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FIEGARCH-M and and International Crises: A Cross-Country Analysis

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Abstract

We apply the fractionally integrated exponential GARCH with volatility-in-mean (FIEGARCH-M) model of Christensen, Nielsen & Zhu (2007) to estimate the risk premium after different crises occurred in major stock markets during the past two decades. The model allows keeping the long memory property in volatility and a filtered volatility-in-mean component is used as a proxy for the risk factor. The estimation results show that the 1987 stock market crash and September 11, 2001 attack have persistent effects on stock markets. A significant risk factor is found for both crises in most crisis-hit markets, and it is nonmonotic for different markets. Either volatility feedback or risk premium is a possible explanation for the risk factor. On the contrary, Asian financial crisis and other market-specific crises have no persistent impact on most markets.

JEL classifications: C22; F36; G15
Keywords: FIEGARCH-M; international stock market crisis; 1987 stock market crash; dotcom bubble; Asian crisis; 9/11 attack; country-specific crisis

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1 Introduction

Many market crises have occurred in the past 20 years, either on cross-country or country-specific level.[1] It is interesting to investigate whether these crises have persistent effects on market returns. The intuition is that since investors worry about potential occurrence of similar crisis in the future, they may change their opinions against risk after the crisis. Because some crises are on global level, it is also interesting to include a cross-country analysis to see whether the same crisis has different effects on different countries. As a tool for studying the effect of international crises on risk premia while accounting for the observed long memory property in volatility, we apply the FIEGARCH-M of Christensen et al. (2007) to international stock markets that suffered from crises for the past two decades. As far as we know, this paper is the first attempt to estimate the crisis-related risk premium in the FIEGARCH-M framework by avoiding long memory property of volatility carrying over to return and introducing volatility innovations instead of volatility level in mean equation, thus it sheds some new light to the literature on risk-return analysis for stock markets.

Studying the relation between risk and return has long been an important topic in financial econometrics and empirical finance. According to asset pricing theory, a rational risk-averse investor will require a higher expected return for holding a more risky asset, thus there should exist a positive relation between risk and expected return. This positive relation should always hold from an *ex ante* point of view, although *ex post* analysis may lead to different results.

As a proxy, volatility is crucial in measuring risk. Since Engle (1982) and Bollerslev (1986) introduce ARCH and GARCH model to capture time-varying and clustering feature in volatility, there has been numerous literature focusing on Garch-type models.[2] In particular, Bollerslev & Mikkelsen (1996) propose FIEGARCH (fractionally integrated exponential generalized autoregressive conditional heteroskedasticity) model based on Baillie, Bollerslev & Mikkelsen's (1996) FIGARCH model and Nelson's (1991) EGARCH model in order to capture the long-memory property of volatility and skewness in return, both features are well observed in empirical studies.

[1] For the cross-country crises, there are 1987 stock market crash, 1990s Latin America currency crisis, 1997 Asian financial crisis and 2000 collapse of dotcom bubble; for the country-specific crisis, there are even more, including Japan, South Africa, Russia, just to name a few. More details on these crises are given in Section 3.

[2] See e.g. Terasvirta (2006) for a survey of univariate GARCH models.

Recent research by Christensen et al. (2007) introduces a FIEGARCH-M model with a in-mean filtered volatility innovation component. Following recent literature (Ang, Hodrick, Xing & Zhang (2006) and Christensen & Nielsen (2007)), it is changes in volatility that enter the return equation, and this filtering of volatility when entering in the return specification implies that the long memory property of volatility (the fractionally integrated feature) does not spill over into return, which would be empirically unrealistic. The generalization allows volatility feedback or risk-premium effect of conditional volatility innovation on conditional expected stock return.

The skewness patterns observed particularly in stock return distributions may be accommodated using the EGARCH model of Nelson (1991). Here, negative return innovations induce higher volatility than positive innovations of the same magnitude, which in turn generates skewness in asset returns. This model feature corresponds to an empirically observed regularity which may stem from a financial leverage effect, see e.g. Black (1976), Engle & Ng (1993) and Yu (2005). A standard argument from Black (1976) is that bad news decreases the stock price and hence increases the debt-to-equity ratio (i.e. the financial leverage), making the stock more risky and increasing future expected volatility. Alternatively, a volatility feedback effect may be present, that is, if volatility is increased, then so is the risk premium, given a positive risk-return relation, and hence the discounted rate, which in turn lowers stock prices.

Both the leverage effect and the volatility feedback effect generate a negative relation between return and volatility, although the causality is reversed.[3] The volatility feedback effect should be strongest at the market level, whereas the leverage effect should apply to individual stocks. As a negative return-volatility relation leads to skewness, the two may be seen as supplementing each other as explanations of the asymmetry or skewness. Instead, a positive return-volatility relation implies investors require for higher risk-premium as a compensation for holding more risky stocks, which is also well addressed in empirical works, i.e. French, Schwert & Stambaugh (1987), Bollerslev, Engle & Wooldridge (1988) and Chou (1988). Thus the empirical studies of the relation between risk and return are mixed. Furthermore, it is also possible that the relation between these two variables is time-varying, which makes it interesting to compare the relation before and after some crucial event, for example a market crisis, occurs.

In the next section, we present the FIEGARCH-M model where volatility innovation

[3] As we mentioned earlier, this *ex post* negative relation between risk and return shouldn't refute the *ex ante* understanding of a positive relation between the two.

is introduced in the expected return equation in a manner that precludes the return series from inheriting the long memory property from the volatility series, and which also includes crisis-related in-mean component. Section 3 briefly reviews major market crises occurred in the past two decades. Section 4 compares performance between FIEGARCH and other GARCH models by presenting some preliminary estimations and diagnostic tests. Data and empirical results are presented in Section 5, including wild-bootstrap analysis for exploring the inference of our QML estimates. Section 6 gives the concluding remarks.

2 The FIEGARCH-M Model

The model applies in this paper is the same of the FIEGARCH-M model in Christensen et al. (2007), which is an extension of FIEGARCH model in Bollerslev & Mikkelsen (1996) by introducing volatility into the return equation, along the lines of the GARCH-M literature, but in addition also including the crisis-specific risk premium component. Since long memory in volatility introduced into the return equation in a linear fashion generates long memory in return, which may not be empirically warranted, as in Christensen et al. (2007), we follow Ang et al. (2006) and Christensen & Nielsen (2007) and consider the possibility that it is changes in volatility rather than volatility levels that enter the in-mean specification and induce a volatility-return relation.

Let the daily continuously compounded return on the stock market index be given by

$$r_t = \ln(P_t) - \ln(P_{t-1}), \tag{1}$$

where t is the daily time index, and P_t the index level at time t. In the FIEGARCH-M model, we use the conditional mean specification

$$r_t = \mu_0 + \lambda g(z_{t-1}) + \varepsilon_t, \tag{2}$$

where the most recent volatility innovation enters in the form of $g(z_{t-1})$, the news impact function, as given in (6) below. Let $\mathcal{F}_{t-1}$ denotes the filtration generated by the set of available information up to time $t-1$, and $g(z_{t-1})$ is $\mathcal{F}_{t-1}$-measurable, so the return innovation is $\varepsilon_t = r_t - E(r_t|\mathcal{F}_{t-1})$.

The key is the modeling of the conditional return variance

$$\sigma_t^2 = Var(r_t|\mathcal{F}_{t-1}) = E(\varepsilon_t^2|\mathcal{F}_{t-1}). \tag{3}$$

As in the FIEGARCH model, the specification is

$$\phi(L)(1-L)^d(\ln\sigma_t^2-\omega)=\psi(L)g(z_{t-1}), \tag{4}$$

where ω is the long-run mean logarithmic variance, $\phi(L)$ and $\psi(L)$ are the GARCH and ARCH polynomials in the lag operator, $\phi(L)=1-\sum_{i=1}^{p}\phi_iL^i$ and $\psi(L)=1+\sum_{i=1}^{q}\psi_iL^i$, and $(1-L)^d$ is the fractional difference operator defined by its binomial expansion

$$(1-L)^d=\sum_{i=0}^{\infty}\frac{\Gamma(i-d)}{\Gamma(-d)\Gamma(i+1)}L^i, \tag{5}$$

where d is the order of fractional integration in log-variance, and $\Gamma(\alpha)=\int_0^\infty x^\alpha e^{-x}dx$ is the Gamma function. The fractional difference with $0<d<1$ allows for stronger volatility persistence than that of the Garch-type generated by the lag-polynomials $\phi(L)$ and $\psi(L)$. The exponential or skewness feature is ensured by modeling $\ln\sigma_t^2$ as opposed to σ_t^2 in (4), and by the definition of the news impact function, $g(\cdot)$ governs the manner in which past returns impact current volatility,

$$g(z_t)=\theta z_t+\gamma(|z_t|-E|z_t|), \tag{6}$$

where $z_t=\varepsilon_t/\sigma_t$ is the normalized innovation.

Bollerslev & Mikkelsen (1996) and Christensen et al. (2007) in fact use the model with $p=q=1$. Defining $h_t=(1-L)^d[\ln\sigma_t^2-\ln(1+\delta N_t)-\omega]$ as the fractionally differenced log-variance in deviation from the long run level, it is convenient to rewrite the resulting FIEGARCH(1,d,1) model as

$$h_t=(1-L)^d[\ln\sigma_t^2-\ln(1+\delta N_t)-\omega]=\phi_1h_{t-1}+g(z_{t-1})+\psi_1g(z_{t-2}). \tag{7}$$

Where N_t is the nontrading indicator, which is equal to the number of nontrading days between $t-1$ and t to account for the fact that volatility tends to be higher following weekend and holiday nontrading periods, but with each nontrading day contributing less to volatility than a trading day. For more details on the FIEGARCH-M model, please see Christensen et al. (2007) and reference in that paper.

