-dependent approach in a TGARCH(1,1)-M framework, we investigate a contemporaneous version of the CAPM by accounting for negative and positive market price of variance risk. We find a significant positive relationship between risk premium and variance in all markets in upstate, as well as a significant negative relationship in downstate. Also, we validate our findings by showing that implied state-dependent market prices of variance risk explain risk premia across markets. Finally, we investigate how the model can be used to uncover overreaction and improve the number of correct directional calls in a tactical asset allocation strategy. Our results provide support for a contrarian strategy that individual investors can follow. © 2001 Elsevier Science Inc. All rights reserved.

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1. Introduction

The Capital Asset Pricing Model is extremely popular among individual investors. It remains the favored tool used in portfolio allocation and selection strategies. Its main component, namely beta, is often used as proxy for measuring the sensitivity of an asset or a group of assets to a change in the underlying benchmark. As Fama (1991) wrote, “market professionals and academics still think of risk in terms of beta”. This is fine as long as the asset is correlated with the benchmark (see Pettengill, Sundaram and Mathur (1995) and Fletcher (1997, 2000), who find considerable support for the CAPM in developed markets).

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However, emerging markets do not necessarily have a strong correlation with a world market benchmark. In that case, beta is meaningless and investors do not know anymore how to use the CAPM to detect overreaction or forecast returns. The purpose of this study is to provide individual investors with a tool to price and forecast equity returns in emerging capital markets. Inherently, we first establish and validate a contemporaneous relationship between risk and return in markets with different degree of integration with the world portfolio. In particular, we investigate the risk–return relationship in United States and nine Asian capital markets involved in the Asian crisis.

To establish and validate a contemporaneous relationship between risk and return in equity markets is a very ambitious task. Usually, researchers and traders use beta for valuation purposes. However, there are several problems associated with using beta as a measure of risk. Firstly, beta is based on the correlation with a domestic or global benchmarks; as Roll (1977) points out, none of these benchmarks are mean-variance efficient. Secondly, while a statistically significant beta can be found in the highly correlated developed markets, many emerging markets have zero or little correlation with the World benchmark; in fact, it is not possible to find a relationship between market risk premia and world risk premia in segmented markets. Thirdly, betas are extremely volatile and past betas are biased predictors of future betas; furthermore, because emerging markets are more likely to experience crisis-related contagious volatility shocks and correlation shifts, betas are even more unpredictable.

Besides beta, risk can also be measured using variance or covariance of returns (see Harvey, 1998, 2000). As an illustration, we use MSCI US and MSCI AC World daily index series to generate daily variances, covariances and inherent betas (the ratio of covariance to MSCI AC World variances) with a multivariate GARCH model; we graph our findings in Fig. 1. Notice that the beta series behave more wildly than the variance or covariance series. Moreover, it is obvious that anyone would rather predict risk using the “better-behaved” variance or covariance series in the highly integrated U.S. market (average correlation of 0.71 with the MSCI AC World from 1990 to 2001). Next, we look at Fig. 2, which depicts daily beta, covariance and variance series in a more segmented emerging market such as the Thai capital market (average correlation of 0.18 with the MSCI AC World from 1990 to 2001). We observe that daily beta and covariance series oscillate around zero. This observation is common to segmented markets and indicates that variance will be preferred to measure risk in less integrated capital markets. In fact, whether markets are integrated or segmented, variance seems to be a commonly manageable proxy for risk. In that case, an *ex-post* version of the market-based CAPM, which relates risk premia to concomitant variance, should work.

Now, we have a problem because we don’t know how to relate contemporaneous returns to concomitant variance. In fact, a contemporaneous relationship between risk premia and variance is deemed to fail. It can be explained very simply. *Ex-ante* risk premia are unobservable and *ex-post* risk premia are commonly used as a proxy for *ex-ante* risk premia. *Ex-post* risk premia can be either positive if market returns are greater than the risk-free rates or negative if risk-free rates are greater than market returns. Then, how is it possible to relate contemporaneously a variable that can either be positive or negative with variance, which is always positive? The answer is simple: the same way that we break a parabolic function into

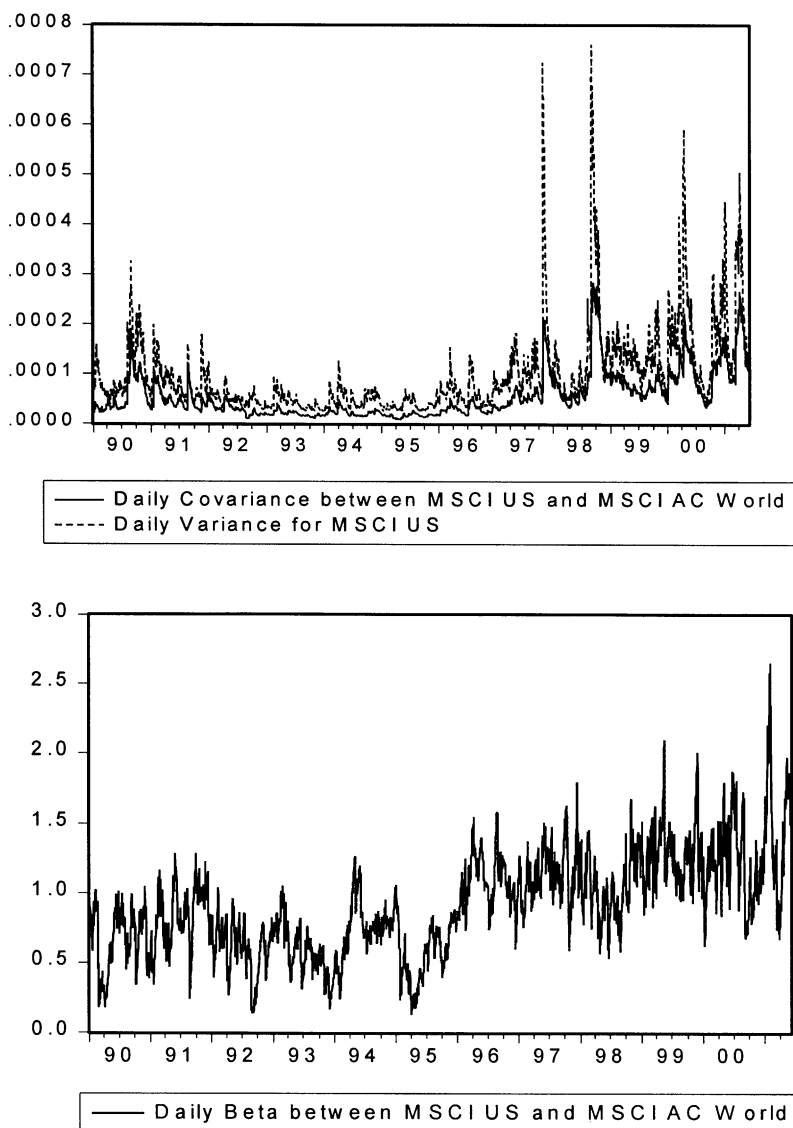


Fig. 1. Daily variance, covariance and beta using MSCI US and MSCI AC World dollar return series (January 1, 1990 to June 1, 2001).

two piece-wise linear functions—i.e., a positive state and a negative state. Indeed, recent studies argue that the CAPM holds if it is studied piecewise in upstate and downstate. For example, Pettengill et al. (1995) and Fletcher (1997, 2000) utilize a state-dependent CAPM that provides an explanation on cross-sections between beta and risk premium in developed markets. Avard, Nam and Pyun (2001) observe an asymmetry in stock return behaviors in upstate and downstate and suggest that the mere existence of this asymmetry can be justified by the existence of an overreaction unwarranted by variance alone.

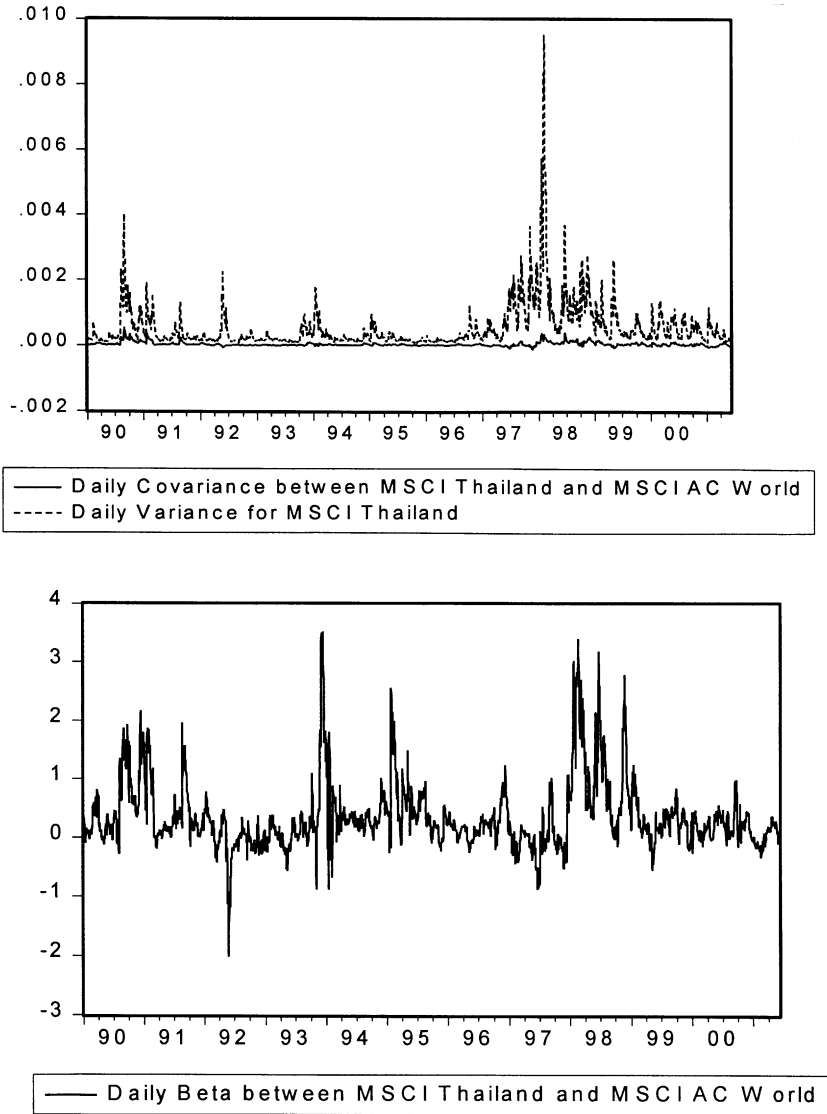


Fig. 2. Daily variance, covariance and beta using MSCI Thailand and MSCI AC World dollar return series (January 1, 1990 to June 1, 2001).

