Emerging Markets Finance & Trade, 52:2195–2207, 2016

ISSN: 1540-496X print/1558-0938 online
DOI: 10.1080/1540496X.2015.1068613

Beta Asymmetry in the Global Stock Markets Following the Subprime Mortgage Crisis

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ABSTRACT: I set out in this study to examine the asymmetry in beta responses using the dynamic conditional correlation threshold generalized autoregressive conditional heteroskedasticity (DCC-GJR-GARCH) model. The empirical results reveal that asymmetry is discernible in both volatility and betas in the global stock markets. Furthermore, when leverage is linked with the price-to-book ratio, the results indicate that the beta asymmetry is attributable to the leverage effect. The results of this study also reveal that the declines in the price-to-book ratio following the subprime mortgage crisis have led to an overall increase in betas.

KEY WORDS: asymmetric beta, DCC-GJR-GARCH model, subprime mortgage crisis

Introduction

Between the years 2007 and 2009, the global financial markets experienced a severe crisis that had been triggered by massive defaults among subprime borrowers within the mortgage markets. The crisis was to subsequently lead to declines in the value of the real estate mortgage-backed securities held by many financial institutions and, ultimately, the collapse of many of these institutions (Chen et al. 2010; Duchin, Ozbas, and Sensoy 2010; Nijskens and Wagner 2011).

The bankruptcy events led to a widespread loss of confidence among investors within the banking sector, thereby igniting the subprime mortgage crisis, a crisis that was to spread very quickly throughout 2008, ultimately becoming the catalyst for the current global financial crisis. Nevertheless, the ravages of the subprime financial crisis now provide researchers with a unique opportunity to study the explanatory role of leverage with regard to systematic risk.

There are already numerous studies available on the asymmetric variance of stock return series for various financial assets, with Black (1976) and Christie (1982) having pioneered the study of asymmetric volatility (the inverse movements of current stock returns and future volatility).

There are two specific theories within the extant literature aimed at explaining asymmetric volatility. First, Black (1976) and French, Schwert, and Stambaugh (1987) attribute this phenomenon to the financial leverage of firms. Given that such leverage indicates that declining security prices will tend to produce a higher debt-to-equity ratio, investors under such a scenario will automatically expect higher returns for those firms with higher debt-to-equity ratios. However, the declining security price is invariably accompanied by higher volatility (Lee and Chang 2011; Lee and Wei 2012).

Second, Campbell and Hentschel (1992) and Pindyck (1984) argue that the primary reason for asymmetric volatility is volatility feedback; that is, if the market risk premium is an increasing function of expected volatility, then an increase in volatility should cause a drop in the stock price, contributing to the variance in asymmetric returns.

Asymmetric beta means that the systematic risk is higher in a falling market than in a rising market. Braun, Nelson, and Sunier (1995) propose an investigation of asymmetry beta using a bivariate exponential GARCH (EGARCH) model within which the constant contemporaneous correlations between the market and nonmarket portfolio returns are assumed. Quite unexpectedly, however,

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while asymmetric volatility is clearly discernible in the market returns, such asymmetry is not discernible for the conditional betas and variances in the nonmarket portfolio returns.

Bekaert and Wu (2000) use the BEKK-GARCH model to carry out an examination of beta asymmetry, with their primary aim being to avoid limiting the correlations to a constant condition.[1] However, despite having relaxed the constant correlation limitation, Bekaert and Wu (2000) are still unable to find any asymmetry in the beta.[2] Koutmos and Knif (2002a) subsequently model a time-varying beta using a constant conditional correlation bivariate threshold GARCH model (CCC-GJR-GARCH), a model that enables them to allow conditional covariance to asymmetrically respond to positive and negative shocks, and find that the bivariate GJR-GARCH model provides a better explanation of the dynamics of systematic risk.[3]

Drawing upon these concepts, Koutmos and Knif (2002a) find the evidence of beta asymmetry in both bull and bear markets, while Bekaert and Wu (2000) and Braun, Nelson, and Sunier (1995) do not find the result. Therefore, the asymmetry of the betas in the stock markets is a controversial issue that is clearly in need of further examination.

Given that systematic risk may well be affected by macroeconomic factors, such as inflation rates and business conditions, Choudhry (2005) and Choudhry and Peng (2010) examine the effects of the Asian financial crisis on the time-varying beta, with the former study considering that market turbulence results in changes in the risk attitude of investors toward financial assets, implying that a financial crisis influences asset risk.

However, these studies provide mixed results since they indicate that after the financial crisis, there was a rise in the beta in some cases, as compared to a fall in other cases. Furthermore, Bartov, Bodnar, and Kaul (1996) and Chen and So (2002) note that a rise in market risk would also tend to occur during periods of increased exchange rate variation. It is, therefore, quite clear that the prior empirical works on beta asymmetry, as well as the effects of a financial crisis on betas, have failed to provide any consistent results.

In the present study, I set out to investigate the interactions among beta asymmetry, the leverage effect, and financial crises, with my study differing from the extant empirical studies in a number of ways. First, while many of the prior studies have examined beta asymmetry using a constant conditional correlation or BEKK-GARCH model, in the present study, I adopt a dynamic conditional correlation GJR-GARCH (DCC-GJR-GARCH) model since this model is capable of solving time-varying correlations as well as the influence of different news effects on volatility (covariance) problems.[4]

Second, the prior empirical studies have tended to investigate the correlations among betas, leverage, and financial crises using the Asian financial crisis as the primary event. For example, Bris and Koskinen (2002) note that after 1990, moves to liberalize the capital markets in Asian countries prompted expansive foreign currency–denominated borrowing, which led to the financial crisis.