We can decompose the parameter λ in (2) in order to include crisis-specific impact. Let d_{it} be the dummy variable for crisis i, i.e., d_{it} equal to zero before the crisis i triggered on date t and equal to one after date t. Suppose there are m crises occurred, then (2) becomes:

$$r_t = \mu_0 + (\lambda_0 + \sum_{i=1}^{m} \lambda_i d_{it}) g(z_{t-1}) + \varepsilon_t, \tag{8}$$

In this way λ_0 is the risk premium for volatility innovation regardless of crises and λ_i captures the specific impact of crisis i on return.

Of course we can also consider other functional forms for the in-mean effect. Some researchers argue that the relation between return and risk is nonlinear and nonmonotonic, see Linton & Perron (2003) for more details. One natural extension to (8) is to include more lags of r_t and $g(z_{t-1})$ in mean equation, this allows for dynamic in-mean effects. For example, if the model includes n lags of return and p lags of $g(z_{t-1})$ in mean equation, then (8) becomes:

$$r_t = \mu_0 + \sum_{i=1}^{n} \mu_i r_{t-n} + \sum_{j=0}^{p} (\lambda_j + \sum_{k=1}^{m} \lambda_{jk} d_{kt}) g(z_{t-1-j}) + \varepsilon_t. \tag{9}$$

One disadvantage for this model is that the number of risk factors λs will increase dramatically when including more lags of $g(z_{t-1})$, for example, introducing an additional lag of $g(z_{t-1})$ will incur $m + 1$ additional risk factors, where m is the number of crises. Thus the model becomes complicated and difficult to estimate. Indeed we have estimated the generalized model of (9) for US market and find that the inclusion of more lag returns and volatility innovations leads to some parameters difficult to interpret. We believe that the simplified model (8) does focus on the impact of the latest volatility innovation $g(z_{t-1})$ on return. Thus in this paper we adopt the simplified model (8) for the empirical work and leave the generalized model (9) including dynamic in-mean effects for future research.

Using (7) for volatility and (8) to define return innovation ε_t, the model is estimated by Quasi-Maximum Likelihood method. Thus, the sample log-likelihood function for return data $r_t, t = 1, ..., T$, is

$$\ln L(\eta) = -\frac{T}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left(\ln \sigma_t^2 + \frac{\varepsilon_t^2}{\sigma_t^2} \right), \tag{10}$$

where $\eta = (\mu_0, \lambda_0, ..., \lambda_m, \omega, \delta, \theta, \gamma, \psi_1, \phi_1, d)$ is the unknown parameter vector to be estimated with $m + 9$ parameters. Estimation is carried out by numerical maximization of $\ln L(\eta)$. To initialize the recursions on (7) and (8) we use the unconditional sample average and variance of r_t for the presample $(t = 0, -1, \ldots)$ values of r_t and σ_t^2, and we use $\varepsilon_t = 0$ for $t = 0, -1, \ldots$. The distributional assumption behind the likelihood function is that the return innovations ε_t are conditionally normal. For robustness against departures from normality, we calculate robust standard errors based on the sandwich-formula $H^{-1}VH^{-1}$, where H is the Hessian of $\ln L(\eta)$ and V the sum of the outer products of the individual quasi score contributions. Since no asymptotic theory is available for this model, we also apply wild-bootstrap algorithm to check the validity of analytical standard errors obtained from sandwich formula.

3 Market crises in the past two decades

In the past two decades, many market crises occurred on both cross-country and country-specific level. A lot of literature has been devoted to giving detailed reviews of these crises, for example, see Kindleberger (2005). Table 1 lists these crises, including the crisis name, triggered date and affected countries.

Table 1 about here

In Table 1, the first four crises, the 1987 Stock market crash, the 1997 Asian financial crisis, the 2000 Dotcom collapse and 9/11 Terrorist attack in 2001 are considered to be cross-country crises. Each of these crises has spill-over effects spread to different countries. A brief review of each of these crises is given as follows:

1987 **Stock market crash** On October 19, 1987, the S&P 500 lost 57.64, or falling 20.4% on that date. It was the greatest single-day loss that Wall Street had ever suffered. In addition to US market, almost all major markets declined substantially during the crash. 17 markets listed in Table 1 are affected, with the least impact on Australia (dropped by 11.4%) and the most impact on Hong Kong with a drop of 45.8%, the average drop of these 17 markets is over 20%. See Abken (1988) for more details on this crisis.

1997 **Asian financial crisis** The crisis was triggered on July 2, 1997 in Thailand, on which date the Thai government announced to give up the pegged exchange rate to US dollar and then Thai baht dipped significantly afterwards, as a consequence the Thai stock market dropped 75% during the year. Later the crisis spread to other Asian countries in the following two years. Thailand, Indonesia and South Korea were most affected by the crisis, Hong Kong, Philippines and Malaysia were moderately affected and China, Singapore and Taiwan were less affected. Most countries mentioned above experienced a significant loss on their stock markets in the following years. See Radelet & Sachs (1998) for more details.

2000 **Collapse of dotcom bubble** The Dotcom bubble ran roughly from 1995 to 2000, during which the speculative investors in western countries saw their value increase rapidly in new internet sector and related fields. Technically speaking, the bubble burst on March $10, 2000$, on which day the NASDAQ index reached its peak of $5, 048$ and then dropped significantly afterwards. In the following two years, the market lost more than half of its value. The bubble also affected other countries, including Germany, Italy, and UK,[4] see Kindleberger (2005) for further reading.

9/11 **Terrorist attack** The 9/11 attack has a significant economic impact on the US and world market. The Dow Jones Industrial Average (DJIA) stock market index fell 684 points, or 7.1% in a single day after the attack, and dropped by 14.3% in the following week. The other major markets in the world also lost from 5% to 30% in value in the following several weeks after the attack, the most affected industries include insurance, airline and aviation and tourism. The GAO (2002) offers a detailed review of economic impact suffered from the attack.

Figure 1 about here

Figure 1 presents the time-series evolution for S&P 500 index from January 1987 to June 2007. It can be seen from the figure that the index climbs up from year 1987 (except for the decline due to 1987 market crash) and reaches its local maximum around year 2000, then declines drastically until year 2002, after then it increases and keeps the upward tendency up to now. Obviously during the collapse of internet bubble and 9/11 terrorist attack, the index level decreases significantly.

[4] These are the most affected countries and thus they are included in the empirical analysis in Section 4.

All the four crises mentioned above are cross-country crises, i.e. there are more than one country affected by the crisis when it occurs. Followings are country-specific crisis, the countries affected by the crises include Japan, Russia, South Africa and some Latin America countries in 1990s. For more details, see Kindleberger (2005).

1990 **Collapse of Japanese asset bubble** The Japanese economy experienced skyrocketing land and stock prices in 1980s. The Nikkei 225 index reached its peak in February 1990 of $38,915$. After that the market suffered from a continuing drop in the following decade and lost more than 70% of its value as measured in 2003.

1998 **Russian Crisis** The crisis hit Russia in August 1998. As a country heavily dependent on the export of raw materials, the sharp decline in the price of oil had severe consequences for Russia. The non-payment of taxes by the energy and manufacturing industries made the government default on its debt and thus a significant decline in stock market value.

1998 **South Africa's crisis** South Africa suffered from political unstable and low economic growth in late 1990s, which caused the local currency depreciating against US dollar. The exchange rate dropped from 5.53 per US dollar in 1998 to 10.5 per US dollar in 2002. The stock market also lost significant value during the same period.

1990s **Latin America crisis** In 1990s, several country-level crises occurred in Latin America, including 1994 Mexico's peso crisis, 1995 Venezuela economic crisis, 1997 Chile and Peru crises, 1998 Brazilian financial crisis and 2000 Argentine economic crisis. Most of these crises occurred due to low economic growth, over-borrowed of government debt and unbalanced foreign trade, which caused public finance deficit. The consequences were deep currency depreciation and significant loss in stock market. For example, Mexico peso dropped from 3.3 per US dollar before crisis to 7.2 per US dollar after the peso crisis occurred in 1994. The other countries mentioned above suffered from similar experiences during their respective crisis period.

Many questions relating to these crises have been addressed in the literature, e.g. the cause of crises, the impact of crises to economics, the predictability of crises and so on. What has not been studied is the impact of crises on the risk premium and its relation with return, while allowing for the observed long memory property in volatility, which is the central topic of this paper and the empirical results are presented in section 5.

4 Comparison between FIEGARCH and Other GARCH Models without In-Mean Effect

Before including the in-mean effect and applying the model to data, we need to justify that FIEGARCH model does really do a better job than other GARCH models. In this section, we provide some preliminary estimations between FIEGARCH and several other GARCH models, some diagnostic tests and simulation results are also provided for robust check.

The other models chosen for comparison include GARCH (Engle (1982)), IGARCH (Engle & Bollerslev (1986)), EGARCH (Nelson (1991)) and FIGARCH (Baillie et al. (1996)) models. These are most typical GARCH models used in empirical studies. GARCH and IGARCH models are the simplest models in GARCH class and may be the most widely used models in industry, EGARCH captures asymmetry effect of return to volatility, and FIGARCH allows for fractional difference in volatility. As we mentioned in preceding sections, the FIEGARCH model includes all these features, thus we predict that it should outperform the other models.

We apply the models to the Center for Research on Security Prices (CRSP) value-weighted index obtained from Wharton Research Data Services, from January 2, 1926, the inception of the data, to December 31, 2006, for a total of $T = 21,519$ return observations. We use daily closing prices including dividends. This long period is selected since it is argued in the literature that longer data series will give more accurate and unbiased estimates for GARCH models, see Hwang & Pedro (2006). Following Nelson (1991) and Bollerslev & Mikkelsen (1996), we include a variable N_t equal to the number of nontrading days between $t-1$ and t to account for the fact that volatility tends to be higher following weekend and holiday nontrading periods, but with each nontrading day contributing less to volatility than a trading day. The empirical results are reported in Table 2.