In the second part of our study, we test for overreaction in the Asian Capital Markets. Indeed, if a simple serial state-dependent relationship between contemporaneous compensation for risk and forecasted variance exists, we certainly have an instrument to detect contemporaneous abnormal gain or loss—i.e., overly optimistic or pessimistic investors' behaviors unwarranted by risk alone. As a result, if we can determine whether prices are contemporaneously significantly above or below their intrinsic value, their reversals can be predicted from past data alone. Overreaction is more likely to be observed in emerging markets since younger markets are more prone to crisis-contingent shocks and

thus evidence crisis-related herding or panic behaviors. Additionally, in more segmented markets, there are barriers to portfolio investments across borders. Furthermore, currency risk, transaction costs differentials, insider trading laws enforcement differentials, or infrequent trading can also contribute to local market inefficiencies in less developed capital markets. For example, Lee and Ohk (1991), Bekaert and Harvey (1995) and Harvey (1995) conclude that emerging markets are more speculative as evidenced by non-justifiable stock price swings.

Finally, we examine how a state-dependent formulation of the CAPM can improve the number of correct directional predictions. Indeed, if we can relate risk and returns over time, we potentially provide active investors with a forecasting tool to significantly increase the number of correct directional predictions in different national equity markets. In this paper, we examine a state-dependent model that basically tells us that a negative risk premium is likely followed by a negative risk premium. Therefore, a simple strategy would consist of (1) investing in Treasury Bills, if the current market risk premium is negative, or (2) investing in a local market if the current market risk premium is positive. We conduct sign tests to see if this active tactical strategy is more likely to provide correct calls as compared to flipping a coin.

The remainder of the paper is organized as follows. In Section 2, we discuss the methodology and econometric framework. Section 3 describes the data and provides preliminary descriptive findings. Section 4 reports the empirical results. Section 5 provides some concluding remarks.

2. Methodology

The purpose of our study is to investigate a contemporaneous relationship between risk premia and concomitant volatility in Asian capital markets. Thus, we first test for a relationship between each stock index return series and inherent conditional variance with a TGARCH(1,1)-in-mean equation; in that sense, we replicate the methodology used in previous studies. Secondly, we transform the TGARCH(1,1)-in-mean into a state-dependent TGARCH(1,1)-in-mean model in order to capture “state-dependent” market prices of variance risk. Thirdly, we investigate whether upstate and downstate market price of variance risk implied from the state-dependent TGARCH(1,1)-in-mean explain the cross-sections of average positive and negative risk premia. Fourthly, we check for overreaction by testing for the presence of asymmetric reverting behaviors in each market. Fifthly, we assess whether the state-dependent model can be used to improve the prediction of correct directional calls.

As mentioned in Section 1, a main attraction to having a model that relates contemporaneous risk premia to concomitant risk is its ability to uncover overreaction—a short-run condition that can be exploited with the so-called contrarian portfolio strategies. A catastrophic event like the Asian crisis provides an ideal setting for testing overreaction. Accordingly, we investigate the risk–return relationship in Asian capital markets by testing two models, which are econometric variants of the single-factor CAPM. The first model applies the conditional one-factor CAPM to capture market price of variance risk, and uses

forecasted variance to explain realized returns. Then, we test a model that relaxes the conditional one-factor CAPM by accounting for state-dependent specifications.

First, we define the single-factor CAPM in a purely segmented market. The market-based CAPM is written as follows:

$$E_{t-1}[\text{RP}_{i,t}] = \frac{E_{t-1}[\text{RP}_{i,t}]}{\sigma_{i,t}^2} \sigma_{i,t}^2 = \lambda_{i,t} \sigma_{i,t}^2, \quad \forall i \quad (1)$$

where $E_{t-1}[\text{RP}_{i,t}]$ is the expected risk premium in market i , $\sigma_{i,t}^2$ the future local market variance and $E_{t-1}[\text{RP}_{i,t}]/\sigma_{i,t}^2 = \lambda_{i,t}$ is the market price of variance risk (also known as reward to local variance).

In order to model Eq. (1), we follow French, Schwert and Stambaugh (1987), Glosten, Jagannathan and Runkle (1993), and Scruggs (1998), and test for the relationship between realized excess return (market risk premium) and market conditional volatility. Conditional volatility of excess return is modeled using a GARCH methodology. In fact, we use a TGARCH(1,1)-in-mean model in order to impose restrictions on the dynamics of the conditional second moments, capture volatility clustering, and allow for the “leverage effect”—i.e., the asymmetric impact of good and bad news on the dynamic of second moments. Note that we leave market price of variance risk as inter-temporally constant and assume that market price of currency risk is zero. It is well known in the literature that market price of risk is time/state-dependent and many additional instrumental variables are voluntarily omitted. For example, Harvey (1991), Domowitz, Glen and Madhavan (1998), Dumas and Solnik (1995), De Santis and Gerard (1997), and Jan, Chou and Hung (2000) suggest that currency risk is likely to be an important omitted factor for international assets. It is not our intent to conduct a test of a multi-factor version of the CAPM; our goal is simply to restore conditional variance as relevant measure of risk to determine risk premia in segmented and integrated markets. Eq. (1) is first modeled with a TGARCH(1,1)-M procedure, where “(1,1)” refers to the number of lags in the error term and conditional variance term, respectively, “-M” or “-in-mean” refers to the presence of variance in the mean equation. The specifications of the mean and variance equations for model (1) are shown as follows:

$$\begin{aligned} \text{RP}_{i,t} &= \alpha_i + \beta_i \sigma_{i,t}^2 + e_{i,t}, & e_{i,t} &= \sigma_{i,t} \varepsilon_t, & \varepsilon_t &\sim N(0, 1), \\ \sigma_{i,t}^2 &= \gamma_i + \omega_i e_{i,t-1}^2 + \eta_i e_{i,t-1}^2 d_{i,t-1} + \psi_i \sigma_{i,t-1}^2, & & & & \forall i \end{aligned} \quad (2)$$

where $\text{RP}_{i,t}$ is the realized risk premium in market i , $\sigma_{i,t}^2$ the conditional variance, the coefficient α_i (abnormal return) is expected to be insignificant; the coefficient β_i is the market price of variance risk; $e_{i,t-1}^2$ is the lag of the squared residual from the mean equation (the ARCH term) and provides news about volatility clustering; $\sigma_{i,t-1}^2$ is last period's forecast variance (GARCH term); $d_{i,t} = 1$, if $e_{i,t} < 0$, and 0 otherwise, so that good news ($e_{i,t} < 0$) and bad news ($e_{i,t} > 0$) are allowed to have a different impact on the conditional variance (good news has an impact of ω_i , while bad news has an impact of $\omega_i + \eta_i$); accordingly, if $\eta_i > 0$, a leverage effect exists (bad news has greater impact than good news); if $\eta_i \neq 0$, the news impact is asymmetric.

In empirical tests, realized market risk premium is used as an unbiased estimate of the expected market risk premium. Consistent with rational expectations, the *ex-ante* market

price of risk should always be positive (see Bollerslev, Engle and Woolridge, 1988; Chou, 1988; Scruggs, 1998 who report a significant positive market price of risk). However, *ex-post*, the market price of risk may be negative, particularly in downstate markets, and that would imply a negative risk premium (see Glosten et al., 1993; Pettengill et al., 1995; Fletcher, 2000; Avard et al., 2001 who report a significant negative market price of risk). As a result, there might be some very simple and intuitive explanations for the conflicting findings of previous studies. If realized market risk premia are positive (upstate market), market price of variance risk is positive. If realized market risk premia are negative (downstate market), market price of variance risk must be negative. Thus, *ex-post* facto, a negative market price of risk is associated with downstate markets and a positive market price of risk is consistent with upstate markets. In fact, Pettengill et al. (1995) support this idea and state that “the existence of a large number of negative market excess return periods suggests that previous studies that test for unconditional positive correlation between beta and realized returns are biased against finding a positive relationship”. The authors further suggest considering a state-dependent risk–return relationship, which accounts for the negative portion of the realized market risk premium distribution.

In the same vein, we transform model (1) into a state-dependent Capital Asset Pricing Model by assuming that capital markets are two *uncorrelated* states of nature—i.e., up or down. Model (2) consists of the following TGARCH(1,1)-M representation:

$$\begin{aligned} \text{RP}_{i,t} &= \alpha_i + \beta_{i,\text{up}} \delta_i \sigma_{i,t}^2 + \beta_{i,\text{down}} (1 - \delta_i) \sigma_{i,t}^2 + e_{i,t}, & e_{i,t} &= \sigma_{i,t} \varepsilon_t, \\ \varepsilon_t &\sim N(0, 1), & \sigma_{i,t}^2 &= \gamma_i + \omega_i e_{i,t-1}^2 + \eta_i e_{i,t-1}^2 d_{i,t-1} + \psi_i \sigma_{i,t-1}^2, \quad \forall i \end{aligned} \quad (3)$$

where δ_i is a dummy variable that takes the value of 1 in an upstate (positive contemporaneous risk premium) and 0 in downstate conditions (negative contemporaneous risk premium), $\beta_{i,\text{up}}$ the market price of variance risk in upstate, $\beta_{i,\text{down}}$ the market price of variance risk in downstate, the other variables have the same definitions as that in Eq. (2).