Furthermore, Maroney, Naka, and Wansi (2004) find that leverage increased with exchange rate depreciation as a result of the Asian financial crisis inducing a rise in national equity betas. Apart from demonstrating that the exchange rate was an effective leverage indicator, Maroney, Naka, and Wansi (2004) also show that the price-to-book (PB) ratio had fallen by almost half after the Asian financial crisis, indicating a higher discount rate as a direct result of the crisis.[5]

Nevertheless, to the best of my knowledge, no studies have yet set out to examine the link among betas, leverage, and the subprime mortgage crisis, a crisis that struck in 2007 and has since spread extremely rapidly to the global markets. Therefore, using the PB ratio (*PB*) and exchange rate (*EX*) returns as leverage indicators, I investigate the explanatory power of leverage on systematic risk in the global equity markets in the pre– and post–subprime mortgage crisis periods.

My aim in this study is to determine whether beta asymmetry is discernible in the global stock markets; that is, whether an individual market is found to have a higher (lower) beta when there is a fall (rise) in the global market. I also investigate whether there are discernible differences in the relationship between betas and leverage in the pre– and post–subprime mortgage financial crisis periods. My empirical results provide support for the asymmetric beta hypothesis, and indeed, when leverage is linked to the PB ratio, the results provide evidence of an increase in betas attributable to the declines in the PB ratio after the financial crisis.

This article is organized as follows. The next section discusses the descriptions of the data and methodology adopted for this study. The presentation and comparison of my empirical results are addressed in the subsequent section. The last section discusses some concluding remarks and suggestions for future research.

Data and Methodology

The data set for this study comprises the daily indexes of fourteen stock exchanges, consisting of the S&P/TSX composite, Shanghai composite, Cac 40, Dax 30, Hang Seng, S&P CNX 500, FTSE MIB, Topix, Straits, KSE composite, TSE weighted average, SET, FTSE 100, and NYSE composite. These exchanges correspond to the respective reference stock exchange indexes of the markets of Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Singapore, South Korea, Taiwan, Thailand, the United Kingdom, and the United States.

The Morgan Stanley Capital International (MSCI) world market capital index is considered to be an appropriate proxy for the estimation of systematic risk in a global market portfolio. The U.S. dollar stock indexes for the global markets are computed by translating the local index into U.S. dollars according to the daily exchange rate (expressed in U.S. dollar per local currency). The data are retrieved from *Taiwan Economic Journal*. Following the story of introduction, Duchin, Ozbas, and Sensoy (2010) define the beginning of the subprime crisis as August 2007 and the European debt crisis occurs in the beginning of 2010. My study period runs from January 3, 2005 to December 31, 2009, with the returns being calculated as the percentage logarithmic difference in the daily closing stock indexes. Moreover, the study period is accordingly partitioned into two nearly equal subperiods. The precrisis subperiod covers January 3, 2005–July 31, 2007; the postcrisis subperiod covers August 1, 2007—December 31, 2009.

The statistical properties of the daily index return series are listed in Table 1, from which I can see that with the exceptions of Italy, Japan, and the United Kingdom, each of the markets has positive mean returns, while India is found to have the highest volatility level. According to the Jarque-Bera statistics, the assumption of normality for each of the return series is rejected.

The results of the augmented Dickey-Fuller (ADF) reject the hypothesis of unit root for all return series. Consequently, return is stationary. The Ljung-Box statistics with up to eight lags are applied to the squared returns, which induced significant nonlinear dependence. The Lagrange multiplier statistics with up to eight lags reveal the presence of the ARCH effect. Therefore, return series exhibits volatility clustering. The Ljung-Box statistics are also applied to the cross product of the market returns and global returns, again using eight lags, with the statistics clearly achieving significance in all markets, indicating variance, over time, between the covariance in the market and global returns.

The analysis of conditional variance suggests that a GARCH-class model is appropriate. Nevertheless, the ordinary GARCH models of Bollerslev (1986) do not distinguish the differential effects of good and bad news on volatility.[6] The GJR-GARCH improved by Glosten, Jagannathan, and Runkle (1993) is applied to examine the asymmetric responses of volatility to positive and negative shocks.

Engle (2002) considers that the assumption of constant conditional correlations is too restricting for financial data and, therefore, that a combination of time-varying correlations would be required. I accordingly modify the CCC-GJR-GARCH model developed by Koutmos and Knif (2002a) to introduce the property of dynamic conditional correlation.

The derivation of the DCC-GJR-GARCH model in the present study is based upon the following equations:

$$r_{i,t} = \mu_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$r_{m,t} = \mu_{m,t} + \varepsilon_{m,t} \tag{2}$$

$$\sigma^2_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}\sigma^2_{i,t-1} + \delta_i S_{i,t-1}\varepsilon^2_{i,t-1} \tag{3}$$

$$\sigma^2_{m,t} = \alpha_{m,0} + \alpha_{m,1}\varepsilon^2_{m,t-1} + \alpha_{m,2}\sigma^2_{m,t-1} + \delta_m S_{m,t-1}\varepsilon^2_{m,t-1} \tag{4}$$

$$\sigma_{im,t} = (\rho_{im,t} + \lambda_i S_{m,t-1})\sigma_{i,t}\sigma_{m,t}, \tag{5}$$

where the i (m) subscript refers to the market (global) portfolio; $r_{i,t}$ ($r_{m,t}$) indicates the continuously compounded returns of the market (global) portfolio at time t; $\mu_{i,t}$ ($\mu_{m,t}$) is the conditional mean of the market (global) portfolio at time t; $\varepsilon_{i,t}$ ($\varepsilon_{m,t}$) indicates a news shock to the market (global) portfolio at time t; and $S_{i,t-1}$ ($S_{m,t-1}$) is a dummy variable that takes the value of one if $\varepsilon_{i,t-1} < 0$ ($\varepsilon_{m,t-1} < 0$), otherwise zero.