Table 2 about here

From Table 2, we can see that point estimates for parameters in the mean equation, the constant μ_0 and coefficients of the return lags, μ_1, μ_2 and μ_3 have similar values among different models. The first- and second-order autoregressive parameters μ_1 and μ_2 are significant for all models, which confirms returns are serially correlated. The GARCH effect is obvious from the significance of the parameters α and β in GARCH, IGARCH and FIGARCH models.[5] Also the asymmetry in return is captured by the significantly negative parameter θ in EGARCH and FIEGARCH models. The empirical relevance of each of the elements of the FIEGARCH model is confirmed. Volatility exhibits long memory, with the fractional differencing parameter d positive and strongly significant (robust standard errors in parentheses) throughout the table for both FIGARCH and FIEGARCH. The nontrading-day count N_t gets a coefficient δ estimated to about 0.2 in both EGARCH and FIEGARCH, showing that weekend and holiday contributions to variance per day are about 20% of those for trading days.

The performance of these models can be seen from their log likelihood function values as well as the Akaike and Schwarz (or Bayesian) information criteria values. For example, IGARCH model has the lowest log likelihood function values and highest AIC and SIC values, which indicates it may be the model with the worst performance. The ranking for the rest four models is FIEGARCH, EGARCH, FIGARCH and GARCH models with FIEGARCH has the best performance based on its highest value of log likelihood function and lowest AIC and SIC values.

As mentioned earlier, there exists leverage effect in financial markets, i.e. positive return and negative return has asymmetric impact on volatility. Engle & Ng (1993) define news impact curve to measure how new information is incorporated into volatility estimates. They also suggest some diagnostic tests to capture the asymmetry of the volatility response to news. As suggested in that paper, a good model should be able to explore this asymmetric impact of return to volatility in its estimation. Sign Bias test, Negative Size Bias test, Positive Size Bias test and Joint test can be applied to test the goodness of different models. These tests examine whether we can predict the squared standardized residual by some variables observed in the past which are not included in the volatility model being used. If these variables can predict the squared standardized residual, then the volatility model is misspecified, for details of these tests, please refer to Engle & Ng (1993).

In this paper we follow their approach and implement these diagnostic tests to further compare the performance of these GARCH class models in capturing asymmetry. The testing results are presented in Table 3.

[5] Note that for FIGARCH model, we use a little different model specifications in Table 2 and in Table 5. The reason is to make it comparable with GARCH in Table 2 and FIEGARCH-M in Table 5. In Table 2 we adopt the FIGARCH specification as in Baillie et al. (1996), yet in Table 5 the FIGARCH-M model is specified as FIEGARCH-M but let the asymmetry factor $\theta = 0$.

Table 3 about here

The values of Ljung-Box statistics for 20th order serial dependence in the table show that both EGARCH and FIEGARCH outperform the other three models in eliminating serial dependence in the standardized residuals $\hat{\varepsilon}_t/\hat{\sigma}_t$. Compare the results of diagnostic tests, we see that EGARCH and FIEGARCH model do a good job at capturing the impact of negative and positive return shocks on volatility, both models have the lowest values for Sign Bias test. EGARCH and FIGARCH model are superior to other models in exploring the different effects that large and small negative return shocks have on volatility, reflected by their lower values on Negative Size Bias Test. For the Positive Size Bias test, the GARCH and IGARCH model outperform the others. Finally for the Joint test, again EGARCH and FIEGARCH model lead the others. It seems that different models are focusing on capturing different asymmetric properties of return on volatility. However by combining all the results from these diagnostic tests together, it is fair to say that EGARCH and FIEGARCH models are better than the others.

It is also argued in the literature that some GARCH models may be explosive, see Andersen & Lund (1997). In order to check that property and make sure that our model is non-explosive, Monte Carlo simulation is performed for different GARCH models, including GARCH, IGARCH, EGARCH, FIGARCH and FIEGARCH. The methodology applied here is adopted from Andersen & Lund (1997). The mean equation of these models includes three lags of returns, but conditional volatility innovation is not included. The values for the first three returns are taken from the CRSP data as initial starting values and then simulation is performed based on the parameter values at the point estimates. The sample of size $T = 21,519$ (as the same in CRSP data) is drawn with 100 replications, and then the mean, maximum and minimum realizations for each replication are collected. We then calculate the average values from all replications for these three realizations. The result is shown in Table 4.

Table 4 about here

It can be seen from Table 4 that FIEGARCH model is closest to the actual maximum and minimum value from raw data, EGARCH has the mean which is closest to the sample mean. The mean, maximum and minimum values obtained for IGARCH model have the largest deviation from the sample, GARCH model is also inferior to other models except IGARCH model. The maximum, minimum values for FIEGARCH model is also closest to the sample maximum and minimum values. On the contrary, the maximum and minimum values for EGARCH and FIGARCH models seem to fluctuate too narrow compared to the sample.

Up to now, based on the estimation results from Table 2, results of diagnostic tests from Table 3 and the simulation results in Table 4, we can choose the best models for next step, the estimation including in-mean terms. It seems that there are three candidates: EGARCH, FIGARCH and FIEGARCH models, yet GARCH and IGARCH models behave poorly in all tables, thus we discard these two models.

Next we estimate models of FIGARCH, EGARCH and FIEGARCH including in-mean terms, the estimation procedure for EGARCH model is not converged, so we only consider estimations for FIGARCH and FIEGARCH. For both models, we consider the generalized equation (9), including lags for return and lags for volatility innovation $g(z_{t-1})$ in mean equatioin. Table 5 reports the estimation results with in-mean terms for these two GARCH models.

Table 5 about here

Similar to the case in Table 2, FIGARCH-M model is dominated by FIEGARCH-M model based on the values of log likelihood function and AIC and SIC. The parameters of the first two lags of return, μ_1 and μ_2, are still significant, this may indicate that return keeps its serial dependence even including in-mean terms. The fractional difference parameter d is also significant, emphasizing the long memory property in volatility. The asymmetry in return shocks to volatility is again addressed by the negative parameter of θ in FIEGARCH models. For the parameters of the in-mean terms, it is interesting to see that these two models give different results for some λs. For example all λs for $g(z_{t-1})$ and its first lag are significant for FIEGARCH model, but only λ_1 is significant in the case of FIGARCH. On the other hand, λ_{22} is significant for FIGARCH, but none of λ_{2i} is significant in FIEGARCH. Some of these parameters are difficult to interpret, nevertheless these conflict results may indicate that dynamic in-mean effects are there, yet may be nonlinear and nonmonotonic. In this paper we adopt the simplified model (8) instead of the generalized one (9) to focus on the impact of the latest volatility innovation $g(z_{t-1})$ to return.

5 Data and Empirical Results

5.1 Data Description

The data is collected from Yahoo!Finance, Datastream and Wharton Research Data Services, and we use daily closing prices adjusted for stock splits and dividends for each market. We select 36 countries from different continents, including most major markets in the world. There are 8 countries selected from North and Latin America, 12 countries or regions from Asia and Pacific, 14 countries from Europe and 2 countries from Middle East and Africa. Since we want to use as much data as available for each market, the start date is varied from 1926/1/2 for US to 1995/7/1 for Russia and the end date is set on 2007/6/8 for all markets except for US, which is ended on 2006/12/31. US has the most observations for a total of $T = 21,519$ and Russia has the least observations for a total of $T = 2,871$.[6] Table 6 lists summary for selected countries and indices.

Table 6 about here

It is obvious to see that most developed markets have longer data series than emerging markets, which indicates that developed markets are launched much earlier than emerging markets. Next consider the values for $\overline{r}$ and $\overline{r^2}$. Most emerging markets have higher $\overline{r}$ and $\overline{r^2}$. For example, in American markets, Brazil, Mexico, Peru and Venezuela have $\overline{r}$ values of $0.002197, 0.001183, 0.001654$ and 0.001134 respectively, compare to 0.0002664 and 0.0004306 of $\overline{r}$ for Canada and US respectively. In Asia, China, Pakistan and Philippines have highest values for $\overline{r}$, as a comparison, Malaysia, Thailand and Singapore have lowest values for $\overline{r}$. In Europe, those transitional economies like Russia and Hungary have higher $\overline{r}$, and most markets in western Europe have lower $\overline{r}$. On the other hand, emerging markets also have higher $\overline{r^2}$ than developed markets. Russia and China have the highest $\overline{r^2}$ values of 0.0008102 and 0.0007005 respectively, which are almost ten times higher than those for US and Canada. As a summary, the higher $\overline{r}$ and $\overline{r^2}$ for emerging markets compared to developed markets indicate that emerging markets offer higher returns but also with higher volatilities.

[6] For the internet bubble crisis, we adopt the NASDAQ index for US market, which starts from 1971/2/5 and has a $T = 9,502$ observations.

5.2 Estimation Results

From Table 1 we can see that 1987 Stock market crash and 9/11 Terrorist attack have impact on more countries than other crises, so first we estimate the model with parameters for these two crises, i.e. the return equation is

$$r_t = \mu_0 + (\lambda_0 + \lambda_1 d_{1t} + \lambda_2 d_{2t}) g(z_{t-1}) + \varepsilon_t. \tag{11}$$

Where d_{1t} is the dummy for 1987 Stock market crash and d_{2t} is the dummy for 9/11 Terrorist attack, as mentioned in Section 2, these two dummies are set to zero before crisis date t and is equal to one after that date. Thus λ_1 and λ_2 capture the impact of these crises on returns respectively. Estimation results using (11) are given in Table 7.