Models (1) and (2) are tested on the 10 country indices starting from January 1, 1990 and ending in June 1, 2001. We use Bollerslev–Wooldridge heteroskedasticity-consistent covariance to compute the quasi-maximum likelihood (QML) covariances and standard errors as described by Bollerslev and Wooldridge (1992).

At this point we need to validate model (2). We need to know if the model “makes sense” across markets. Therefore, we investigate the cross-sections of average positive and negative risk premium with “implied” positive ($\beta_{i,\text{up}}$) and negative ($\beta_{i,\text{down}}$) price of risk obtained from model (2). According to the CAPM, we should find that each country has its own average reward to variance risk. Additionally, the relationship between average positive (negative) returns and positive (negative) market price of variance risk should be significant, inverse and linear; finally, the slopes should be the same in upstate and downstate. In that case, it would be true that, across countries, the greater the reward to local variance risk, the smaller the contemporaneous required rate of return.

Once the contemporaneous relationship between risk and return has been validated across markets, we can use the model to uncover overreaction—a condition that can only be observed *ex-post*. Under rational expectations, the positive and negative market price of risk should be equal in intensity. If not, it indicates that the market overreacts to a change in

variance. For example, if the negative market price of variance risk associated with a realized negative risk premia is greater than the positive market price of variance risk associated with a realized positive risk premia, it demonstrates that the stock market exhibits a negative correlation between realized returns and concomitant risk. In this case, it is quite logical to conclude that markets exhibit optimism unwarranted by variance alone (see Glosten et al., 1993; Avard et al., 2001 for reference). In other words, negative returns tend to revert faster than positive returns. Of course, the alternative is also true. If positive returns revert faster than the negative ones, there is evidence of pessimism unwarranted by variance alone—i.e., upstate market price of variance risk is greater than downstate market price of variance risk. Thus, in each market, we use a Wald test for the null hypothesis of $\beta_{i,\text{up}} + \beta_{i,\text{down}} = 0$.

A potential criticism of the state-dependent approach is that it cannot be used to make predictions because realized upstate and downstate conditions are not known *ex-ante*. In that sense, the only practical usefulness of such model would be to uncover overreaction—an *ex-post* condition. This is not true. The model can generate positive as well as negative future risk premia. Accordingly, we investigate the forecasting power of the state-dependent model in two ways. First, we set all parameters in the right-hand side of Eq. (3) at $t - 1$ as follows:

$$\begin{aligned} \text{RP}_t &= \alpha_i + \beta_{i,\text{up}}\delta_{i,t-1}\sigma_{i,t}^2 + \beta_{i,\text{down}}(1 - \delta_{i,t-1})\sigma_{i,t}^2 + e_{i,t}, & e_{i,t} &= \sigma_{i,t}\varepsilon_t, \\ \varepsilon_t &\sim N(0, 1), & \sigma_{i,t}^2 &= \gamma_i + \omega_i e_{i,t-1}^2 + \eta_i e_{i,t-1}^2 d_{i,t-1} + \psi_i \sigma_{i,t-1}^2, & \forall i \end{aligned} \quad (4)$$

where $\delta_{i,t-1}$ is a dummy variable that takes the value of 1 if the risk premium is positive in the previous day, and 0 otherwise. The other variables have the same definitions as that in Eq. (3). We run Eq. (4) in each market. Second, we investigate a simple strategy that reflects the underlying idea of the model (2). That is, a positive (negative) risk premium is likely followed by a positive (negative) risk premium. Accordingly, we invest in the market (Treasury Bill) at time “ t ” if the risk premium is positive (negative). Then, we count the number of correct calls at time “ $t + 1$ ”. A sign test is performed to indicate whether the number of correct calls is greater than 50%.

3. Data

This study uses daily returns data calculated from the percent logarithmic difference between closing prices from January 1, 1990 to June 1, 2001 on MSCI country index series (2,980 observations). We investigate nine Asian markets (Hong Kong, Indonesia, Japan, Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand) and the United States. There is evidence that U.S. capital markets were not affected by the Asian financial crisis; for that reason, we use the MSCI US index as a control variable.

We use daily data to capture potential short-lived interactions for several reasons because it is well known in the literature that using monthly data may not be appropriate in describing the effect of capital movement (an intrinsically short-term occurrence). Also It is usually argued that using high frequency data can be problematic with infrequent trading;

well, this is a trade off, we are willing to take because we also want to perform our tests over three smaller sub-periods and the TGARCH(1,1)-M model will not converge with too few data points.

Morgan Stanley Capital International index series are obtained from Datastream. We choose MSCI indices because they capture the spirit of an all-share index by including replicable subsets of shares. Furthermore, local country indices vary considerably and are not comparable to one another, MSCI indices are often broader and reflect a consistent methodology across all markets. The equity returns are calculated in U.S. dollars; thereby setting the market price of currency risk equal to zero. This is more appropriate in segmented markets because inflation trends are taken into account through Fisher equation (Liew, 1995). Also, it provides uniformity in the comparison of one market to another. When calculating risk premia (return minus risk-free rate), we use the 1-month T-bill rate as a proxy for the risk-free rate.

One aspect of our study is to isolate the crisis period from the rest of the sample. Accordingly, we plot the price levels for each country (Fig. 3). As in Granger, Huang and Yang (2000), we identify two break points, which suggest the study might be broken down into three periods.

Firstly, we define a pre-crisis period starting January 1, 1990 and ending on July 1, 1997 (1,958 observations). During this period, only Japan experiences average losses (−0.14%); Korea (1.85%), Thailand (7.23%), Singapore (11.77%), U.S. (13.36%), Malaysia (13.58%), Taiwan (14.11%), Philippines (15.30%), Hong Kong (17.72%), and Indonesia (19.53%) capital markets experience average positive returns.

Secondly, we define a crisis period starting July 2, 1997, with the collapse of the Thai, Filipino, and Malaysian currencies and ending September 30, 1998 (325 observations). During this period, Japan (−41.25%), Taiwan (−47.68%), Hong Kong (−55.16%), Singapore (−60.56%), Philippines (−86.46%), Korea (−87.14%), Thailand (−100.45%), Malaysia (−147.87%), and Indonesia (−203.59%) experience losses. The U.S. (11.16%) market experiences average positive returns.

Thirdly, we define a post-crisis period starting October 1, 1998 and ending June 1, 2001 characterized by a recovery in many of the markets studied (697 observations). Indeed, Thailand (5.34%), U.S. (5.92%), Japan (9.95%), Hong Kong (11.21%), Indonesia (14.92%), Singapore (15.52%), Korea (30.16%), and Malaysia (31.93%) have average positive returns. Taiwan (−4.79%) and Philippines (−3.93%) markets exhibit average losses during the same period.

Table 1 presents statistics of daily market risk premia for the overall period, pre-crisis, crisis and post-crisis periods, respectively. Mean, standard deviation, skewness (the chance of an unexpected large positive or negative movement in risk premia), kurtosis (the likelihood of big returns—positive or negative), and correlation and beta with the MSCI AC World are presented. Autocorrelation of residuals and squared residuals are also reported.

For the overall period, each country's market risk premium series is characterized by positive or negative skewness, excess kurtosis, serial correlation (significant Q1 and Q9), residual autocorrelation (significant Qres12), and volatility clustering (significant Qres²12). Note that the evidence of residual autocorrelation and volatility clustering suggest that variance is conditional. In that sense, a GARCH parameterization is appropriate to model the