Equations (3) and (4), which express the conditional variance process, also describe the asymmetric response of the conditional variance process to the rise and fall in stock prices. Consequently, positive return shocks have an effect of $\alpha_{i,1}$ ($\alpha_{m,1}$), while negative return shocks have an effect of $\alpha_{i,1} + \delta_i$ ($\alpha_{m,1} + \delta_m$). The presence of asymmetry in the conditional variance is indicated if $\delta_i > 0$ ($\delta_m > 0$).

The process of time-varying covariance, which also allows for asymmetric responses to a rise or fall within the market, is expressed in Equation (5). Since systematic risk is the covariance of the individual market portfolio with the global portfolio divided by the variance of the global portfolio, systematic risk describes the movement of the individual market portfolio relative to global portfolio. Following the setting of Koutmos and Knif (2002a), the covariance of this study focuses on asymmetric responses of global news effects. If λ_i is found to be significantly positive, then the time-varying covariance will be higher during a market decline. Furthermore, $\rho_{im,t}$ refers to the dynamic conditional correlations between the market and global returns; the conditional covariance of the standardized residuals, $q_{im,t}$, as developed by Engle (2002), is shown in Equations (6) and (7):

$$\rho_{im,t} = \frac{q_{im,t}}{\sqrt{q_{ii,t}q_{mm,t}}} \tag{6}$$

$$q_{im,t} = \bar{\rho}_{im} + \gamma(z_{i,t-1}z_{m,t-1} - \bar{\rho}_{im}) + \varphi(q_{im,t-1} - \bar{\rho}_{im}), \tag{7}$$

where $q_{ii,t}$ ($q_{mm,t}$) is conditional variance of the market (global) portfolio standardized residuals at time t; $\bar{\rho}_{im}$, $z_{i,t-1} = \varepsilon_{i,t-1}/\sigma_{i,t-1}$, and $z_{m,t-1} = \varepsilon_{m,t-1}/\sigma_{m,t-1}$ are the respective constant unconditional covariance between the market and global returns, and the standardized residuals of the market and global returns.

Equation (7) expresses the conditional correlation process, where the γ and φ coefficients capture the effects of any previous shocks and dynamic conditional correlations on current dynamic conditional correlations; $\gamma + \varphi < 1$ would indicate that the correlation between the market and global returns reverts to the long-run unconditional level ($\bar{\rho}_{im}$) after the occurrence of a shock. It should also be noted that if $\gamma = \varphi = \lambda_i = 0$, then the DCC-GJR-GARCH model is reduced to the CCC-GJR-GARCH.

Following the estimation of the time-varying variance-covariance matrix based upon Equations (1) to (7), the time-varying beta is subsequently calculated using the following formula:

$$\beta_{i,t} = (\sigma_{im,t}/\sigma^2_{m,t}) \tag{8}$$

The sample period in this study is 2005–09, under the implicit assumption that the estimates would have remained stable during this period if there had been no exogenous event effects; however, the

Table 1. The statistical properties of the daily stock return series

Market	Mean	Standard deviation	Skewness	Kurtosis	JB	ADF	$Q_i^2(8)$	$LM(8)$	$Q_{i,m}(8)$
Canada	0.0295	1.8152	–0.8248	11.6891	4,246***	–8.04***	1,051.00***	391.61***	1,128.3***
China	0.0877	1.9776	–0.3383	5.7205	427***	–16.27***	92.33***	59.43***	127.07***
France	0.0065	1.7865	0.0943	12.3277	4,726***	–12.72***	545.04***	241.82***	691.38***
Germany	0.0301	1.7524	0.0854	11.3621	3,798***	–16.34***	504.55***	234.39***	647.95***
Hong Kong	0.0332	1.8873	0.1043	11.4140	3,846***	–9.88***	836.36***	346.89***	449.29***
India	0.0606	2.0591	–0.0912	10.2829	2,881***	–9.05***	129.76***	75.11***	467.89***
Italy	–0.0172	1.7812	0.0155	11.5420	3,962***	–7.35***	656.20***	285.90***	624.24***
Japan	–0.0105	1.5477	–0.0645	7.9980	1,357***	–18.88***	752.00***	341.96***	448.27***
Singapore	0.0535	1.6768	–0.7503	9.6990	2,559***	–31.68***	185.22***	346.41***	222.68***
South Korea	0.0402	1.5645	–0.2183	7.9641	1,348***	–7.15***	886.10***	256.79***	449.86***
Taiwan	0.0214	1.5392	–0.2448	6.1799	562***	–6.14***	249.43***	145.42***	74.22***
Thailand	0.0191	1.6197	–1.1979	16.3178	9,941***	–7.68***	155.13***	120.39***	502.04***
United Kingdom	–0.0036	1.7189	–0.0649	12.7891	5,203***	–12.62***	752.49***	341.19***	800.43***
United States	0.0001	1.5711	–0.3579	13.0233	5,482***	–8.25***	1,094.60***	422.56***	284.80***
MSCI	0.0005	1.2355	–0.4548	12.7408	13***	–7.46***	1,110.50***	441.89***	—

Notes: JB refers to the Jarque-Bera statistics, which provide a test for normality; *ADF* refers to the augmented Dickey-Fuller unit root tests; the critical values of ADF are –2.57 at the 10 percent level, –2.86 at the 5 percent level, and –3.43 at the 1 percent level. $Q_i^2(8)$ reports the Ljung-Box statistics that test for autocorrelation in the squared returns with up to eight lags; $LM(8)$ reports the Lagrange multiplier statistics, which test for ARCH effect with up to eight lags; $Q_{i,m}(8)$ reports the Ljung-Box statistics that test for the cross correlation between the returns of market i and the global market m with up to eight lags. *Significance at the 10 percent level; **significance at the 5 percent level; ***significance at the 1 percent level.

failure of two highly leveraged Bear Stearns hedge funds was announced at the end of July 2007, and indeed, by August 2007, Countrywide, the biggest mortgage lender in the United States had borrowed USD 11.5 billion, thereby fully extending its entire credit lines, while the Bank of America had also injected USD 2 billion into the company. Such events sparked a widespread loss of confidence among investors within the financial system, thereby igniting the financial crisis that was originally triggered by the U.S. market and subsequently led to a total collapse in the global stock markets.