Table 7 about here

There are 28 countries include in the estimation. Due to lack of data, for 11 countries, only parameter λ_2 for 9/11 attack dummy is estimated.[7]

Again, we can see from Table 7 that the reported estimates confirm the empirical relevance of each of the elements of the FIEGARCH-M model. Thus, volatilities exhibit long memory, with the fractional differencing parameter d positive and strongly significant (robust standard errors in parentheses) except for Indonesia and Switzerland. Skewness (the EGARCH effect) is clearly present, with θ negative for most countries (except for Iceland, Indonesia and Venezuela). The nontrading-day count N_t gets a coefficient δ estimated ranges from 0.03575 to 0.4243 across different countries, showing that weekend and holiday contributions to variance per day are around 4% to 40% of those for trading days. The Ljung-Box portmanteau statistics for serial correlation in the standardized return innovation $\widehat{z}_t = \widehat{\varepsilon}_t / \widehat{\sigma}_t$ are reported as Q_{10} and Q_{100} for 10 and 100 lags respectively. Since the absolute returns are serially correlated in GARCH models even when raw returns are not, we also report Ljung-Box statistics for the absolute standardized return innovations $|z_t|$, indicated as Q_{10}^A and Q_{100}^A in Table 7 and following tables. Although some of the Ljung-Box statistics for standardized innovations and absolute standardized innovations Q_{10} and Q_{100} and Q_{10}^A and Q_{100}^A are significant, they are much smaller compared to

[7] These countries are France, Hungary, Iceland, Indonesia, Italy, Mexico, Parkistan, Portugal, Russia, Switzerland and Venezuela, as shown in Table 7.

the raw returns,[8] indicating that FIEGARCH-M model is successful in eliminating serial correlation in raw date series.

The parameters governing the return-volatility relation, λ_0, λ_1 and λ_2 performs differently both for sign and significance for different markets. For example, for US, λ_0 is negative and both λ_1 and λ_2 are positive, all of the λs are significant. Since λ_0 is negative, it can be explained either as a volatility feedback or leverage effect to returns, as discussed in Introduction. Although these two effects are mutually consistent, we conjecture that volatility feedback effect dominates in this case, since it should be strongest at the market level which we consider, whereas financial leverage should apply to individual stocks. λ_1 and λ_2 are positive, indicating that investors require a risk premium after each crisis for worry of potentially similar crisis which may happen in the future. The positive λ_1 and λ_2 also offset the negative λ_0, so the overall effect $\lambda = \lambda_0 + \lambda_1 + \lambda_2$ is much less in value compared to each individual λ_i $(i = 0, 1, 2)$. On the contrary, Austria has different signs on all three λs compared to US, i.e. it has positive λ_0 and negative λ_1 and λ_2. As we discuss previously, positive risk premium λ is more like a volatility-return tradeoff and negative risk premium λ implies volatility feedback effect. Thus in the case of Austria, it is more like a volatility feedback for the after-crisis period instead of risk premium effect. The overall effect is again the sum of all three λs, it is negative, which is also contrary to US.

More interestingly, the λ parameters for Australia, Canada, Mexico, Norway, South Africa, Sweden, Switzerland and Venezuela have similar features as those for US, i.e. they have negative λ_0 and either positive λ_1 or positive λ_2 or both. We can see that all 4 American markets, i.e. US, Canada, Mexico and Venezuela behave the same for their λs, although it is unclear why these markets have the same feature. On the contrary, most European markets act like Austria does, for example, Belgium, France, Holland, Hungary, Iceland, Russia, all of these markets have positive λ_0 and one of negative λ_i $(i = 1, 2)$. Asian markets have mixed pattern, Australia behaves like US, but Indonesia, Singapore, Taiwan and Thailand behaves in European way. The significance of λ_1 and λ_2 also indicates that both 1987 Stock market crash and 9/11 terrorist attack crises have persistent impact on the markets for after-crisis period.

In order to assess the crisis impact on risk premium, we compute the volatility innovation $g(z_{t-1})$ from (6) at the parameter estimates without the in-mean term λs from Table

[8] The Ljung-Box test is performed for raw returns r_t up to 10 and 100 lags, the results are not presented here in order to save space.

7 for CRSP value-weighted index, and plot the returns r_t against $g(z_{t-1})$ prior to and after the 1987 market crash, the resulting plots are presented in Figure 2 and Figure 3.

Figures 2 and 3 about here

From the figures it can be seen that the relation between r_t and $g(z_{t-1})$ prior to the crash is negative, which is confirmed by the estimated λ_0 in Table 7 and the best-fitting linear regression line (the bold line) in Figure 2. However for the period after the crash, the relation between r_t and the volatility innovation $g(z_{t-1})$ becomes positive, again the positivity is confirmed by the best-fitting line (the bold line) in Figure 3, although the positivity is not as obvious as the negativity prior to the crash, and also by the positive estimated λ_1 and λ_2 in Table 7. These two figures show that the 1987 crash has changed the relation between the returns and corresponding volatility innovation, thus induces the risk premium required by investors for the crisis. However the total effect of $g(z_{t-1})$ to return is still negative, which derives from the sum of all λs and the larger negativity from Figure 2. The similar results also hold for the 9/11 attack, yet the figures are not presented here.

Next we present the estimation result for the dotcom crisis. As mentioned before, the dotcom crisis hit US, Germany, Italy and UK most heavily, so these 4 markets are used in estimating the model. The empirical results are presented in Table 8.

Table 8 about here

The results for other parameters are similar compared to those in Table 7. Again we are interested in the sign and significance for λs. In this case, λ_0 for all 4 markets is negative and λ_1 for all 4 markets is positive, and significant λ_1 is found in the two markets that are most heavily hit by the crisis: US and UK. This result indicates that in the dotcom crisis, all these markets react similarly, a risk premium is required for the after-crisis period, especially for US and UK. The overall effect, i.e. the sum of λ_0 and λ_1 is also positive.

Next move to the 1997 Asian financial crisis. 9 countries (regions) are included in the estimation, results are reported in Table 9 as follows:

Table 9 about here

λ_0 is positive for most markets except for Malaysia, and λ_1 is negative for all markets, thus it can be considered as a volatility feedback effect for the crisis. Although λ_0 is significant for 5 markets, λ_1 is only significant for Indonesia and China. As we mentioned earlier, Indonesia, South Korea and Thailand are three countries that were hit most heavily by the crisis. Yet from the statistics we can see that the crisis only has persistent impact on Indonesia among these three markets. The case for China is also interesting since China is considered to be relatively unaffected by the crisis, yet it has significant risk premium λ_1 for the crisis. However we can also see that parameters d and θ are not significant for China, indicating that both long-memory and skewness effect is not well addressed, which implies that the model is not suitable for China, thus the estimates for λ_0 and λ_1 may also not be reliable.

Finally we perform the estimation for crises related to individual countries and the results are presented in Table 10.

Table 10 about here

For the parameter λs, the result is mixed for both sign and significance. λ_0 is negative for Argentina, Brazil, Mexico and South Africa, and it is positive for the rest. Most λ_0 and λ_1 have opposite sign, except for Japan, for which both λ_0 and λ_1 are positive, yet none of them is significant. λ_0 is significant for Chile, Mexico, Peru and Venezuela, which implies that these markets have a risk premium on volatility innovations. However, Only Peru has significant λ_1. This result indicates that almost all of these country-specific crises has no persistent impact on the corresponding countries which suffered from the crises, the only exception is Peru, which has positive λ_0 and negative λ_1, indicating that it has a volatility feedback effect in the after-crisis period and this effect offsets the risk premium in a total measure.

These empirical results confirm that FIEGARCH-M is a suitable model to address the long memory property in volatility and skewness in returns. Another common feature from these results is that most countries have significant λ_0, although the sign is changing. It implies that volatility innovation is a significant pricing factor to stock returns for most markets. More interestingly, λ_0 has opposite sign against crisis-related parameters.

Positive or negative λ_0 usually follows by negative or positive crisis-related parameters, which means the crisis offsets the prior to crisis risk impact, makeing the total after-crisis effect smaller than the effect before crisis.

5.3 Wild-Bootstrap Implementation

The results in previous subsection show that the FIEGARCH-M model works well in revealing the crises-related risk-return relations for most markets. However one main disadvantage for GARCH models is that few asymptotic theory is available to apply. Weiss (1986) and Lumsdaine (1996) derive asymptotic theory for ARCH (1,1) and GARCH (1,1) model respectively, yet for other specifications in the GARCH class, no asymptotic theory is ready to be applied. The absent of asymptotic theory motivates researchers to provide simulation evidence on these models, i.e. see Bollerslev & Wooldridge (1992). Since we cannot provide the asymptotic property for the estimates, it is not surprising that we will also adopt the wild-bootstrap algorithm to investigate whether the standard errors obtained via the Quasi-Maximum Likelihood method is consistent, the wild-bootstrap algorithm adopted here is the same as applied in Linton & Perron (2003).

Wild bootstrap algorithm

1. Given estimates $\widehat{\boldsymbol{\eta}}$ and normalized residuals $\widehat{z}_t = z_t(\widehat{\boldsymbol{\eta}})$, calculate the recentered standardized residuals, $\widehat{z}_t^c = (\widehat{z}_t - T^{-1}\sum_{t=1}^{T}\widehat{z}_t)$.

2. Let x_t be a random variable with $E(x_t^j) = 0$ for $j = 1,3$ and $E(x_t^j) = 1$ for $j = 2,4$. Draw a random sample $\{x_1, \cdots, x_T\}$ from this distribution and let $z_t^* = \widehat{z}_t^c x_t$. The variable z_t^* will satisfy $E(z_t^*) = 0$, $E(z_t^{*2}) = \widehat{z}_t^{c2}$, $E(z_t^{*3}) = 0$ and $E(z_t^{*4}) = \widehat{z}_t^{c4}$. We choose x_t be a discrete variable which takes values -1 and 1 with equal probability.

3. Given starting value r_0 and z_0^*, as well as the point estimates, generate a time series of r_t^* according to FIEGARH-M model (8) and corresponding point estimates.

4. Given $\{r_t^*\}_1^T$, calculate parameter estimates $\widehat{\boldsymbol{\eta}}^*$ using the foregoing Quasi-Maximum Likelihood method.

5. Repeat steps $2-4$ N times. The standard errors are estimated from the sample standard deviation of the bootstrap parameter estimates $\widehat{\eta}^*$.