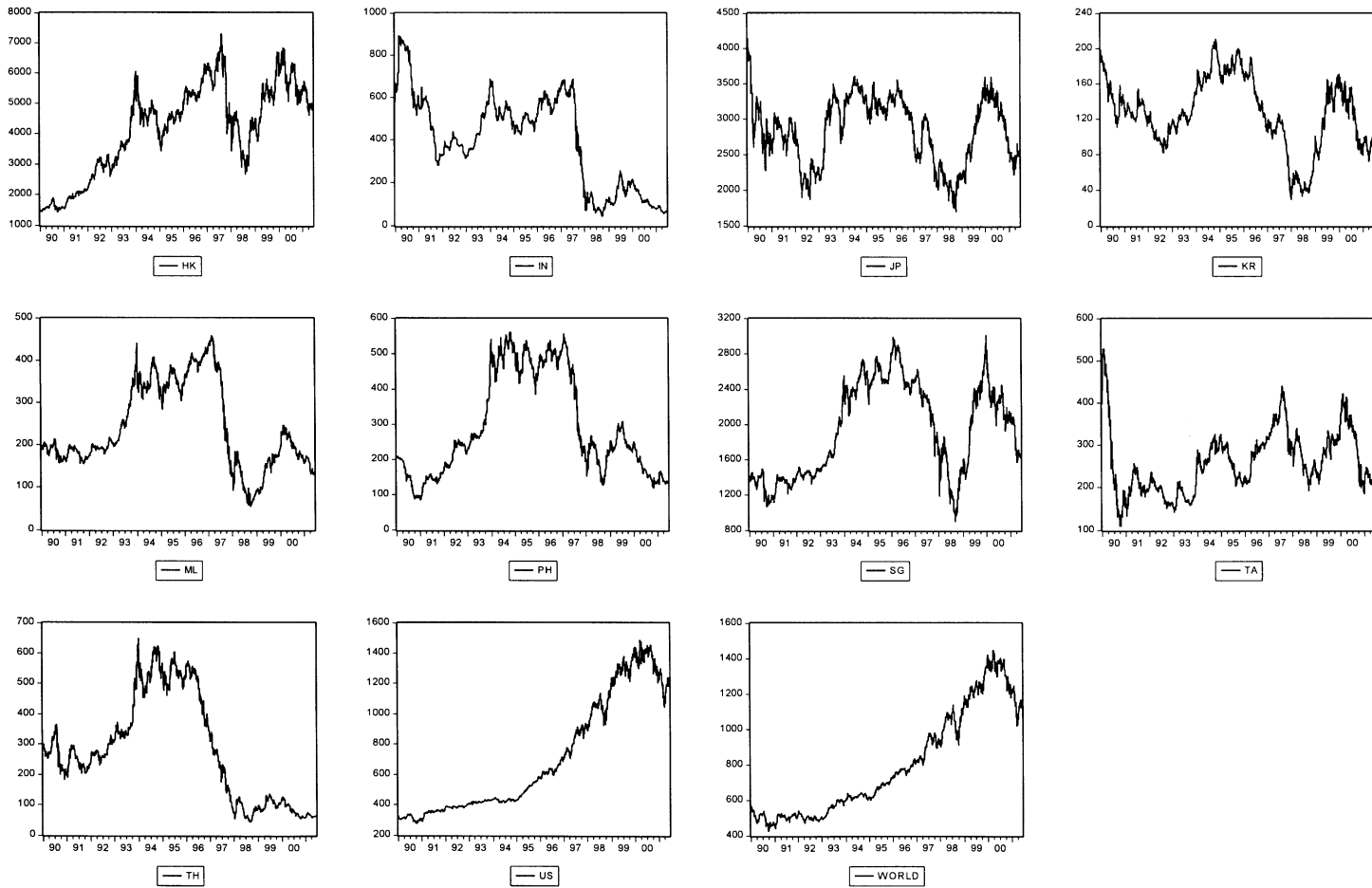


Fig. 3. Level series plots for the nine markets studied, the U.S. and the MSCI AC World (January 1, 1990 to June 1, 2001).

Table 1
Descriptive statistics on daily market risk premia

	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand	U.S.	World
Mean											
Overall	0.00017	-0.0003	-0.0003	-0.0002	-0.0001	-0.0001	0.00002	0.0004	-0.00004	0.0003	0.0001
Pre-crisis	0.0005	0.0006	-0.0002	-0.0002	0.0003	0.0004	0.0003	0.0003	0.00007	0.0003	0.0001
Crisis	-0.0024	-0.0083	-0.0018	-0.0037	-0.0061	-0.0036	-0.0026	-0.0021	-0.0042	0.0002	-0.0002
Post-crisis	0.0002	0.0004	0.0002	0.0010	0.0011	-0.0004	0.0004	-0.0004	0.00001	0.00001	-0.00003
S.D.											
Overall	0.01791	0.029581	0.014178	0.023752	0.020524	0.017899	0.013475	0.021681	0.021852	0.009781	0.007777
Pre-crisis	0.014817	0.017514	0.013689	0.015112	0.012459	0.014298	0.009887	0.021975	0.016646	0.007820	0.006589
Crisis	0.030076	0.068123	0.018399	0.049947	0.050808	0.029299	0.024302	0.019278	0.041051	0.012449	0.009712
Post-crisis	0.017948	0.032619	0.015504	0.030056	0.018950	0.018284	0.016343	0.020898	0.023589	0.012837	0.009391
Skewness											
Overall	-1.03	0.22	0.42	0.44	-0.78	0.75	0.02	0.03	0.42	-0.44	-0.25
Pre-crisis	-0.78	1.36	0.28	0.32	-0.38	-0.12	-0.60	-0.01	-0.22	-0.59	-0.08
Crisis	0.4	-0.79	0.39	0.55	-0.43	0.31	0.59	-0.33	0.78	-0.82	-0.65
Post-crisis	0.13	0.88	0.81	0.16	2.09	3.09	-0.02	0.12	0.48	0.01	-0.09
Kurtosis											
Overall	9.68	17.88	7.92	7.54	16.83	16.52	12.54	6.04	8.75	8.49	6.59
Pre-crisis	10.23	18.59	7.74	5.97	16.82	12.25	11.12	5.84	8.98	9.24	7.74
Crisis	8.05	9.68	4.54	8.08	14.82	4.96	7.99	7.13	5.47	9.57	5.2
Post-crisis	5.41	8.82	8.49	4.17	16.9	18.25	4.57	4.87	5.68	4.43	4.14

Table 1 (Continued)

	Hong Kong	Indonesia	Japan	Korea	Malaysia	Philippines	Singapore	Taiwan	Thailand	U.S.	World
Correlation											
Overall	0.31	0.07	0.61	0.15	0.22	0.12	0.34	0.13	0.18	0.71	1
Pre-crisis	0.28	0.02	0.77	0.11	0.30	0.08	0.41	0.13	0.17	0.57	1
Crisis	0.45	0.18	0.45	0.15	0.24	0.26	0.32	0.17	0.23	0.85	1
Post-crisis	0.29	0.08	0.32	0.26	0.06	0.12	0.32	0.10	0.20	0.88	1
Preliminary tests (overall period only)											
Beta	0.74 a	0.32 a	1.16 a	0.50 a	0.54 a	0.30 a	0.62 a	0.34 a	0.55 a	0.91 a	1
Q1	0.02	0.18 a	0.07 a	0.09 a	0.11 a	0.25 a	0.18 a	0.04 a	0.18 a	0.02	0.04 a
Q9	-0.03 a	0.04 a	0.07 a	0.10 a	0.05 a	0.08 a	-0.04 a	0.03 a	0.08 a	-0.01 a	0.05 a
Qres12	0.041 a	-0.012 a	0.029 a	-0.039 a	0.090 a	0.072 a	0.034 a	-0.039 b	0.015 a	0.014 a	0.018 a
Qres ² 12	0.061 a	0.095 a	0.021 a	0.087 a	0.081 a	0.068 a	0.065 a	0.010 a	0.099 a	0.027 a	0.028 a
CB	6.89 a	7.51 a	5.83 a	4.98 a	6.17 a	7.12 a	7.84 a	4.71 a	4.97 a	0.842	1.09

All computations are based on U.S. dollar MSCI series. We also conducted JB tests (not reported) and found out that for each series, the null hypothesis of normality was rejected. Q1 and Q9 are Ljung-Box Q-statistics for serial correlation (1 and 9 lags). For each country, we regress each market return series against the world market risk premium (MSCI AC World return—T-bill rate)—i.e., $R_{i,t} = \alpha + \beta RP_{m,t} + \varepsilon_{i,t}$. Qres12 and Qres²12 tests on residuals ($\varepsilon_{i,t}$) are performed. We also report the F-statistic for a Chow Break test (CB) for the period starting on July 2, 1997 (Currency crash) and ending in September 30, 1998 (beginning of recovery in all Asian capital markets). The letters a, b and c denote rejection of the null hypothesis at 1, 5, 10% significant levels, respectively.

behavior of daily risk premia. Furthermore, all estimated betas from the regression of individual market returns with the world risk premia are significant for all countries, suggesting some level of correlation with the world portfolio. Finally, a Chow breakpoint stability test further indicates that the relationship between market risk premium and forecasted volatility significantly differs in all three periods of study.

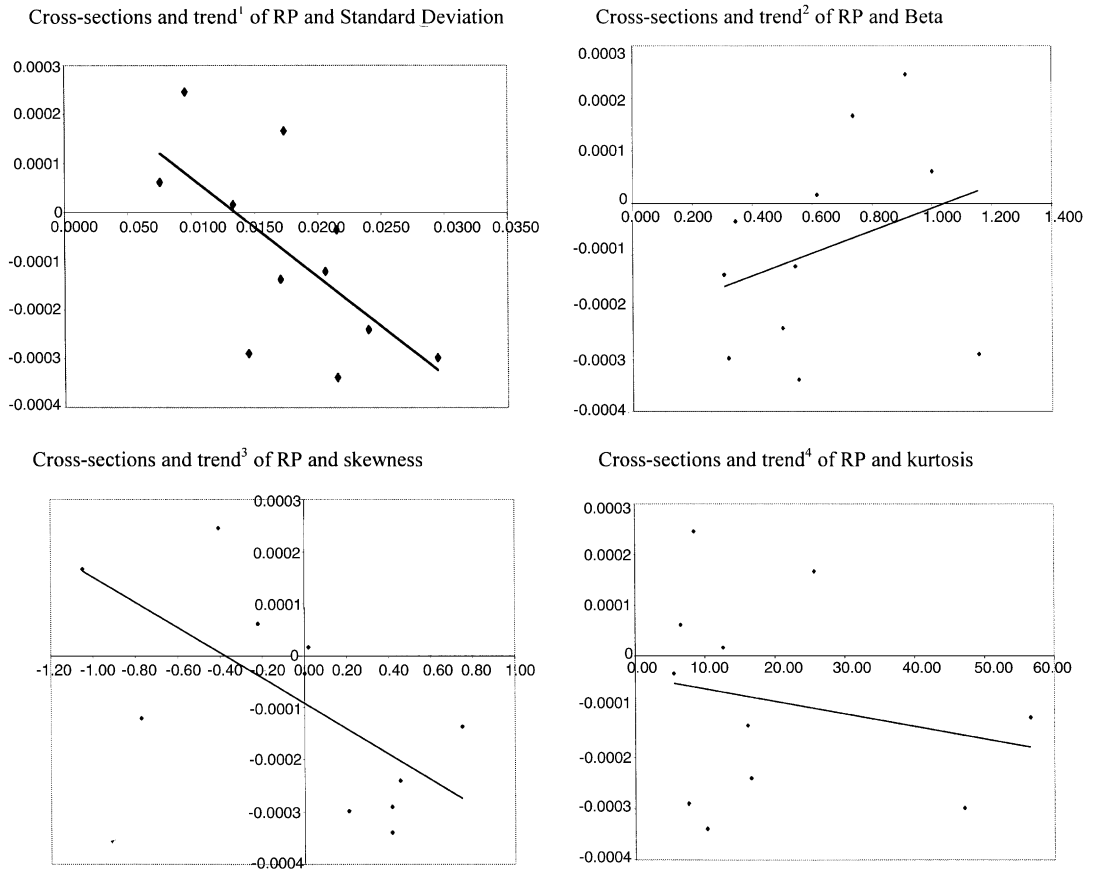
Before the crisis, only Japan and Korea have negative risk premia. The U.S. market is less volatile than Asian markets, and Taiwan is the most volatile market. Risk premia are negatively skewed (except in Indonesia, Japan and Korea) and have large excess kurtosis. During the crisis, all Asian markets show negative risk premia with higher amplitude than in those observed in the pre-crisis period. Also, volatility is much greater than in the pre-crisis period. The correlation with the world market substantially increases (decreases) for Hong Kong, Indonesia, Korea, Philippines, Taiwan, Thailand and the U.S. (Japan and Malaysia) as compared to the pre-crisis period. After the crisis, average market premia are positive (except in the Philippines and Taiwan); standard deviations are smaller than during the crisis period, yet greater than before the crisis. Correlation with the world market substantially decreases as compared to during-the-crisis-period (except for U.S. and Korea). Yet, as compared to the pre-crisis period, correlation with the world market increases (decreases) in Indonesia, Korea and U.S. (Japan and Malaysia). Pre and post-crisis correlations are similar in Hong Kong, Philippines, Singapore, Taiwan and Thailand.