Since the volatility that occurred in the stock returns raises the issue of whether such asymmetric systematic risk was caused directly by the subprime crisis, I use leverage indicators to investigate the factors leading to changes in the beta. Maroney, Naka, and Wansi (2004) report that there was depreciation in the exchange rate after the Asian financial crisis and that the price-to-book ratio fell by almost half. I therefore adopt changes in the exchange rate and the price-to-book ratio as the leverage indicators in the present study.

Koutmos and Knif (2002a) assume that time-varying beta at times t and t-1 exist in a linear relationship. Therefore, I estimate the following regression in order to further investigate the changes in the dynamic beta and leverage following the subprime mortgage crisis:

$$\begin{aligned}\beta_{i,t} = c_i + \pi_{i,1}\beta_{i,t-1} + \pi_{i,2}S_{m,t-1} + \pi_{i,3}PB_{i,t-1} \\ + \pi_{i,4}PB_{i,t-1} * D + \pi_{i,5}EX_{i,t-1} + \pi_{i,6}EX_{i,t-1} * D + v_{i,t},\end{aligned} \tag{9}$$

where $\beta_{i,t}$ ($\beta_{i,t-1}$) refers to the time-varying beta at time t (t‾1); $S_{m,t-1}$ is a dummy variable that takes the value of one if $\varepsilon_{m,t-1} < 0$; otherwise zero; $PB_{i,t-1}$ represents the price-to-book ratio at time t‾1; $EX_{i,t-1}$ is the exchange rate at time t‾1; and D is a dummy variable that takes the value of one for the period January 3, 2005 to July 31, 2007, otherwise zero.

Equation (9) describes those factors that may have led to the dynamic characteristics of the beta. Since Koutmos and Knif (2002a) indicate that the time-varying beta is correlated with $\beta_{i,t-1}$, this variable is duly included in the present study in order to capture the effect.

Empirical Analysis

To simplify my analysis, the conditional mean in the DCC-GJR-GARCH model estimations is assumed to be fixed (i.e., $\mu_{i,t} = \mu_i$ and $\mu_{m,t} = \mu_m$). The results are reported in Table 2, from which I can see that the conditional mean, μ_i, is greater than μ_m for the majority of the stock markets, with the notable exceptions of France, Italy, Japan, the United Kingdom, and the United States. This indicates that these five markets exhibit inferior performance over the sample period, while the remaining nine stock markets exhibit relatively better performance.

The $\alpha_{i,2}$ parameter in the conditional variance is found to be significant in all fourteen of the markets, indicating that the GARCH effect is discernible within each market.[7] The asymmetric volatility is captured by δ_i, and indeed, the asymmetric response of volatility to return shocks is found to hold in each market; that is to say, future volatility tends to be influenced more by negative return shocks than by positive return shocks.

Based upon the information provided above, the effect of a positive innovation is equal to $\alpha_{i,1}$, whereas the effect of a negative innovation is $\alpha_{i,1} + \delta_i$, and the degree of asymmetry can be measured by $(\alpha_{i,1} + \delta_i)/\alpha_{i,1}$. Taking Canada as an example, a negative return shock increases the degree of asymmetry 1.85 times more than a positive return shock, with the average ratio of asymmetry within the fourteen markets being found to be 6.93. In summary, a negative innovation increases volatility 6.93 times more than a positive innovation of an equal size for the fourteen markets.

Furthermore, Hadsell (2006) indicated that volatility moves halfway back to its mean following a given deviation, is defined as $\alpha_{i,1} + 0.5\delta_i + \alpha_{i,2}$ in the GJR-GARCH model; $\alpha_{i,1} + 0.5\delta_i + \alpha_{i,2}$ less than one implies a mean-reversion conditional volatility in which shocks are transitory in nature. The volatility persistence measure, $\alpha_{i,1} + 0.5\delta_i + \alpha_{i,2}$, is less than 1.0 in each market

Table 2. Maximum likelihood estimates of the DCC-GJR-GARCH model

$r_{i,t} = \mu_i + \varepsilon_{i,t};\ r_{m,t} = \mu_m + \varepsilon_{m,t};\ \sigma^2_{i,t} = \alpha_{i,0} + \alpha_{i,1}\varepsilon^2_{i,t-1} + \alpha_{i,2}\sigma^2_{i,t-1} + \delta_i S_{i,t-1}\varepsilon^2_{i,t-1};\ \sigma^2_{m,t} = \alpha_{m,0} + \alpha_{m,1}\varepsilon^2_{m,t-1} + \alpha_{m,2}\sigma^2_{m,t-1} + \delta_m S_{m,t-1}\varepsilon^2_{m,t-1};$

$\sigma_{im,t} = (\rho_{im,t} + \lambda_i S_{m,t-1})\sigma_{i,t}\sigma_{m,t};\ \rho_{im,t} = \dfrac{q_{im,t}}{\sqrt{q_{ii,t}q_{mm,t}}};\ q_{im,t} = \bar{\rho}_{im} + \gamma(z_{i,t-1}z_{m,t-1} - \bar{\rho}_{im}) + \varphi(q_{im,t-1} - \bar{\rho}_{im}).$