In the following table, we choose $N = 249$ and the bootstrap method is applied to FIEGARCH-M model with $g(z_{t-1})$ in-mean terms, both standard errors obtained from QML method and wild-bootstrap method are reported in the parentheses. This method of obtaining standard errors is time-consuming for large samples,[9] but it should fully reflect the loss of precision associated with estimates. The replication time N is smaller than usual applications, yet we also check $N = 99$ and find similar results, hence the bootstrap procedure is reliable. Of course if we have more time, it is better to try more replications, say $N = 999$ as in usual case. Also note that we choose $N = 249$ instead of $N = 250$ in order to avoid the possible problem of biased size, see Davidson & MacKinnon (2004) for more discussions.

The following table report the results for US market as a representative for all markets.

Table 11 about here

From Table 11 we see that the standard errors obtained from the QML method and wild-bootstrap method are quite similar, both results give the same significance level for the same parameter estimate. Actually for some estimates, the standard errors obtained from bootstrap is smaller than those obtained from QML method. These results show that QML method is valid for providing consistent standard errors for estimates as from the wild-bootstrap method, thus the t-values obtained from QML are reliable.

6 Concluding Remarks

We have applied the FIEGARCH-M model in which the long memory property of volatility does not carry over to returns and which also includes the crisis-related component in the mean equation, to the stock markets in the world suffered from crises occurred in the past two decades. The avoidance of long memory property of volatility carrying over to returns is accomplished through a filtering (fractional differencing) of the in-mean volatility measure. The dummy variables are used to test the persistent impact in the after-crisis period.

The empirical application of the resulting FIEGARCH-M model to the market indices confirms the long memory property of volatility and skewness in return. The in-mean filtered volatility innovation is a significant pricing factor to return for most markets. It also performs differently before and after specific crises for different countries. The 1987 Stock

[9] It takes 29 hours to perform 100 replications for CRSP value-weighted index with $T = 21,519$ observations.

market crash and 9/11 terrorist attack have persistent impacts for most markets. Interestingly, American markets and European markets react differently after crisis. American markets have positive impacts, yet most European markets have negative impacts. As we have discussed, a leverage effect, a volatility feedback effect, or both could be linked to such a negative relation. We conjecture that the negative results more likely reflect the volatility feedback effect, since this should be strongest at the market level which we consider, whereas financial leverage should apply to individual stocks. According to asset pricing theory, a risk-averse investor requires higher compensation for holding a more risky asset, thus a positive risk-return relation can be considered as a risk premium for volatility. The American markets have risk premium for the crises, yet most European markets have volatility feedback effect for the crises. The impact of dotcom crisis also reflects a risk premium. The 1997 Asian financial crisis and other country-specific crises have little impact on most markets. For most markets, the incremental risk carried by crises moves in the opposite direction against the original one, thus reduces the overall after-crisis volatility-related impact to returns.

Our result shows that FIEGARCH-M model is a useful tool to address the in-mean volatility-related impact to return and impact from crises for many countries. Recent developments in asset pricing, e.g., Ang et al. (2006), point out it should be innovation to volatility rather than volatility level that affects expected return. Our using of volatility innovation confirms their findings. We also make contribution to the literature with the confirmation of crises impact to the markets in the world. As we show before, we may also consider other functional forms, i.e. including lags of return and volatility innovation to allow for dynamic in-mean effects to return. The way in which the breaks enter the conditional mean function may be more flexible, for example, we can allow for smooth transition and let the data determines the breaks. All these are left for future research.

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Table 1: Major cross-country and country-specific crises in the past 20 years

Name	Triggered Date	Affected Countries
Global Crisis		
1987 Stock Market Crash	1987/10/19	US
	1987/10/20	Australia
	1987/10/19	Austria
	1987/10/19	Belgium
	1987/10/19	Canada
	1987/10/19	Holland
	1987/10/20	Hong Kong
	1987/10/19	Israel
	1987/10/20	Japan
	1987/10/19	Norway
	1987/10/20	Singapore
	1987/10/19	South Africa
	1987/10/19	Spain
	1987/10/19	Sweden
	1987/10/20	Taiwan
	1987/10/20	Thailand
	1987/10/19	UK
1997 Asian Financial Crisis		
	1997/7/18	Indonesia
	1997/10/22	South Korea
	1997/7/2	Thailand
	1997/10/20	Hong Kong
	1997/7/11	Malaysia
	1997/7/10	Philippines
	1997/7/2	China
	1997/8/7	Singapore
	1997/7/7	Taiwan
2000 Dotcom Bubble Collapse		
	2000/3/10	US
	2000/3/27	Germany
	2000/3/20	Italy
	2000/4/3	UK
9/11, 2001 Terrorist Attack		
	2001/9/11	US
	2001/9/12	Australia

Table 1 (Cont): Major cross-country and country-specific crises in the past 20 years

Name	Triggered Date	Affected Countries
9/11, 2001 Terrorist Attack		
	2001/9/11	Austria
	2001/9/11	Belgium
	2001/9/11	Canada
	2001/9/11	France
	2001/9/11	Holland
	2001/9/12	Hong Kong
	2001/9/11	Hungary
	2001/9/11	Iceland
	2001/9/12	Indonesia
	2001/9/11	Israel
	2001/9/11	Italy
	2001/9/12	Japan
	2001/9/11	Mexico
	2001/9/11	Norway
	2001/9/11	Pakistan
	2001/9/11	Portugal
	2001/9/11	Russia
	2001/9/12	Singapore
	2001/9/11	South Africa
	2001/9/11	Spain
	2001/9/11	Sweden
	2001/9/11	Swiss
	2001/9/12	Taiwan
	2001/9/12	Thailand
	2001/9/11	UK
	2001/9/11	Venezuela
Country-Specific Crises		
Argentine Economic Crisis	2000/4/14	Argentina
Brazilian Financial Crisis	1999/1/18	Brazil
Chile Recession	1997/11/5	Chile
Japan's Collapse of Bubble	1990/2/20	Japan
Mexican Peso Crisis	1994/12/20	Mexico
Peru Recession	1997/11/10	Peru
Russian Economic Crisis	1998/8/17	Russia
South Africa's Currency Crisis	1998/6/25	South Africa
Venezuela Economic Crisis	1995/11/29	Venezuela

Figure 1: S&P 500 Price Index (1987/1/1 - 2007/6/8)

Table 2: Estimation results for CRSP value-weighted (dividend included) index (1926.1.2 - 2006.12.31) with no mean effect

Parameter	GARCH	IGARCH	EGARCH	FIGARCH	FIEGARCH
μ_0	0.6466×10^{-3} (0.0153×10^{-3})	0.6446×10^{-3} (0.073×10^{-3})	0.4534×10^{-3} (0.0537×10^{-3})	0.6746×10^{-3} (0.0191×10^{-3})	0.4803×10^{-3} (0.0503×10^{-3})
μ_1	0.1150 (7.80×10^{-3})	0.1152 (7.68×10^{-3})	0.1093 (7.53×10^{-3})	0.1188 (7.78×10^{-3})	0.1135 (6.28×10^{-3})
μ_2	-0.03891 (7.55×10^{-3})	-0.03892 (7.43×10^{-3})	-0.03518 (7.87×10^{-3})	-0.03939 (7.65×10^{-3})	-0.03373 (3.71×10^{-3})
μ_3	9.752×10^{-3} (7.66×10^{-3})	9.721×10^{-3} (7.57×10^{-3})	0.01254 (6.86×10^{-3})	8.000×10^{-3} (7.81×10^{-3})	7.051×10^{-3} (4.77×10^{-3})
ω	7.411×10^{-3} (1.29×10^{-3})	6.224×10^{-3} (1.13×10^{-3})	-9.036 (0.124)	0.02096 (3.84×10^{-3})	-8.945 (0.149)
δ	–	–	0.2223 (0.0384)	–	0.2176 (0.0379)
α	0.08486 (8.79×10^{-3})	0.08753 (8.48×10^{-3})	–	0.2615 (0.0319)	–
β	0.9114 (8.45×10^{-3})	0.9125	–	0.5974 (0.0420)	–
θ	–	–	-0.1114 (0.0116)	–	-0.1179 (0.0132)
γ	–	–	0.2239 (0.0171)	–	0.2150 (0.0163)
ψ_1	–	–	-0.4399 (0.0565)	–	-0.4775 (0.140)
ϕ_1	–	–	0.9913 (1.34×10^{-3})	–	0.7218 (0.0921)
d	–	–	–	0.4466 (0.0363)	0.5451 (0.0271)
$\ln L(\eta)$	$71,911.4$	$71,908.3$	$72,259.75$	71993.7	$72,341.80$
AIC	$-143,808.8$	$-143,804.6$	$-144,499.49$	$-143,969.3$	$-144,661.62$
SIC	$-143,752.9$	$-143,756.7$	$-144,419.72$	$-143,897.5$	$-144,573.87$

Note: Quasi maximum likelihood estimates (QMLE) estimates are reported for daily returns on the CRSP value-weighted index from January 2, 1926, to December 31, 2006, i.e. $T = 21,519$ return observations, with robust standard errors in parentheses. Also reported are $\ln L(\eta)$, the value of the maximized log-likelihood function, and the Akaike and Schwarz (or Bayesian) information criteria, respectively.

Table 3: Diagnostic test results for CRSP value-weighted (dividend included) index (1926.1.2 - 2006.12.31) with no mean effect

	GARCH	IGARCH	EGARCH	FIGARCH	FIEGARCH
Ljung-Box (20)	33.53*	31.06*	13.52	33.42**	11.31
Sign Bias	2.873**	2.944**	1.590	3.004**	1.33
Negative Size Bias	3.648**	3.239**	2.112*	2.448*	3.66**
Positive Size Bias	1.536	1.800	3.086*	2.196*	3.65**
Joint Test	62.67**	60.73**	20.69**	55.54**	29.31**

Note: The values of the Ljung-Box portmanteau statistic for up to 20th order serial dependence in the standardized residuals, $\hat{\varepsilon}_t/\hat{\sigma}_t$, the results of Sign Bias test, Negative Size Bias test, Positive Size Bias test as well as Joint test are reported for daily returns on the CRSP value-weighted index from January 2, 1926, to December 31, 2006, i.e. $T = 21,519$ return observations. * indicates significance level at 5% and ** indicates significance level at 1%

Table 4: Maximum, Minimum and Mean Realizations for Simulation Results

	CRSP data	GARCH	IGARCH	EGARCH	FIGARCH	FIEGARCH
Average$\times 10^4$	4.31	7.01	6.73	5.01	0.74	5.22
Maximum	0.1694	0.3498	4.037	0.0721	0.124	0.152
Minimum	-0.1946	-0.3477	-4.951	-0.0617	-0.106	-0.130

This table reports results for simulation of different models. The mean equation includes three lags of returns, but conditional variance is not included. The value for the first three returns is taken from the CRSP data as initial starting values and then simulation is performed based on the parameter values at the point estimates. The random sample of size $T = 21519$ (as the same in CRSP data) is drawn with 100 replications, and then the mean value, maximum and minimum realizations for each replication are collected. After all replications are done, the average values for these three realizations, the mean, the maximum and the minimum from each replication, are calculated and reported in the table.