From these observations, it is evident that correlation with the world changes over time. Indeed, while Japan and Malaysia appear to have become more segmented as a result of the crisis, Indonesia and Korea have become more integrated with the World market. Interestingly, the level of integration in the majority of Asian capital markets has remained unchanged as a result of the Asian financial crisis.

Next, we use the results from Table 1 to get an insight on which measure of risk matters more. Accordingly, we investigate how the cross-sections of risk premia are explained by four measures of “deviation” commonly believed to be instrumental in markets’ return generating process—i.e., standard deviation, beta, skewness and kurtosis. We only report the findings in the overall period for sake of brevity; also, findings are similar for the three sub-periods. Fig. 4 summarizes these cross-sectional relationships.

As in Fama and French (1992), we find a flat cross-sectional relationship between risk premia and beta. The relationship between kurtosis and risk premia is also flat. Those results are puzzling because these relationships should be upward-sloping as investors naturally require a higher return for a greater likelihood of big positive or negative returns. Interestingly, cross-sections of risk premia and (1) standard deviation or (2) skewness are statistically significant at the 5% level, but suggest a negative relationship. This is problematic because it is inconsistent with the risk–return principle and the idea that investors prefer positively skewed distributions to the negatively skewed ones.

In conclusion, we reject beta, local standard deviation, skewness and kurtosis as explanatory variables of returns’ cross-sections in all markets. Indeed, these relationships cannot be explained by the theory and might stem from a small number of cross-sectional observations. These findings are consistent with the risk–return relationship puzzle reported in the academic literature (e.g., Scruggs, 1998) and call for a re-examination of the CAPM.



Independent Variable		Coefficients	t-stat	F-stat	Observations	R Square
(1) Standard Deviation	Intercept	0.000273	1.90	7.06b	11	0.439
	Slope	-0.02026	-2.65b			
(2) Beta	Intercept	-0.00023	-1.50	0.99	11	0.099
	Slope	0.000217	0.99			
(3) Skewness	Intercept	-9.2E-05	-2.02c	7.97b	11	0.469
	Slope	-0.00024	-2.82b			
(4) Kurtosis	Intercept	-4.1E-05	-0.43	0.44	11	0.045
	Slope	-2.4E-06	-0.65			

“RP” are the risk premia for each country in Table 1 (we also include the World index in the cross-sections). a, b and c denote rejection of the null hypothesis at 1%, 5%, 10% significant levels, respectively

Fig. 4. Cross-sections and trends of each market average risk premium with inherent standard deviation, beta, skewness and kurtosis (January 1, 1990 to June 1, 2001).

4. Empirical findings

We summarize the results of the relationship between realized return and conditional volatility in all markets from January 1990 to June 2001 in Table 2. For model (1), market prices of variance risk (β) are never significant (with the sole exception of Japan). As a

Table 2
Test of Sharpe–Litner’s CAPM using models (1) and (2)

Country	Model (1): TGARCH(1,1)-M							Model (2): state-dependent TGARCH(1,1)-M									
	Mean equation		Variance equation				\bar{R}^2	DW	Mean equation			Variance equation				\bar{R}^2	DW
	α	β	γ	ω	η	ψ			α	β_{up}	β_{down}	γ	ω	η	ψ		
Hong Kong <i>t</i> -statistic	0.000652 1.71 c	-1.143 -0.68	0.000007 2.95 a	0.041 2.76 a	0.107 3.72 a	0.880 50.24 a	-0.001	1.91	0.00001 0.02	39.039 8.39 a	-34.63 -7.62 a	0.00001 2.38 b	0.095 2.95 a	0.196 3.99 a	0.725 34.74 a	0.52	1.73
Indonesia <i>t</i> -statistic	-0.000367 -1.69 c	0.199 0.38	0.000004 3.58 a	0.264 3.29 a	0.036 0.44	0.778 29.33 a	0.003	1.71	0.00054 1.80 c	8.946 5.88 a	-14.552 -15.74 a	0.00001 20.86 a	0.413 4.15 a	0.022 0.16	0.684 34.14 a	0.32	1.75
Japan <i>t</i> -statistic	-0.001336 -3.19 a	4.679 2.10 b	0.000004 4.91 a	0.045 3.64 a	0.086 3.64 a	0.899 69.19 a	0.001	1.87	-0.00046 -1.59	48.37 25.60 a	-43.444 -23.94 a	0.00001 2.05 b	0.077 4.47 a	0.088 2.76 a	0.849 46.71 a	0.41	1.87
Korea <i>t</i> -statistic	-0.000844 -2.24 b	0.751 0.83	0.000004 2.95 a	0.062 4.07 a	0.052 2.33 b	0.909 79.46 a	0.007	1.83	-0.00016 -0.50	33.374 27.37 a	-28.489 -24.94 a	0.00001 2.45 b	0.079 5.05 a	0.044 1.75 c	0.882 81.53 a	0.4	1.75
Malaysia <i>t</i> -statistic	0.000088 0.37	-0.093 -0.10	0.000002 2.44 b	0.054 4.37 a	0.082 3.62 a	0.906 75.61 a	-0.001	1.79	-0.00061 -1.76 c	37.246 15.32 a	-29.256 -12.91 a	0.00001 1.69 c	0.11 3.38 a	0.074 1.82 c	0.81 25.64 a	0.31	2.04
Philippines <i>t</i> -statistic	-0.000121 -0.36	-0.595 -0.47	0.000004 3.22 a	0.063 2.28 b	0.088 2.12 b	0.892 44.18 a	0.004	1.59	-0.00004 -0.15	38.122 24.22 a	-38.443 -21.93 a	0.00001 3.64 a	0.241 5.37 a	0.003 1.74 c	0.714 18.72 a	0.19	1.88
Singapore <i>t</i> -statistic	-0.000171 -0.77	1.157 0.65	0.000004 4.34 a	0.100 4.48 a	0.102 2.79 a	0.836 38.59 a	-0.001	1.69	0.00051 2.42 b	45.67 22.78 a	-52.755 -21.95 a	0.00001 1.26	0.137 3.75 a	0.155 2.71 a	0.735 25.86 a	0.45	2.01
Taiwan <i>t</i> -statistic	-0.000557 -1.09	0.699 0.49	0.000009 3.41 a	0.044 3.39 a	0.060 2.83 a	0.903 55.65 a	0.001	1.92	-0.00043 -0.99	35.483 28.18 a	-29.364 -22.43 a	0.00001 2.02 b	0.047 3.80 a	0.062 2.72 a	0.886 51.81 a	0.49	1.99
Thailand <i>t</i> -statistic	-0.000229 -0.61	-0.575 -0.55	0.000007 3.84 a	0.086 4.47 a	0.062 2.11 b	0.874 50.03 a	-0.005	1.68	0.00026 0.87	28.109 22.86 a	-28.571 -25.09 a	0.00001 3.41 a	0.131 4.73 a	0.031 0.85	0.823 42.89 a	0.29	1.77
U.S. <i>t</i> -statistic	-0.000032 -0.17	3.501 1.29	0.000001 3.37 a	0.012 1.12	0.093 4.83 a	0.928 92.75 a	0.009	1.97	-0.00015 -0.75	70.582 25.46 a	-61.296 -22.43 a	0.00001 1.58	0.028 1.51	0.12 3.99 a	0.846 36.16 a	0.43	1.86

Since the residuals are highly leptokurtic, we use heteroskedasticity consistent covariance to compute the quasi-maximum likelihood (QML, with Marquardt method) covariances and standard errors as described by Bollerslev and Wooldridge (1992). \bar{R}^2 is the adjusted *R*-squared. “DW” is the Durbin Watson statistic. The letters a, b and c denote rejection of the null hypothesis at 1, 5, and 10% levels, respectively.

result, we do not find any significant relationship between market risk premia and conditional volatility. Results from the variance equation provide information about variance persistence and leverage effect. Variance is persistent in most markets ($\omega + \psi \leq 1$). However, we find the variance process to be explosive in Indonesia. The leverage effect (significant positive asymmetry measured with η) is present in all markets, but Indonesia. It indicates that bad news has a greater impact on conditional variance than good news.