Market	Canada	China	France	Germany	Hong Kong	India	Italy	Japan	Singapore	South Korea	Taiwan	Thailand	United Kingdom	United States
μ_i	0.0740	0.1341	0.0071	0.0430	0.0447	0.1290	–0.0028	–0.0259	0.0547	0.0457	0.0505	0.0475	0.0056	–0.0088
	(0.033)**	(0.045)***	(0.030)	(0.031)	(0.029)	(0.037)***	(0.031)	(0.033)	(0.021)**	(0.039)	(0.036)	(0.038)	(0.029)	(0.022)
$\alpha_{i,0}$	0.0316	0.0410	0.0404	0.0375	0.0165	0.0703	0.0368	0.0491	0.0218	0.1219	0.0314	0.4367	0.0252	0.0192
	(0.006)***	(0.012)***	(0.006)***	(0.006)***	(0.005)***	(0.016)***	(0.006)***	(0.010)***	(0.002)***	(0.025)***	(0.007)***	(0.043)***	(0.004)***	(0.003)***
$\alpha_{i,1}$	0.0526	0.0542	0.0123	0.0096	0.0781	0.0763	0.0146	0.0097	0.0591	0.0545	0.0360	0.1666	0.0259	0.0109
	(0.015)***	(0.011)***	(0.010)	(0.013)	(0.016)***	(0.019)***	(0.013)	(0.016)	(0.003)***	(0.022)**	(0.012)***	(0.028)***	(0.011)**	(0.009)
$\alpha_{i,2}$	0.9110	0.9242	0.8974	0.8958	0.9034	0.8672	0.8934	0.8966	0.8896	0.8013	0.9217	0.5505	0.9044	0.9133
	(0.010)***	(0.008)***	(0.011)***	(0.012)***	(0.011)***	(0.016)***	(0.012)***	(0.014)***	(0.003)***	(0.027)***	(0.010)***	(0.025)***	(0.010)***	(0.009)***
δ_i	0.0447	0.0250	0.1673	0.1550	0.0301	0.0830	0.1430	0.1411	0.0820	0.2186	0.0514	0.3070	0.1147	0.1418
	(0.015)***	(0.013)*	(0.017)***	(0.014)***	(0.019)*	(0.026)***	(0.015)***	(0.023)***	(0.006)***	(0.042)***	(0.015)***	(0.035)***	(0.017)***	(0.019)***
μ_m	0.0290	0.0265	0.0183	0.0216	0.0218	0.0222	0.0184	0.0168	0.0203	0.0161	0.0196	0.0230	0.0137	0.0140
	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.011)	(0.020)	(0.020)	(0.021)	(0.021)	(0.018)
$\alpha_{m,0}$	0.0102	0.0097	0.0136	0.0123	0.0085	0.0113	0.0133	0.0097	0.0106	0.0101	0.0108	0.0152	0.0121	0.0135
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.001)***	(0.002)***	(0.002)***	(0.003)***	(0.002)***	(0.002)***
$\alpha_{m,1}$	0.0238	0.0088	–0.0044	0.0025	0.0027	0.0100	0.0028	0.0036	0.0058	–0.0056	0.0093	0.0431	–0.0033	0.0090
	(0.012)**	(0.014)	(0.009)	(0.008)	(0.013)	(0.013)	(0.010)	(0.013)	(0.001)***	(0.013)	(0.013)	(0.020)***	(0.010)	(0.012)
$\alpha_{m,2}$	0.9201	0.9126	0.9151	0.9151	0.9275	0.9172	0.9174	0.9183	0.9143	0.9255	0.9170	0.8734	0.9224	0.9001
	(0.010)***	(0.012)***	(0.010)***	(0.009)***	(0.010)***	(0.012)***	(0.010)***	(0.011)***	(0.002)***	(0.010)***	(0.012)***	(0.015)***	(0.009)***	(0.011)***
δ_m	0.0875	0.1304	0.1324	0.1290	0.1177	0.1143	0.1217	0.1313	0.1349	0.1358	0.1170	0.1318	0.1296	0.1468
	(0.014)***	(0.022)***	(0.016)***	(0.015)***	(0.020)***	(0.022)***	(0.017)***	(0.020)***	(0.004)***	(0.021)***	(0.020)***	(0.028)***	(0.018)***	(0.019)***
γ	0.0253	0.0112	0.0186	0.0161	0.0071	0.0370	0.0179	0.0179	0.0105	0.0095	–0.0050	0.0387	0.0207	0.0004
	(0.005)***	(0.014)	(0.010)*	(0.005)***	(0.000)***	(0.031)	(0.006)***	(0.006)***	(0.004)***	(0.010)	(0.006)	(0.015)***	(0.007)***	(0.001)
φ	0.9727	0.9050	0.9736	0.9813	0.9928	0.7900	0.9769	0.9798	0.9894	0.9391	0.9449	0.9200	0.9748	0.9991
	(0.006)***	(0.142)***	(0.015)***	(0.007)***	(0.000)***	(0.173)***	(0.010)***	(0.008)***	(0.005)***	(0.085)***	(0.121)***	(0.024)***	(0.010)***	(0.002)***
λ_i	0.0032	–0.0350	–0.0309	0.0019	0.0038	–0.1066	0.0025	0.0003	0.0047	–0.0002	–0.0551	–0.0720	0.0023	0.0002
	(0.001)***	(0.038)	(0.013)**	(0.000)***	(0.000)***	(0.029)***	(0.000)***	(0.001)	(0.001)***	(0.001)	(0.035)	(0.0338)***	(0.000)***	(0.000)***
Log L	–3,314	–4,245	–3,075	–3,121	–3,654	–4,083	–3,174	–3,774	–3,488	–3,923	–3,808	–3,883	–3,011	–2,430

(*Continued*)