Table 5: Estimation results for CRSP value-weighted (dividend included) index (1926.1.2 - 2006.12.31) with cirsis risk factors

Parameter	FIGARCH-M	FIEGARCH-M
μ_0	0.7277×10^{-3} (0.0557×10^{-3})	0.4892×10^{-3} (0.0525×10^{-3})
λ_0	0.3958×10^{-3} (0.517×10^{-3})	-1.703×10^{-3} (0.513×10^{-3})
λ_{01}	1.516×10^{-3} (1.06×10^{-3})	3.358×10^{-3} (0.982×10^{-3})
λ_{02}	-1.363×10^{-3} (1.49×10^{-3})	2.535×10^{-3} (1.39×10^{-3})
λ_1	1.303×10^{-3} (0.436×10^{-3})	1.376×10^{-3} (0.382×10^{-3})
λ_{11}	-0.7438×10^{-3} (1.02×10^{-3})	-2.889×10^{-3} (1.03×10^{-3})
λ_{12}	-0.7620×10^{-3} (1.60×10^{-3})	3.028×10^{-3} (1.44×10^{-3})
λ_2	-0.2787×10^{-3} (0.400×10^{-3})	-0.4754×10^{-3} (0.380×10^{-3})
λ_{21}	-1.360×10^{-3} (1.09×10^{-3})	0.1053×10^{-3} (0.887×10^{-3})
λ_{22}	4.349×10^{-3} (1.96×10^{-3})	1.178×10^{-3} (1.79×10^{-3})
μ_1	0.1102 (5.69×10^{-3})	0.1032 (7.46×10^{-3})
μ_2	-0.03870 (5.62×10^{-3})	-0.01956 (7.85×10^{-3})
μ_3	6.111×10^{-3} (4.95×10^{-3})	0.8228×10^{-3} (7.00×10^{-3})
ω	-8.445 (0.189)	-8.978 (0.145)
δ	0.2104 (0.0333)	0.2203 (0.0382)
θ	$-$	-0.1240 (0.0126)
γ	0.2428 (0.0215)	0.2116 (0.0155)
ψ_1	-0.5887 (0.107)	-0.4850 (0.135)
ϕ_1	0.8148 (0.0584)	0.7262 (0.0871)
d	0.5495 (0.0319)	0.5439 (0.0262)
$\ln L(\eta)$	$72,085.38$	$72,370.80$
AIC	$-144,132.76$	$-144,701.59$
SIC	$-143,981.20$	$-144,542.06$

Note: Quasi maximum likelihood estimates (QMLE) estimates are reported for daily returns on the CRSP value-weighted index from January 2, 1926, to December 31, 2006, i.e. $T = 21,519$ return observations, with robust standard errors in parentheses. Also reported are $\ln L(\eta)$, the value of the maximized log-likelihood function, and the Akaike and Schwarz (or Bayesian) information criteria, respectively. For FIEGARCH-M model, volatility innovation $g(z_{t-1})$ and its two lags are included in mean equation.

Table 6: Summary Statistics for selected countries and indices

No	Country	Selected Index	Start Date	End Date	N[1]	$\overline{r} \times 10^4$	$\overline{r^2} \times 10^4$
America							
1	Argentina	MARVAL	1993/8/2	2007/6/8	3427	4.871	5.163
2	Brazil	IBOVESPA	1993/4/27	2007/6/18	3494	21.97	6.737
3	Canada	S&P/TSX Com.[2]	1969/1/1	2007/6/8	9608	2.664	0.7138
4	Chile	IPSA	1991/1/2	2007/6/8	4025	7.882	0.7761
5	Mexico	IPC	1988/1/4	2007/6/8	4848	11.83	2.762
6	Peru	IGBVL	1991/1/2	2007/6/8	4057	16.54	2.064
7	US	S&P 500	1926/1/3	2006/12/31	21519	4.306	1.254
8	Venezuela	IBC	1993/4/1	2007/6/8	3420	11.34	3.636
Asia and Pacific							
9	Australia	ALL ORDS	1980/1/1	2007/6/8	6912	3.657	0.8652
10	China	SSE Com.	1991/1/2	2007/6/8	4025	8.483	7.005
11	Hong Kong	Hang Seng	1969/11/25	2007/6/8	9300	5.241	3.495
12	Indonesia	JSX Com.	1983/4/4	2007/6/8	5680	5.288	2.564
13	Japan	Nikkei 225	1950/4/3	2007/6/8	14182	3.690	1.291
14	Malaysia	JKSE Com.	1993/12/3	2007/6/8	3330	0.8358	2.583
15	Pakistan	KSE 100	1988/12/30	2007/6/8	4232	7.362	2.626
16	Philippines	PSE Com.	1986/1/2	2007/6/8	5261	6.256	3.135
17	Singapore	STI	1985/1/4	2007/6/8	5616	3.056	1.873
18	South Korea	KOSPI	1975/1/7	2007/6/8	7949	4.421	2.520
19	Taiwan	TWII	1971/1/5	2007/6/8	8872	4.745	3.378
20	Thailand	SET	1975/5/1	2007/6/8	7790	2.590	2.202
Europe							
21	Austria	ATX	1986/1/7	2007/6/8	5294	3.756	1.345
22	Belgium	All Shares	1980/1/1	2007/6/8	6760	3.841	0.7530
23	France	CAC 40	1990/3/1	2007/6/8	4356	2.679	1.714
24	Germay	DAX	1990/11/26	2007/6/8	4170	3.982	1.932
25	Holland	SE MIDCAP	1983/1/3	2007/6/8	6112	4.036	1.675
26	Hungary	BUX	1991/1/4	2007/6/8	4094	7.962	2.620
27	Iceland	OMXICEX[3]	1993/2/24	2007/6/8	3436	8.851	0.5509
28	Italy	MIBTEL	1993/7/16	2007/6/8	3510	3.620	1.559
29	Norway	OBX	1987/6/8	2007/6/8	5006	3.602	1.980
30	Portugal	PSI General	1988/1/5	2007/6/8	4758	2.976	0.7902
31	Russia	RTSI	1995/9/1	2007/6/8	2871	10.05	8.102
32	Spain	IGBM	1974/1/2	2007/6/8	7680	3.277	1.263
33	Switzerland	SMI	1988/7/1	2007/6/8	4759	3.790	1.274
34	UK	FTSE 100	1984/1/2	2007/6/8	5908	3.170	1.047
Middle East / Africa							
35	Israel	TA 100	1987/4/23	2007/6/8	4879	6.778	2.584
36	South Africa	JSE Index	1973/1/1	2007/6/8	8839	3.317	2.479

Note: This table presents the summary statistics for 36 stock markets.

[1] N is the number of daily observations.

[2] Com. in the table stands for Composite.

[3] The All Share OMXICEX Index is used.

[4] $\overline{r} = \frac{1}{T}\sum_{i=1}^{T} r_i$ and $\overline{r^2} = \frac{1}{T}\sum_{i=1}^{T} r_i^2$

Table 7: FIEGARCH-M$(1, d, 1)$ model of daily market indices returns for 1987 stock market crash and 2001/9/11 terrorist attack crises

Parameter	US	Australia	Austria	Belgium	Canada	France	Holland
$\mu_0 \times 10^3$	0.4971	0.3010	0.4422	0.4785	0.4498	0.3454	0.4876
	(0.0551)	(0.111)	(0.130)	(0.0821)	(0.0788)	(0.181)	(0.121)
$\lambda_0 \times 10^3$	-4.585	-6.601	6.089	2.153	-3.552	-3.722	8.829
	(0.520)	(2.98)	(2.55)	(1.01)	(1.13)	(2.22)	(3.29)
$\lambda_1 \times 10^3$	2.862	4.952	-5.254	-2.276	1.826	-	-7.178
	(1.02)	(2.53)	(2.65)	(1.08)	(1.09)		(3.63)
$\lambda_2 \times 10^3$	3.637	2.068	-2.631	-0.3789	1.900	7.766	0.1395
	(1.42)	(1.28)	(1.36)	(1.08)	(1.50)	(3.67)	(3.18)
ω	-9.002	-9.160	-7.900	-9.259	-8.949	-8.763	-8.547
	(0.146)	(0.206)	(0.424)	(0.239)	(0.387)	(0.180)	(0.248)
δ	0.2371	0.1166	0.2230	0.1721	0.1633	0.1289	0.2571
	(0.0389)	(0.0537)	(0.0512)	(0.0595)	(0.0379)	(0.0614)	(0.0535)
θ	-0.1327	-0.1753	-0.04459	-0.05459	-0.08582	-0.06856	-0.04758
	(0.0132)	(0.0496)	(0.0185)	(0.0171)	(0.0192)	(0.0186)	(0.0115)
γ	0.2058	0.3582	0.4081	0.3451	0.3154	0.1169	0.1509
	(0.0138)	(0.121)	(0.0420)	(0.0435)	(0.0443)	(0.0293)	(0.0246)
ψ_1	-0.4996	-0.6986	-0.5781	-0.4726	-0.8908	-0.3209	0.09326
	(0.133)	(0.140)	(0.163)	(0.117)	(0.0643)	(0.311)	(0.358)
ϕ_1	0.7332	0.8105	0.7391	0.8756	0.9579	0.8452	0.7174
	(0.0870)	(0.0882)	(0.112)	(0.0305)	(0.239)	(0.112)	(0.130)
d	0.5460	0.4218	0.5183	0.2855	0.4660	0.4634	0.5018
	(0.0251)	(0.0788)	(0.0531)	(0.0804)	(0.0643)	(0.116)	(0.0690)
Q_{10}	93.21**	71.51**	226.79**	303.31**	307.74**	18.13	32.48**
Q_{100}	199.05**	182.27**	355.14**	445.88**	407.09**	103.31	113.66
Q_{10}^A	38.47**	21.51*	4.20	11.62	17.13	22.36*	9.47
Q_{100}^A	256.25**	134.89*	94.26	117.51	113.16	117.02	119.68

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to $K'th$ order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$, are denoted Q_K and Q_K^A respectively. As in (8), λ_1 represents the risk premium for the 1987 stock market crash, λ_2 represents the risk premium for the 9/11 attack. * and ** indicate significance level of 5% and 1% respectively.