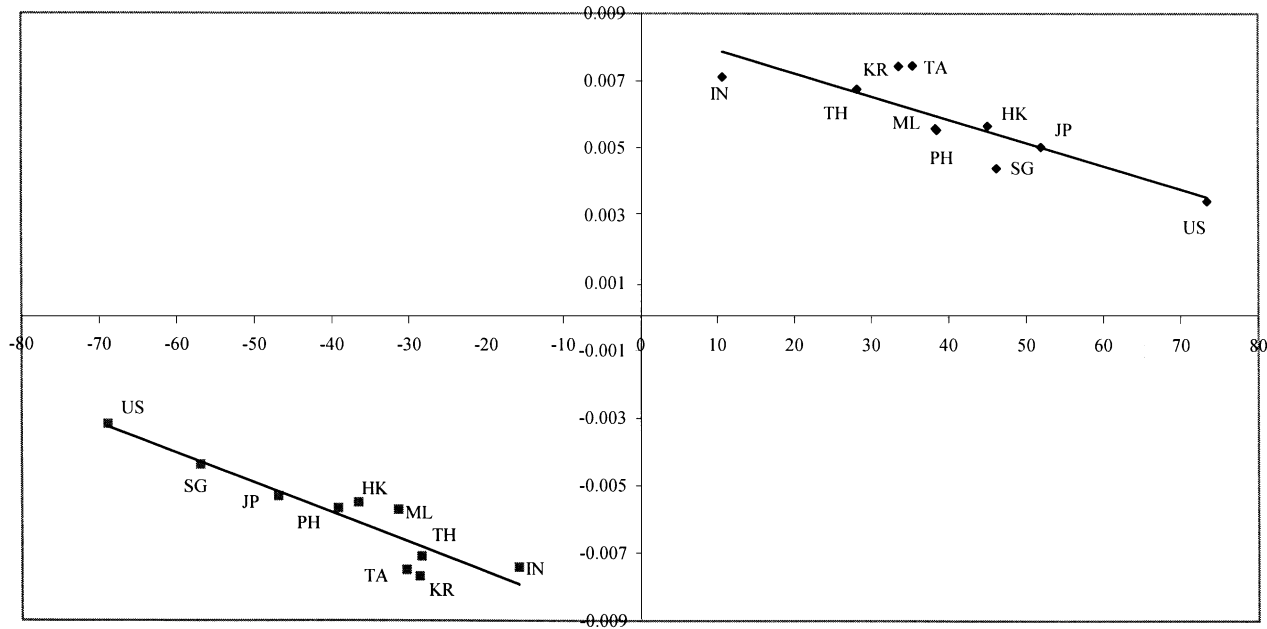
In summary, model (1) does a poor job modeling the relationship between risk premium and time-varying volatility. All R -squared values are extremely low (<0.01) and market price of variance risk (β) is never significant. These findings are similar to those of many studies such as in French et al. (1987) and Baillie and De Gennaro (1990).

In its *ex-ante* form, the CAPM suggests that market price of risk should be positive. Yet, only a post hoc formulation of Sharpe–Lintner’s CAPM can be tested. Since the realized risk premium can be positive or negative, it points to a positive or negative market price of risk, which can be explained as follows. During periods of growth, volatility does not keep the investors away from the market because the stock index generally trends upwards. However, once growth falters, volatility drives investors away from equity markets and brings about a direct relationship between volatility and returns. Thus, the effect of volatility on investor behavior and consequent risk–return relationship is state-dependent and model (1) must be modified to reflect this reality.

Results from model (2) are also summarized in Table 2. For all markets, we find significant positive market prices of variance risk in upstate and significant market prices of variance risk in downstate. This result indicates that an increase in market conditional variance leads to an increase (further decrease) in market risk premium in upstate (downstate). Furthermore, model (2) provides a better fit than model (1) as R -squared values range from 0.19 to 0.52. Results from the variance equation are similar to those of model (1). These findings restore local variance as explanatory variable of the return generating process in all markets studied.

The results from Table 2 help answer the inevitable question: does the market-based CAPM hold? The market-based CAPM suggest a direct relationship between required compensation for risk and local variance. In that case, the market price of (or reward to) variance risk is idiosyncratic to each market and it is expected to be serially constant. Also, this relationship, which theoretically holds *ex-ante*, can only be empirically tested *ex-post*. The idea of the state-dependent approach is to overcome that obstacle by allowing for the negative portion of the market risk premium distribution. Before the fact, investors have perfect market timing ability in their rational expectations and will always choose between the market return and the risk-free rate, whichever is greater. After the fact, investors do not have perfect market ability and may allocate funds to a market in which realized return is smaller than the risk-free rate.

After simply adjusting for the two states of the world, we find that positive (negative) market prices of variance risk are associated with positive (negative) risk premia. Therefore, we conclude that forecasted variance explains contemporaneous returns. In order to infer on whether the market-based CAPM holds across countries, we look at the following cross-sectional relationships from January 1990 to June 2001. Average positive and negative risk premium are computed in each market and plotted against the inherent “average” positive (β_{up}) and negative (β_{down}) price of risk obtained from model (2). Results are graphed in Fig. 5.



Independent Variable		Coefficients	t-stat	F-stat	Observations	R Square
(1) β_{up}	Intercept	0.008623	12.44a	18.41a	10	0.701
	Slope	-6.9E-05	-4.29a			
(2) β_{down}	Intercept	-0.00951	-14.97a	35.40a	10	0.816
	Slope	-9.9E-05	-5.95a			

a,b and c denote rejection of the null hypothesis at 1%, 5%, and 10% levels, respectively

Fig. 5. Cross-sections and trends statistics of each market average positive (1) and negative (2) risk premium with inherent implied positive (β_{up}) and negative (β_{down}) market price of variance risk (January 1, 1990 to June 1, 2001).

Results from these cross-sections are stunning. Each country has its own average reward to variance risk. Additionally, the relationship between average positive (negative) returns and positive (negative) market price of variance risk is significant, inverse and linear (significant F -statistics at the 1% level). The slopes in the two states are also significant and similar. As a result, the greater the reward to variance risk, the smaller the contemporaneous required rate of return. This finding fails to invalidate the market-based CAPM and reinforces our belief that the risk–return generating process is contemporaneously state-dependent.

Note that several remarks can be made from these observations. First, the low number of cross sectional observations might have altered our statistical findings. Second, it might be argued that other local variables are instrumental in the risk–return generating process. Third, many researchers have suggested that reward to risk is time-varying, which challenges the validity or the meaning of an “average reward to local variance”. In fact, we performed a factorial analysis and fail to accept the null hypothesis of equal “market price of variance risk” in each period (results are available upon request). This finding reflects a well-known limitation of the Sharpe–Lintner CAPM—i.e., it imposes constant market price of risk. Indeed, risk aversion changes with the state of the economy and time (see De Santis and Gerard, 1997).

At this point, we follow Avard et al. (2001) and investigate asymmetric reverting behaviors before, during and after the Asian Financial Crisis. We use Wald tests to measure the asymmetry between upstate and downstate market price of variance risk. We do not find evidence of asymmetry before the crisis. Yet, upstate market price of variance risk (β_{up}) is significantly greater than negative market price of variance risk (β_{down}) in all Asian markets during the crisis and in the U.S. after the crisis, suggesting excessive pessimism unwarranted by variance alone. The same tests show that upstate market price of variance risk (β_{up}) is significantly smaller than negative market price of variance risk (β_{down}) in the U.S. during the crisis and in Japan, Korea, Malaysia, Philippines, and Singapore after the crisis, suggesting excessive optimism unwarranted by variance alone. Consistent with the asymmetry previously detected, intercepts are also significant and reveal that the same markets experience significant abnormal losses or gains (α). Results are summarized in Table 3.

The observed excessive pessimism in most Asian markets during the crisis is consistent with the belief that crisis-related volatility shocks trigger panic. Interestingly, we find that a period of excessive optimism (pessimism) is followed by a period of excessive pessimism (optimism) in the U.S. (Japan, Korea, Malaysia, Philippines, and Singapore). This observation provides a basis for contrarian portfolio strategies. These strategies are based on the premise that if a market consistently underperforms (outperforms) other markets, it will outperform (underperform) current outperforming (underperforming) markets over subsequent periods (see De Bondt and Thaler, 1985; Mun et al., 2000; Avard et al., 2001 for a detailed description of “systematic reversal of fortune” and consequent justifications for the use of Contrarian portfolio strategies). It is well known that overreaction occurred during the Asian financial crisis in the form of panic or herding; in that sense, our findings are not groundbreaking. However, model (2) is able to uncover it, and this is quite interesting.