Table 2. Maximum likelihood estimates of the DCC-GJR-GARCH model (Continued)

Market	Canada	China	France	Germany	Hong Kong	India	Italy	Japan	Singapore	South Korea	Taiwan	Thailand	United Kingdom	United States
$(\alpha_{i,1}+\alpha_i)/a_{i,1}$	1.8509	1.4609	14.6007	17.0655	1.3850	2.0878	10.8086	15.6047	2.3882	5.0108	2.4290	2.8427	5.4296	14.0461
$\alpha_{i,1}+0.5\delta_i+\alpha_{i,2}$	0.9859	0.9909	0.9934	0.9830	0.9965	0.9850	0.9795	0.9768	0.9897	0.9651	0.9834	0.8706	0.9876	0.9951
$\gamma+\varphi$	0.9980	0.9162	0.9921	0.9974	0.9999	0.8270	0.9948	0.9977	0.9999	0.9486	0.9399	0.9587	0.9955	0.9996
$Q_i^2(8)$	4.57	2.01	9.94	7.41	8.83	2.26	9.68	5.68	16.08**	3.03	15.05*	3.68	3.83	6.63
$Q_m^2(8)$	4.24	5.07	5.33	4.92	6.21	4.70	5.21	4.57	7.43	6.28	4.68	7.41	6.72	6.49
$Q_{i,m}(8)$	9.15	3.16	8.00	5.97	4.5	4.51	8.64	23.21***	4.65	11.74	7.02	14.15*	3.85	9.24

Notes: $Q^2(8)$ reports the Ljung-Box statistics that test for autocorrelation in the squared returns with up to eight lags; $Q_{i,m}(8)$ reports the Ljung-Box statistics that test for the cross correlation between the residuals of market *i* and the global market *m* with up to eight lags. Log *L* shows the log likelihood function value. *Significance at the 10 percent level; **significance at the 5 percent level; ***significance at the 1 percent level.

(ranging from 0.871 in Thailand to 0.997 in Hong Kong), which indicates that the shocks are largely transitory. There is also evidence of asymmetry in the covariance of these fourteen markets, with λ_i being positive (negative), indicating a higher (lower) correlation during a fall (rise) in the market.[8]

The effect of the mean reversion on the long-run unconditional correlation $\bar{\rho}_{im}$ is represented by γ and φ; γ is found to be significantly positive at the 10 percent level for most markets, with the exceptions of China, India, South Korea, Taiwan, and the United States, while φ is found to be significantly positive at the 1 percent level for all markets. Therefore, the dynamic conditional correlation model could describe the relationship between the market and global returns. The sum of γ and φ ranges between 0.827 for India and 0.999 for Hong Kong and Singapore.

The $\gamma + \varphi < 1$ condition is observed in each market. This implies that the dynamic conditional correlation moves around a long-run constant level while also displaying a mean-reversion dynamic process. I therefore carry out diagnostic tests on the appropriateness of the model on the standardized residuals, squared standardized residuals, and the cross product of the standardized residuals using the Ljung-Box test. The results, which are reported in the final three columns of Table 2, indicate that the majority of the DCC-GJR-GARCH specifications are appropriate for the data set in the sample period under examination.

I subsequently split the full sample period into two subperiods, the pre– and post–subprime mortgage crisis periods, based upon the event date of August 1, 2007, in order to compare the differences in the stock market betas. The summary statistics of the leverage indicators for the pre- and postcrisis are presented in Table 3.

The results reveal a reduction in the PB ratio in the postcrisis period for most of the markets, with the exceptions of China, Hong Kong, and South Korea. A lower PB ratio in the post–financial crisis

Table 3. Summary statistics of the leverage indicators

	Price-to-book ratio				Foreign exchange returns			
	Precrisis		Postcrisis		Precrisis		Postcrisis	
Market	Mean	Corr ($\beta_{i,t}$,$L_{i,t-1}$)	Mean	Corr ($\beta_{i,t}$,$L_{i,t-1}$)	Mean	Corr ($\beta_{i,t}$,$L_{i,t-1}$)	Mean	Corr ($\beta_{i,t}$,$L_{i,t-1}$)
Canada	2.7765	–0.1154	2.2623	–0.2987	0.0184	–0.0006	0.0073	0.0321
China	3.6544	0.4400	5.5362	0.1732	0.0133	–0.1987	0.0165	–0.1226
France	2.2413	0.0820	1.8079	–0.0089	0.0022	–0.0907	0.0105	–0.0404
Germany	2.2655	0.1672	2.0566	–0.4637	0.0022	–0.0764	0.0105	–0.0254
Hong Kong	2.6358	0.1325	2.9556	0.0693	–0.0010	0.0073	0.0015	–0.0575
India	3.4256	0.0114	3.2827	0.2138	0.0113	0.0846	–0.0211	0.1202
Italy	2.8162	0.1860	1.9793	–0.4108	0.0022	–0.0348	0.0105	0.0198
Japan	1.8634	0.2454	1.2330	–0.0561	–0.0210	–0.0168	0.0427	–0.0673
Singapore	1.8925	0.2222	1.5956	0.1386	0.0112	0.0022	0.0131	0.1101
South Korea	1.2504	–0.1433	1.3557	0.1263	0.0184	–0.0997	–0.0290	–0.0569
Taiwan	1.5047	–0.2625	1.4912	0.3102	–0.0048	0.0898	0.0045	0.0712
Thailand	1.3874	0.0482	1.3457	0.0027	0.0226	–0.1731	0.0024	–0.0014
United Kingdom	3.2459	0.2814	2.9204	0.2851	0.0096	–0.0006	–0.0326	–0.0065
United States	3.8683	–0.4709	2.2515	–0.1515	–0.0072	0.0316	–0.0009	–0.0133
Market Average	2.4877	0.0589	2.2910	–0.0050	0.0055	–0.0340	0.0026	–0.0027