Table 7 (Cont): FIEGARCH-M$(1, d, 1)$ model of daily market indices returns for 1987 stock market crash and 2001/9/11 terrorist attack crises

Parameter	Hong Kong	Hungary	Iceland	Indonesia	Israel	Italy	Japan
$\mu_0 \times 10^3$	0.9123	0.7093	1.041	0.02723	0.5893	0.4330	0.4182
	(0.133)	(0.171)	(0.124)	(0.276)	(0.179)	(0.175)	(0.0729)
$\lambda_0 \times 10^3$	4.223	3.500	1.999	1.801	3.470	-1.934	0.9077
	(1.76)	(0.866)	(0.673)	(0.558)	(23.2)	(4.30)	(0.912)
$\lambda_1 \times 10^3$	-1.524	-	-	-	4.306	-	-1.266
	(2.12)				(23.0)		(1.46)
$\lambda_2 \times 10^3$	-2.130	-4.473	-2.601	-3.380	1.015	3.320	4.538
	(1.76)	(1.54)	(1.25)	(1.21)	(2.70)	(4.45)	(1.66)
ω	-7.676	-7.771	-8.249	-5.434	-7.844	-8.707	-8.627
	(0.254)	(0.297)	(0.459)	(2.26)	(0.311)	(0.250)	(0.210)
δ	0.3011	0.04361	0.07476	0.1500	0.03575	0.1759	0.3309
	(0.0393)	(0.0642)	(0.0511)	(0.0815)	(0.0299)	(0.0414)	(0.0475)
θ	-0.04982	-0.03518	0.04060	0.06712	-0.06634	-0.06084	-0.1136
	(0.0139)	(0.0435)	(0.0183)	(0.0338)	(0.0206)	(0.0151)	(0.0269)
γ	0.2056	0.5340	0.3461	0.5357	0.2173	0.2147	0.3337
	(0.0207)	(0.0394)	(0.0547)	(0.0765)	(0.0322)	(0.0371)	(0.0522)
ψ_1	-0.5602	-0.7499	0.5690	-0.9415	0.1582	-0.09210	-0.3598
	(0.107)	(0.0917)	(0.775)	(0.130)	(0.458)	(0.321)	(0.170)
ϕ_1	0.8574	0.8961	-0.1997	0.9877	0.5982	0.7205	0.6478
	(0.0545)	(0.0443)	(0.787)	(0.0158)	(0.239)	(0.129)	(0.101)
d	0.4655	0.3210	0.5761	0.3518	0.4600	0.4651	0.4885
	(0.0663)	(0.0869)	(0.0621)	(0.228)	(0.0754)	(0.0831)	(0.0330)
Q_{10}	172.64^{**}	117.24^{**}	149.16^{**}	411.13^{**}	47.52^{**}	24.52^{**}	152.91^{**}
Q_{100}	277.18^{**}	196.45^{**}	339.59^{**}	744.00^{**}	121.41^{**}	107.98	261.84^{**}
Q^A_{10}	16.86^{**}	11.97	7.97	49.26^{**}	15.19	13.08	28.95^{**}
Q^A_{100}	123.11^{**}	98.00	105.11	259.25^{**}	99.71	121.53	131.26^{*}

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to $K'th$ order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$, are denoted Q_K and Q^A_K respectively. As in (8), λ_1 represents the risk premium for the 1987 stock market crash, λ_2 represents the risk premium for the 9/11 attack. * and ** indicate significance level of 5% and 1% respectively.

Table 7 (Cont): FIEGARCH-M$(1, d, 1)$ model of daily market indices returns for 1987 stock market crash and 2001/9/11 terrorist attack crises

Parameter	Mexico	Norway	Pakistan	Portugal	Russia	Sg[1]	S. Africa[2]
$\mu_0 \times 10^3$	0.7102	0.5715	0.7319	0.4065	2.001	0.5034	0.5259
	(0.219)	(0.191)	(0.188)	(0.129)	(0.380)	(0.151)	(0.121)
$\lambda_0 \times 10^3$	-11.87	-6.864	2.069	0.3142	9.947	7.553	-4.575
	(2.08)	(1.35)	(1.02)	(0.570)	(4.80)	(2.19)	(2.03)
$\lambda_1 \times 10^3$	-	6.282	-	-	-	-6.924	3.562
		(1.70)				(2.28)	(2.21)
$\lambda_2 \times 10^3$	8.713	-0.4115	-2.980	-1.395	-11.23	-1.155	-1.155
	(2.56)	(1.91)	(1.76)	(0.822)	(5.01)	(2.13)	(2.56)
ω	-7.102	-8.417	-8.068	-8.544	-6.837	-8.448	-7.847
	(0.210)	(0.214)	(0.236)	(0.421)	(0.294)	(0.263)	(0.231)
δ	0.1482	0.1779	0.2468	0.3800	0.1627	0.4243	0.05574
	(0.0401)	(0.0720)	(0.0519)	(0.144)	(0.0452)	(0.0992)	(0.0346)
θ	-0.1448	-0.1249	-0.002266	-0.02039	-0.02005	-0.08531	-0.07241
	(8.26×10^{-3})	(0.0312)	(0.0162)	(0.0367)	(0.0220)	(0.0284)	(0.0210)
γ	0.2576	0.3370	0.4505	0.5104	0.3786	0.3781	0.2833
	(0.0198)	(0.0655)	(0.0449)	(0.0624)	(0.0519)	(0.0458)	(0.0545)
ψ_1	0.3069	-0.3701	-0.1618	-0.6921	0.2216	-0.5324	-0.4042
	(0.283)	(0.196)	(0.544)	(0.604)	(0.225)	(0.236)	(0.244)
ϕ_1	0.1664	0.6982	0.5674	0.6969	0.6631	0.7793	0.7646
	(0.178)	(0.115)	(0.435)	(0.565)	(0.140)	(0.118)	(0.113)
d	0.5484	0.4092	0.4351	0.5050	0.4344	0.4204	0.3987
	(0.0326)	(0.0827)	(0.110)	(0.0518)	(0.0672)	(0.0555)	(0.0934)
Q_{10}	80.36^{**}	49.49^{**}	271.08^{**}	295.56^{**}	93.83^{**}	194.37^{**}	100.14^{**}
Q_{100}	189.16^{**}	140.16^{**}	330.47^{**}	490.30^{**}	178.13^{**}	312.99^{**}	182.41
Q^A_{10}	20.98^{*}	9.21	13.21	21.66^{*}	8.83	12.46	7.47
Q^A_{100}	107.66	84.96	104.22	125.93^{*}	85.24	107.69	120.89

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to $K'th$ order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$, are denoted Q_K and Q^A_K respectively. As in (8), λ_1 represents the risk premium for the 1987 stock market crash, λ_2 represents the risk premium for the 9/11 attack. * and ** indicate significance level of 5% and 1% respectively.

[1] Singapore, [2] South Africa

Table 7 (Cont): FIEGARCH-M$(1, d, 1)$ model for daily market indices returns for 1987 stock market crash and 2001/9/11 terrorist attack crises

Parameter	Spain	Sweden	Switzerland	Taiwan	Thailand	UK	Venezuela
$\mu_0 \times 10^3$	0.4351	0.7522	0.3527	0.5056	0.2698	0.3384	0.9827
	(0.120)	(0.186)	(0.154)	(0.144)	(0.110)	(0.114)	(0.263)
$\lambda_0 \times 10^3$	−1.771	−4.343	−3.107	4.283	1.648	−3.132	4.701
	(4.10)	(4.02)	(1.28)	(1.83)	(0.385)	(2.19)	(2.19)
$\lambda_1 \times 10^3$	−2.168	−1.035	-	−4.403	−1.516	0.6558	-
	(3.15)	(4.12)		(3.39)	(1.17)	(2.49)	
$\lambda_2 \times 10^3$	4.174	6.089	5.864	1.404	−1.233	5.009	−2.699
	(4.61)	(2.12)	(1.64)	(3.53)	(2.91)	(2.37)	(2.14)
ω	−8.930	−8.901	−9.147	−8.095	−7.684	−9.211	−7.352
	(0.190)	(0.164)	(0.138)	(0.186)	(0.286)	(0.190)	(0.486)
δ	0.2895	0.2589	0.3101	0.3309	0.1605	0.1106	0.2858
	(0.0493)	(0.0775)	(0.0851)	(0.0475)	(0.0498)	(0.0583)	(0.0729)
θ	−0.07537	−0.1396	−0.1537	−0.04165	−0.01040	−0.07703	0.09262
	(0.0534)	(0.0180)	(0.0446)	(0.0107)	(0.0322)	(0.0177)	(0.0281)
γ	0.3783	0.2211	0.2344	0.3337	0.4905	0.1862	0.5026
	(0.0437)	(0.0317)	(0.0343)	(0.0522)	(0.0562)	(0.0326)	(0.0705)
ψ_1	−0.6935	−0.4181	−0.4851	0.2256	−0.3887	−0.2698	−0.4520
	(0.0641)	(0.145)	(0.158)	(0.0330)	(0.405)	(0.287)	(0.193)
ϕ_1	0.9045	0.8185	0.9040	0.4893	0.6094	0.6995	0.7964
	(0.0257)	(0.0788)	(0.0957)	(0.204)	(0.334)	(0.151)	(0.123)
d	0.3347	0.3582	0.2390	0.4898	0.4798	0.5299	0.3341
	(0.0831)	(0.106)	(0.199)	(0.0440)	(0.0687)	(0.0581)	(0.120)
Q_{10}	325.18**	27.93**	15.05	85.86**	368.30**	17.73	152.45**
Q_{100}	439.91**	141.63**	93.26	218.58**	553.98**	103.70	248.97**
Q^A_{10}	15.29	33.59**	17.70	23.11*	16.90	17.68	15.57
Q^A_{100}	131.73*	194.67**	163.71**	121.97	119.94	125.37*	115.16

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to $K'th$ order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$, are denoted Q_K and Q_K^A respectively. As in (8), λ_1 represents the risk premium for the 1987 stock market crash, λ_2 represents the risk premium for the 9/11 attack. * and ** indicate significance level of 5% and 1% respectively.