An *ex-post* state-dependent model is not a forecasting model. Rather, it provides a contemporaneous relationship between risk and return, which can be used to detect

Table 3
Test of model (2) before, during and after the Asian financial crisis

Country	Pre-crisis (January 1, 1990 to July 1, 1997)						Crisis (July 2, 1997 to September 30, 1998)						Post-crisis (October 1, 1998 to June 1, 2001)					
	α	β_{up}	β_{down}	WT	\bar{R}^2	DW	α	β_{up}	β_{down}	WT	\bar{R}^2	DW	α	β_{up}	β_{down}	WT	\bar{R}^2	DW
Hong Kong	0.0006	53.1217	-51.6289	0.88	0.377	1.75	-0.0034	24.2733	-17.907	3.34 c	0.449	1.69	-4E-04	37.434	-35.513	0.1	0.398	1.66
<i>t-statistic</i>	0.9	10.49 a	-8.99 a				-2.94 a	10.07 a	-7.59 a				-0.22	6.90 a	-5.23 a			
Indonesia	-6E-04	50.2098	-46.7941	2.04	0.459	1.72	-0.0061	16.15	-10.85	3.97 b	0.415	1.63	0	28.642	-25.12	0.85	0.472	1.79
<i>t-statistic</i>	-0.87	9.94 a	-7.81 a				-2.57 b	12.30 a	-4.98 a				-0.03	7.99 a	-7.92 a			
Japan	0.0002	61.383	-59.036	0.15	0.519	1.79	-0.0011	64.638	-45.597	3.56 c	0.431	1.79	0.0022	43.12	-48.494	3.17 c	0.455	1.96
<i>t-statistic</i>	0.35	10.25 a	-10.26 a				-2.19 b	7.76 a	-5.17 a				1.83 c	4.56 a	-5.97 a			
Korea	-2E-04	43.8656	-42.8976	0.65	0.525	1.81	-0.0037	21.513	-15.248	4.16 b	0.538	1.88	0.0023	24.268	-29.05	3.34 c	0.51	1.94
<i>t-statistic</i>	-0.29	9.88 a	-9.23 a				-3.07 a	11.90 a	-7.89 a				1.69 c	5.14 a	-5.59 a			
Malaysia	-7E-04	64.4486	-59.947	1.99	0.432	1.73	-0.0048	25.9772	-21.201	3.36 c	0.332	1.82	0.0016	35.493	-39.988	3.23 c	0.454	1.82
<i>t-statistic</i>	-1.47	11.64 a	-9.64 a				-2.40 b	10.19 a	-5.57 a				1.70 c	7.67 a	-7.28 a			
Philippines	0.0002	56.0941	-56.9038	0.08	0.473	1.94	-0.0044	32.679	-20.77	4.23 b	0.425	1.86	0.0007	38.168	-45.79	3.09 c	0.448	1.78
<i>t-statistic</i>	0.39	11.48 a	-10.42 a				-3.16 a	7.60 a	-6.08 a				1.76 c	6.87 a	-8.51 a			
Singapore	-7E-04	78.7593	-76.4146	2.12	0.381	1.43	-0.0022	31.3045	-28.054	4.04 b	0.231	2.18	0.0027	28.739	-34.79	3.91 b	0.438	1.68
<i>t-statistic</i>	-1.45	10.96 a	-9.40 a				-2.07 b	7.25 a	-6.82 a				2.25 b	5.76 a	-9.09 a			
Taiwan	0.001	39.093	-41.4662	0.14	0.488	1.97	-0.0021	45.1877	-32.275	3.28 c	0.543	2.07	0.0026	36.624	-37.29	0.45	0.504	1.63
<i>t-statistic</i>	0.76	6.56 a	-7.24 a				-2.06 b	6.16 a	-4.07 a				1.4	5.34 a	-6.75 a			
Thailand	-0.001	44.531	-39.7468	1.02	0.483	1.81	-0.0102	30.5554	-10.351	13.81 a	0.478	1.78	-9E-04	31.878	-29.649	0.14	0.412	1.73
<i>t-statistic</i>	-1.3	10.60 a	-9.18 a				-3.80 a	9.50 a	-3.91 a				-0.42	6.34 a	-6.57 a			
U.S.	0.0001	80.256	-81.987	0.12	0.431	1.85	0.0044	58.362	-77.256	4.25 b	0.451	1.85	-0.001	66.325	-52.952	5.91 a	0.507	1.89
<i>t-statistic</i>	0.25	11.56 a	12.51 a				2.26 b	10.52 a	-12.95				-2.31 b	10.21 a	-9.51 a			

For sake of brevity, we only report the findings for the mean equation. Since the residuals are highly leptokurtic, we use heteroskedasticity consistent covariance to compute the quasi-maximum likelihood (QML, with Marquardt method) covariances and standard errors as described by Bollerslev and Wooldridge (1992). Also the Wald tests (WT) consist of testing the null hypothesis of $H_0: \beta_{up} + \beta_{down} = 0$. \bar{R}^2 is the adjusted R -squared. “DW” is the Durbin Watson statistic. The letters a, b and c denote rejection of the null hypothesis at 1, 5, and 10% levels, respectively.

Table 4
Test of an *ex-ante* version of model (2)

Country	Mean equation			Variance equation				\bar{R}^2
	α	β_{up}	β_{down}	γ	ω	η	ψ	
Hong Kong	0.00049	3.048	-3.497	8.93E-06	0.051	0.132	0.853	0.007
<i>t-statistic</i>	1.51	2.16 b	-2.24 b	3.74 a	3.44 a	3.95 a	47.94 a	
Indonesia	0.00029	1.445	-1.754	7.22E-06	0.329	0.083	0.72	-0.003
<i>t-statistic</i>	1.04	2.49 b	-2.36 b	3.88 a	3.80 a	0.83	23.94 a	
Japan	-0.00092	1.92	-3.67	3.56E-06	0.042	0.091	0.898	0.005
<i>t-statistic</i>	-2.63 a	1.68 c	-3.12 a	5.05 a	3.61 a	4.05 b	75.30 a	
Korea	-0.00052	1.884	-1.375	3.86E-06	0.06	0.049	0.91	-0.001
<i>t-statistic</i>	-1.52	1.69 c	-1.71 c	3.21 a	4.53 a	2.39 b	82.81 a	
Malaysia	-0.00018	6.581	-4.326	5.11E-06	0.047	0.072	0.901	-0.045
<i>t-statistic</i>	-0.48	3.25 a	-2.82 a	5.60 a	2.45 b	2.11 b	43.38 a	
Philippines	0.000211	5.964	-7.529	5.27E-06	0.071	0.069	0.885	0.019
<i>t-statistic</i>	0.62	3.59 a	-4.86 a	6.78 a	2.45 b	1.68 c	53.94 a	
Singapore	-1.98E-05	8.363	-6.255	6.48E-06	0.095	0.1	0.816	-0.003
<i>t-statistic</i>	-0.08	3.66 a	-2.56 b	1.95 c	4.30 a	2.14 b	16.61 a	
Taiwan	-0.00058	2.38	-1.41	1.16E-05	0.047	0.073	0.89	0.001
<i>t-statistic</i>	-1.11	1.43	-1.32	3.97 a	3.79 a	3.67 b	55.94 a	
Thailand	1.92E-05	3.591	-4.382	7.81E-06	0.103	0.065	0.854	0.009
<i>t-statistic</i>	0.06	2.84 a	-3.37 a	5.15 a	4.60 a	2.08 b	47.29 a	
U.S.	-5.21E-05	5.646	1.611	1.67E-06	0.008	0.092	0.925	0
<i>t-statistic</i>	-0.25	1.97 b	0.55	2.46 b	0.77	5.40 a	106.18 a	

Since the residuals are highly leptokurtic, we use heteroskedasticity consistent covariance to compute the quasi-maximum likelihood (QML, with Marquardt method) covariances and standard errors as described by Bollerslev and Wooldridge (1992). \bar{R}^2 is the adjusted *R*-squared. The letters a, b and c denote rejection of the null hypothesis at 1, 5, and 10% levels, respectively.

overreaction, an interesting condition to the contrarian investor. Accordingly, we investigate next the forecasting power of the state-dependent model. First, we set all parameters in the right-hand side of the mean equation of model (2) at time “*t* - 1”, and run Eq. (4) in all markets from January 1990 to June 2001. Results are summarized in Table 4.

First notice that the results from the variance equation are consistent with those of Table 2 and that *R*-squared values are extremely low. However, β_{up} and β_{down} are significant in all markets at least at the 10% level (except for Taiwan in upstate and downstate and U.S. in downstate). This finding indicates that a negative (or positive) risk premium is likely followed by a negative (or positive) risk premium. Accordingly, we further investigate whether the model can increase the number of correct calls in an active tactical allocation strategy—i.e., the ability to predict the direction of price movements. Indeed, assume that an investor allocates tactically between the risk free rate and the market; he/she needs a model that delivers short term forecasts in order to overweight either the investment in Treasury Bills or in local equity market. This is traditionally done using a multiple regression with

forward-looking variables that are capable of capturing expectation in future price movements, such as interest rates spreads, dividend yield, *P/E* ratio, etc. In fact, the reward from a forecast comes in the form of making correct calls regarding future trends—i.e., selling the future looser. As a result, the ability to make correct calls coupled with the

Table 5
Active tactical allocation strategy with model (2)