Notes: This table reports the results of the leverage indicators ($L_{i,t-1}$) within the various markets, which are the price-to-book (PB) ratio and the foreign exchange (EX) returns. Corr($\beta_{i,t}$,$L_{i,t-1}$) refers to the correlation of each leverage indicator with systematic risk. The pre- and postcrisis subperiods are separated by August 1, 2007, with the precrisis subperiod running January 3, 2005–July 31, 2007, and the postcrisis subperiod running August 1, 2007–December 31, 2009.

period indicates a stock price decline, with such decline coming in response to an increase in both leverage and business risk; thus, the increase in beta caused by increases in leverage and business risk results in a higher discount rate.[9] It is worth noting that the United States had the highest precrisis PB ratio but that this fell by almost half in the postcrisis period, thereby revealing that the United States suffered the largest decline after the subprime mortgage crisis.

The average returns on foreign exchange holdings were 0.006 in the precrisis period and 0.003 in the postcrisis period, which indicates that currency depreciation was not the primary channel through which the global markets were adversely affected by the subprime mortgage crisis. The beta is generally found to have a positive correlation with *PB* in the precrisis period, with the correlation reversing to negative after the financial crisis; however, there was an increase in the correlation between the beta and *EX* in the postcrisis period.

I go on to investigate whether there is any discernible increase in leverage and whether asymmetric beta responses to good and bad news are found in the post–subprime crisis period; the estimates of the time-series properties of the time-varying beta with the leverage indicator are reported in Table 4. First, the estimates of $\pi_{i,1}$ are found to be significant and close to 1.0 for each market, indicating that the past beta has a dragging effect. The results indicate that beta asymmetry operates during both rising and

Table 4. Estimates of time-varying beta with leverage indicators for the subprime crisis $\beta_{i,t} = c_i + \pi_{i,1}\beta_{i,t-1} + \pi_{i,2}S_{m,t-1} + \pi_{i,3}PB_{i,t-1} + \pi_{i,4}PB_{i,t-1} * D + \pi_{i,5}EX_{i,t-1} + \pi_{i,6}EX_{i,t-1} * D + v_{i,t}$

Market	c_i	$\pi_{i,1}$	$\pi_{i,2}$	$\pi_{i,3}$	$\pi_{i,4}$	$\pi_{i,5}$	$\pi_{i,6}$
Canada	0.0735	0.9458	0.0275	–0.0072	–0.0011	–0.0185	0.0131
	(0.016)***	(0.009)***	(0.004)***	(0.004)**	(0.001)	(0.005)***	(0.005)**
China	0.0950	0.8150	–0.0900	0.0038	–0.0043	–0.0103	0.0162
	(0.005)***	(0.013)***	(0.003)***	(0.001)***	(0.001)***	(0.020)	(0.029)
France	0.1358	0.9075	–0.0372	0.0008	–0.0033	–0.0438	0.0148
	(0.017)***	(0.011)***	(0.004)***	(0.005)	(0.002)	(0.006)***	(0.007)**
Germany	0.1020	0.9332	0.0126	–0.0064	–0.0070	–0.0255	0.0117
	(0.019)***	(0.010)***	(0.004)***	(0.005)	(0.002)***	(0.006)***	(0.007)*
Hong Kong	0.0387	0.9332	0.0277	–0.0030	0.0022	0.1025	–0.0579
	(0.009)***	(0.010)***	(0.003)***	(0.002)	(0.001)**	(0.082)	(0.102)
India	0.2984	0.7157	–0.2376	0.0191	–0.0090	–0.0684	0.0284
	(0.019)***	(0.015)***	(0.008)***	(0.005)***	(0.002)***	(0.021)***	(0.023)
Italy	0.0994	0.9337	0.0071	–0.0079	–0.0037	–0.0239	0.0096
	(0.018)***	(0.010)***	(0.004)*	(0.003)**	(0.002)*	(0.006)***	(0.006)
Japan	0.0233	0.9603	–0.0113	0.0062	–0.0110	–0.0189	0.0124
	(0.011)**	(0.008)***	(0.003)***	(0.006)	(0.004)***	(0.004)***	(0.005)**
Singapore	0.0299	0.9421	0.0238	–0.0007	0.0017	–0.0220	0.0222
	(0.009)***	(0.009)***	(0.004)**	(0.003)	(0.001)	(0.010)**	(0.011)**
South Korea	0.1146	0.8732	–0.0202	0.0063	–0.0193	–0.0702	0.0505
	(0.017)***	(0.013)***	(0.006)***	(0.011)	(0.005)***	(0.010)***	(0.011)***
Taiwan	0.1248	0.7848	–0.1086	0.0326	–0.0123	–0.0448	0.0060
	(0.009)***	(0.013)***	(0.003)***	(0.006)***	(0.002)***	(0.008)***	(0.011)
Thailand	0.2166	0.6599	–0.1376	0.0669	–0.0522	–0.0731	0.0003
	(0.028)***	(0.019)***	(0.009)***	(0.020)***	(0.007)***	(0.011)***	(0.026)
United Kingdom	0.0744	0.9098	0.0241	0.0056	0.0017	–0.0220	0.0094
	(0.016)***	(0.012)***	(0.004)***	(0.004)	(0.001)	(0.005)***	(0.006)*
United States	0.1357	0.8846	0.0139	–0.0033	0.0007	–0.0419	0.0238
	(0.017)***	(0.013)***	(0.002)***	(0.001)***	(0.001)	(0.007)***	(0.008)***

Note: Numbers in parentheses are standard errors. *Significance at the 10 percent level; **significance at the 5 percent level; ***significance at the 1 percent level.

falling markets because the asymmetric parameter $\pi_{i,2}$ is found to be statistically significant at the 10 percent level.