Country	State	Overall period		Pre-crisis		Crisis		Post-crisis	
		Correct calls	%	Correct calls	%	Correct calls	%	Correct calls	%
Hong Kong	All	1,569 b	52.30	1,022 b	52.22	174	53.37	373	52.02
	Downstate	823 a	53.51	526 b	52.97	98 c	56.32	199	53.64
	Upstate	746	51.03	496	51.45	76	50.00	174	50.29
Indonesia	All	1,713 a	57.10	1,134 b	57.95	193 a	59.20	386 b	53.84
	Downstate	961 a	59.91	617 a	60.02	125 a	65.10	219 a	57.03
	Upstate	752 a	53.87	517 a	55.65	68	50.75	167	50.15
Japan	All	1,539	51.30	1,005	51.35	172	52.76	362	50.49
	Downstate	865 a	54.23	560 b	54.05	112 b	59.26	193	52.16
	Upstate	674	47.97	445	48.32	60	43.80	169	48.70
Korea	All	1,645 a	54.83	1,064 a	54.37	189 a	57.98	392 b	54.67
	Downstate	979 a	59.12	647 a	59.19	127 a	64.80	205 b	55.86
	Upstate	666	49.55	417	48.26	62	47.69	187	53.43
Malaysia	All	1,711 a	57.03	1,110 a	56.72	195 a	59.82	406 a	56.62
	Downstate	914 a	58.66	548 a	56.44	134 a	67.00	232 a	59.95
	Upstate	797 a	55.27	562 a	57.00	61	48.41	174	52.73
Philippines	All	1,689 a	56.30	1,109 a	56.67	196 a	60.12	384	53.56
	Downstate	915 a	58.24	573 a	57.47	118 a	64.48	224 a	57.29
	Upstate	774 a	54.16	536 a	55.83	78	54.55	160	49.08
Singapore	All	1,645 a	54.83	1,094 a	55.90	183 b	56.13	368	51.32
	Downstate	846 a	55.55	550 a	56.07	112 a	60.87	184	51.40
	Upstate	799 a	54.10	544 a	55.74	71	50.00	184	51.25
Taiwan	All	1,525	50.83	977	49.92	180 b	55.21	368	51.32
	Downstate	901 a	55.01	558 b	53.24	127 a	63.50	216 b	55.38
	Upstate	624	45.81	419	46.09	53	42.06	152	46.48
Thailand	All	1,657 a	55.23	1,070 a	54.68	194 a	59.51	393 b	54.81
	Downstate	944 a	58.42	601 a	57.51	131 a	66.50	212 b	56.68
	Upstate	713	51.52	469	51.43	63	48.84	181	52.77
U.S.	All	1,511	50.37	983	50.23	171	52.45	357	49.79
	Downstate	764	50.63	491	50.20	81	50.94	192	51.61
	Upstate	747	50.10	492	50.26	90	53.89	165	47.83

Simple strategy that consists in investing in the market (Treasury Bill) at time “*t*”, if the risk premium is positive (negative). Correct calls are counted at time “*t* + 1”. A sign test is performed to indicate whether the strategy is better than flipping a coin. The sign test is as follows: $z = (\text{correct call} - \mu) / \sigma$ with $\mu = \text{total calls} \times 0.5$ and $\sigma = \sqrt{\text{total calls} \times 0.25}$. The letters a, b and c denote rejection of the null hypothesis at the 1, 5 and 10% levels, respectively.

willingness to reallocate dynamically might lead an investor to perform outside the efficient “fixed” frontier. Indeed, active portfolio allocation is similar to introducing new assets in the portfolio; it provides the investor with a potential to perform above and beyond what is commonly called the “fixed frontier strategy”.

The state-dependent model basically tells us that a negative (positive) risk premium is likely followed by a negative (positive) risk premium. Therefore, a simple strategy would consist of (1) investing in Treasury Bills, if the current market risk premium is negative, or (2) investing in a local market if the current market risk premium is positive. We conduct sign tests to see if this strategy is more likely to provide correct calls as compared to flipping a coin. Thus, we invest in the market (Treasury Bill) given a positive (negative) risk premium at time “ t ”. Then, we count the number of correct calls at time “ $t + 1$ ”. A sign test is performed to indicate whether the number of correct calls is greater than 50%. A summary of the results is compiled in Table 5.

We first look at the results in all states from January 1990 to June 2001. We conclude that the strategy works extremely well in most markets, except for the U.S., Japan and Taiwan where investors are better off flipping a coin. Then, we examine the number of correct directional calls in upstate and downstate during the overall period and conclude that negative risk premia are likely followed by negative risk premia in all markets but the U.S. We also observe that positive risk premia are only likely to be followed by positive risk premia in Indonesia, Malaysia, Philippines and Singapore.

Next, we investigate predictability before, during and after the crisis. While observations for the pre-crisis period are exactly the same as for the overall period, the strategy only works in downstate in all countries but the U.S. during the crisis. After the crisis, it only works in downstate in emerging markets—i.e., Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand.

5. Conclusion

Our paper investigates the contemporaneous relationship between market risk premium and conditional variance in nine Asian markets and the U.S. We find evidence of a significant state-dependent relationship between risk premium and conditional variance in all markets. Indeed, the state-dependent TGARCH(1,1)-M model points out to significant positive and negative market price of variance risk in upstate and downstate, which are consistent across markets. Our findings fail to invalidate the market-based CAPM and restore variance as an important instrumental variable in the return generating process in all markets. In the light of Wald tests for asymmetry, we find that most markets exhibit overreaction unwarranted by variance alone during and after the Asian financial crisis. This result provides grounds for contrarian portfolio strategies. We further investigate the forecasting ability of the state-dependent TGARCH(1,1)-M model in a tactical asset allocation framework. We conclude that (1) negative risk premia are likely to be followed by negative risk premia and (2) emerging markets such as Indonesia, Korea, Malaysia, Philippines, Taiwan and Thailand consistently demonstrate more predictability than more developed markets. Also, in practice, the efficiency of these strategies can be adversely

affected by the high cost of trading in emerging capital markets (see Bekaert, Erb, Harvey and Viskanta, 1998).

In the quest of finding the “optimal” allocation proportion between capital markets, most global portfolio managers make predictions of returns by using fundamentals. We suggest that a state-dependent CAPM does a decent job in defining a risk–return relationship and, therefore, restores conditional variance as an important explanatory variable for the return generating process. Furthermore, such model can be used to uncover overreaction and/or forecast. In that sense, it provides a better understanding of emerging markets and, thus a mean of comparison and selection between these markets.

References

- Avard, S., Nam, K., & Pyun, C. (2001). Asymmetric reverting behavior of short-horizon stock returns: An evidence of stock market overreaction. *Journal of Banking and Finance*, 25(4), 807–824.
- Baillie, R. T., & De Gennaro, R. P. (1990). Stock returns and volatility. *Journal of Financial and Quantitative Analysis*, 25, 203–215.
- Bekaert, G., Erb, C., Harvey, C., & Viskanta, T. (1998). Distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management*, 24, 102–116.
- Bekaert, G., & Harvey, C. (1995). Time-varying world market integration. *Journal of Finance*, 50, 403–444.
- Bollerslev, T., Engle, R. F., & Woolridge, J. M. (1988). A Capital Asset Pricing Model with time varying covariances. *Journal of Political Economy*, 96, 116–131.
- Bollerslev, T., & Wooldridge, J. M. (1992). Quasi-maximum likelihood estimation and inference in dynamic models with time varying covariances. *Econometric Reviews*, 11, 143–172.
- Chou, R. Y. (1988). Volatility persistence and stock valuations: Some empirical evidence using GARCH. *Journal of Applied Econometrics*, 3, 279–294.
- De Bondt, W., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance*, 40, 793–808.
- De Santis, G., & Gerard, B. (1997). International asset pricing and portfolio diversification with time-varying risk. *Journal of Finance*, 52(5), 1881–1912.
- Domowitz, I., Glen, J., & Madhavan, A. (1998). Country and currency risk premia in an emerging market. *Journal of Financial and Quantitative Analysis*, 33, 189–216.
- Dumas, B., & Solnik, B. (1995). The world price of foreign exchange risk. *The Journal of Finance*, 50, 445–479.
- Fama, E. (1991). Efficient capital markets: II. *Journal of Finance*, 46, 1575–1617.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47, 427–465.
- Fletcher, J. (1997). An examination of the cross-sectional relationship of beta and return: UK evidence. *Journal of Economics and Business*, 49, 211–221.
- Fletcher, J. (2000). On the conditional relationship between beta and return in international stock returns. *International Review of Financial Analysis*, 9, 235–245.
- French, K. R., Schwert, W. G., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3–30.
- Glosten, L. R., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48, 1779–1801.
- Granger, C., Huang, B., & Yang, C. (2000). A Bivariate causality between stock prices and exchange rates: Evidence from recent Asian flu. *The Quarterly Review of Economics and Finance*, 40, 337–354.
- Harvey, C. (1991). The world price of covariance risk. *Journal of Finance*, 46, 111–157.
- Harvey, C. (1995). The cross-section of volatility and autocorrelation in emerging markets. *Finanzmarkt und Portfolio Management*, 9, 12–34.
- Harvey, C. (1998). The future of investment in emerging markets. *NBER Reporter*, Summer, 5–8.

- Harvey, C. (2000). The drivers of expected returns in international markets. *Emerging Markets Quarterly*, 3, 32–49.
- Jan, Y., Chou, P., & Hung, M. (2000). Pacific Basin stock markets and international capital asset pricing. *Global Finance Journal*, 11, 1–16.
- Lee, S. B., & Ohk, K. Y., (1991). Time-varying volatilities and stock market returns: International evidence. In S. Rhee & R. Chang (Eds.), *Pacific-Basin Capital Market Research* (Vol. II). Amsterdam: Elsevier.
- Liew, J. (1995). Stock returns, inflation and the volatility of growth in the money supply: Evidence from emerging markets. University of Chicago, Working Paper Series.
- Mun, J., Vasconcellos, G., & Kish, J. (2000). The contrarian/overreaction hypothesis: An analysis of the U.S. and Canadian stock markets. *Global Finance Journal*, 11, 53–72.
- Pettengill, G. N., Sundaram, S., & Mathur, I. (1995). The conditional relation between beta and returns. *Journal of Financial and Quantitative Analysis*, 30, 101–116.
- Roll, R. (1977). A critique of the asset pricing theory's tests. Part 1. *Journal of Financial Economics*, 1, 129–176.
- Scruggs, J. T. (1998). Resolving the puzzling intertemporal relation between the market risk premium and the conditional variance: A two-factor approach. *Journal of Finance*, 53, 575–603.