A positive sign for $\pi_{i,2}$ reveals that the systematic risk is higher in a falling market than in a rising market; therefore, the stock assets will be found to have higher downside betas. For example, the asymmetric beta coefficient for Canada is found to be 0.0275, indicating a higher beta in a falling market than in a rising market. Ceteris paribus, the mean beta for Canada, over time, can be described as $E(\beta_{i,t}) = 0.0735 + 0.9458\, \beta_{i,t-1}$ in a rising market and $E(\beta_{i,t}) = 0.1010 + 0.9458\, \beta_{i,t-1}$ in a falling market.

Conversely, a negative sign for $\pi_{i,2}$ indicates that the systematic risk is proportionately lower following a falling market. Markets with a negative sign will have a lower downside beta and, thus, will exhibit a "defensive" characteristic. Prudent advice for investors in a falling market would therefore be that in order to become defensive, more stocks from these markets should be included in a portfolio.

Table 4 also reports the effects of the leverage indicators on systematic risk, with the results showing that the PB ratio has a negative correlation with beta for six of the fourteen markets, indicating that while a negative shock has a detrimental effect on the value of a market, there will be a rise in its financial leverage, causing a higher beta for the market's equity. Furthermore, the coefficients of $\pi_{i,2}$ and $\pi_{i,3}$ exhibit reverse relationships for all but one of the fourteen markets, implying that the asymmetric beta response to good and bad news originates from the leverage effect.

The exchange rate (EX) returns are also important leverage indicators, with the empirical results showing that the EX returns have a negative correlation with beta, with statistical significance at the 5 percent level, for most markets, with the exceptions of China and Hong Kong; this is, however, essentially because China and Hong Kong pegged their currency to the U.S. dollar, preventing the EX returns in these regions from reflecting the actual effect on their betas.

A dummy variable is included in Table 4 in order to observe whether there was any discernible rise in the leverage effect leading to a consequent increase in beta during the subprime mortgage crisis, and indeed, $\pi_{i,4}$ is found to be significantly negative for eight of the fourteen markets. This result indicates that the increase in beta was attributable to an increase in the link between the leverage and PB ratio after the subprime mortgage crisis. However, $\pi_{i,6}$ is not found to be significantly negative for each market, which indicates that none of the increases in beta within these fourteen markets were attributable to any depreciation in their currencies after the subprime mortgage crisis.

Drawing on their investigations into beta asymmetry in the stock markets, Braun, Nelson, and Sunier (1995) and Koutmos and Knif (2002a) attribute the phenomenon to the leverage effect. In the present study, I test the asymmetry of the betas using leverage connected with the PB ratio and EX returns to observe the relationship between beta and leverage in the post–subprime mortgage crisis period. My results provide evidence of negative return shocks increasing the future beta more that positive return shocks, implying that the leverage effect causes a higher beta in a bear market than in a bull market.

Furthermore, the negative relationship that is discernible between the beta and the PB ratio after the subprime mortgage crisis reveals that any higher betas after the crisis were essentially due to an increase in leverage. The results after the subprime mortgage crisis differ from the Asian financial crisis of Chen and So (2002) and Maroney, Naka, and Wansi (2004) show that while EX returns are linked to leverage, stock market changes are not the result of any currency depreciation.

Conclusions and Implications

I set out in the present study with the aim of testing the asymmetry found in volatility and betas using the DCC-GJR-GARCH model, with my empirical results ultimately providing support for the asymmetric volatility and beta hypothesis; that is, the results suggest that negative shocks have detrimental effects on the value of a market, leading to a rise in the market's financial leverage ratio and causing higher volatility (a higher beta) in the equity of the market.

I also carry out an investigation into whether any differences are discernible in the relationships that existed between beta and leverage in the pre– and post–subprime mortgage financial crisis periods, with the results providing some evidence of an increase in beta, which appears to be attributable to a decline in the price-to-book ratio following the financial crisis period.

Although the major objectives of my investigation in the present study have been achieved, there are still several issues that remain unresolved and therefore warrant further research in the future. It is to be hoped that the findings of this investigation will help to stimulate further research on stock behavior in general within the global markets; for example, future studies could set out to examine whether the asymmetric reversion effect is also found to exist in conditional betas.

Notes

1. Refer to Baba et al. (1989), Engle and Kroner (1995), and Kroner and Ng (1998) for details of the BEKK-GARCH model.
2. Using Japanese stock returns, Bekaert and Wu (2000) conclude that asymmetric volatility and covariance were significantly caused by the volatility feedback hypothesis rather than pure leverage.
3. Conrad, Gultekin, and Kaul (1991), Dean and Faff (2004), Koutmos and Knif (2002b), and Kroner and Ng (1998) find that the responses to good and bad news in the conditional covariance between stocks and market returns was asymmetric.
4. Using a DCC-GARCH model, Marshall, Maulana, and Tang (2009) suggest that dynamic betas can improve beta out-of-sample predicting ability and therefore offer potential gains for investors.
5. Fama and French (1993) and Ferguson and Shockley (2003) demonstrate that financial leverage was strongly correlated with the price-to-book ratio essentially because the price-to-book ratio contains the stock price, which responds to changes in both leverage and business risk.
6. In the present study, I follow Nelson (1991) to classify the positive lagged return shocks as good news and negative lagged return shocks as bad news.
7. The conditional variance in all fourteen of the markets is stationary but not reported.
8. The anonymous referee suggests that $\rho_{im,t} + \lambda_i S_{m,t-1}$ have to be within the (−1, 1) interval. The condition is confirmed but not reported.
9. An understanding of the link between leverage and the discount factor, based upon the discount cash flow model, is provided by Maroney, Naka, and Wansi (2004).

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