Figure 2: Scatter Plot of r_t vs $g(z_{t-1})$ from FIEGARCH(1,1) model without in-mean term for CRSP value-weighted index, prior to the 1987 market crash (1926/1/2 – 1987/10/18)

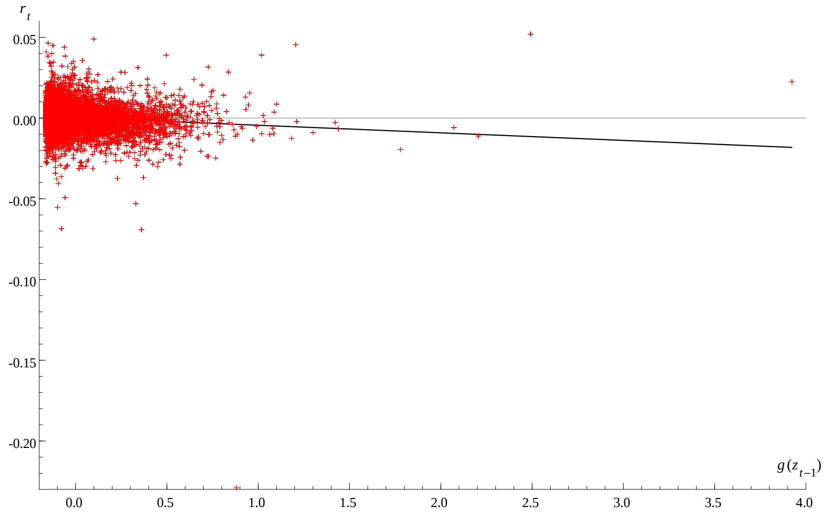

Figure 3: Scatter Plot of r_t vs $g(z_{t-1})$ from FIEGARCH(1,1) model without in-mean term for CRSP value-weighted index, after the 1987 market crash (1987/10/19 – 2006/12/31)

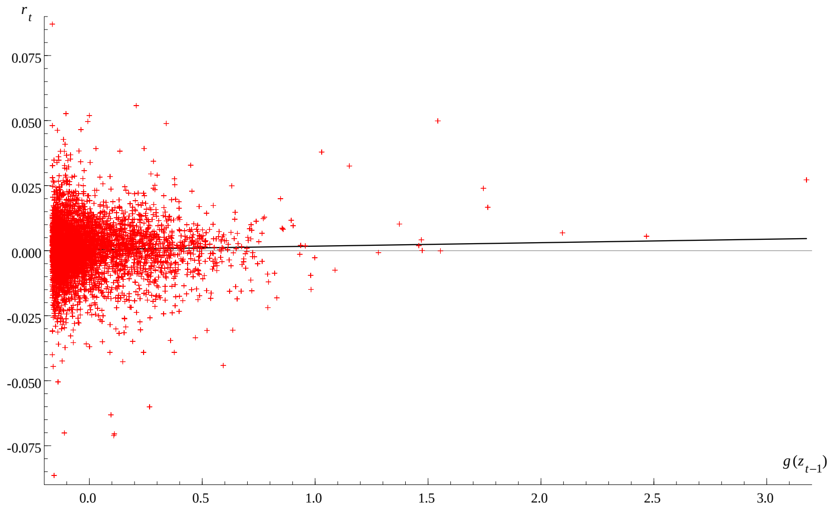

Table 8: FIEGARCH-M$(1, d, 1)$ model of daily market indices returns for 2000 dotcom crisis

Parameter	US	Germany	Italy	UK
$\mu_0 \times 10^{-3}$	0.2973 (0.0587)	0.2997 (0.167)	0.4212 (0.313)	0.3339 (0.108)
$\lambda_0 \times 10^{-3}$	-4.333 (0.625)	-0.6899 (1.60)	-5.004 (10.4)	-3.139 (1.13)
$\lambda_1 \times 10^{-3}$	5.887 (1.13)	3.101 (3.69)	7.024 (10.2)	6.095 (2.42)
ω	-9.082 (0.232)	-8.361 (0.287)	-8.711 (0.246)	-9.211 (0.188)
δ	0.1998 (0.0407)	0.2270 (0.0871)	0.1795 (0.0413)	0.1113 (0.0583)
θ	-0.1250 (0.0191)	-0.04734 (0.0158)	-0.06343 (0.0168)	-0.07679 (0.0174)
γ	0.2071 (0.0277)	0.1200 (0.0260)	0.2137 (0.0414)	0.1851 (0.0314)
ψ_1	-0.6938 (0.153)	0.1109 (0.350)	-0.08605 (0.370)	-0.2619 (0.282)
ϕ_1	0.8364 (0.0966)	0.7541 (0.0897)	0.7185 (0.130)	0.6998 (0.148)
d	0.5500 (0.0543)	0.4656 (0.0586)	0.4645 (0.0819)	0.5282 (0.0583)
Q_{10}	69.28^{**}	10.15	24.27^{**}	368.30^{**}
Q_{100}	160.81^{**}	119.91	107.84	553.98^{**}
Q_{10}^A	23.39^{**}	20.71^{*}	12.80	16.90
Q_{100}^A	160.63^{**}	157.31^{**}	121.59	119.94

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to K^{th} order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$ re denoted Q_K and Q_K^A respectively. As in (8), λ_1 represents the risk premium for the 2000 dotcom bubble. * and ** indicate significance level of 5% and 1% respectively.

Table 9: FIEGARCH-M $(1, d, 1)$ model of daily market indices returns for 1997 Asian financial crisis

Parameter	Indonesia	South Korea	Thailand	Hong Kong	Malaysia
$\mu_0 \times 10^{-3}$	2.292 (33.1)	0.4646 (0.146)	0.2544 (0.161)	0.9084 (0.141)	0.2269 (0.166)
$\lambda_0 \times 10^{-3}$	1.819 (0.579)	0.8299 (1.59)	1.510 (0.463)	3.282 (1.65)	-0.1163 (4.19)
$\lambda_1 \times 10^{-3}$	-2.811 (1.25)	-1.057 (2.21)	-1.493 (6.24)	-2.189 (2.04)	0.4025 (4.12)
ω	-5.432 (2.57)	-8.313 (0.208)	-7.681 (0.347)	-7.678 (0.254)	-7.595 (0.474)
δ	0.1492 (0.0809)	0.5375 (0.0623)	0.1588 (0.0500)	0.3463 (0.0524)	0.2582 (0.0526)
θ	-0.06640 (0.0485)	-0.04178 (0.0122)	-5.707×10^{-3} (0.0454)	-0.05013 (0.0148)	-0.06409 (0.0217)
γ	0.5353 (0.0870)	0.2788 (0.0294)	0.4851 (0.0719)	0.3018 (0.0393)	0.3419 (0.0455)
ψ_1	-0.9426 (0.135)	-0.1856 (0.225)	-0.3009 (1.08)	-0.5602 (0.108)	0.9586 (0.295)
ϕ_1	0.9878 (0.0175)	0.6067 (0.133)	0.5380 (0.939)	0.8572 (0.0556)	-0.5815 (0.271)
d	0.3533 (0.240)	0.5207 (0.0466)	0.4890 (0.127)	0.4649 (0.0682)	0.6460 (0.0414)
Q_{10}	414.44^{**}	82.20^{**}	370.86^{**}	171.42^{**}	123.10^{**}
Q_{100}	753.16^{**}	185.71^{**}	557.12^{**}	275.56^{**}	200.56^{**}
Q_{10}^A	49.79^{**}	10.44	17.29	17.34	3.80
Q_{100}^A	258.51^{**}	122.11	118.77	124.04	114.79

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to K^{th} order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$ re denoted Q_K and Q_K^A respectively. As in (8), λ_1 represents the risk premium for the 1997 Asian financial crisis. * and ** indicate significance level of 5% and 1% respectively.

Table 9 (Cont): FIEGARCH-M $(1, d, 1)$ model of daily market indices returns for 1997 Asian financial crisis

Parameter	Philippines	China	Singapore	Taiwan
$\mu_0 \times 10^{-3}$	0.3386	0.4834	0.5162	0.5057
	(0.177)	(0.441)	(0.137)	(0.141)
$\lambda_0 \times 10^{-3}$	2.280	12.90	1.580	3.449
	(2.05)	(4.62)	(1.22)	(1.82)
$\lambda_1 \times 10^{-3}$	−1.516	−10.73	−1.661	−2.534
	(2.11)	(4.26)	(1.59)	(2.76)
ω	−6.846	−6.034	−8.485	−8.096
	(0.937)	(0.743)	(0.222)	(0.186)
δ	0.3364	0.1312	0.4232	0.6724
	(0.0870)	(0.0479)	(0.0994)	(0.0538)
θ	−0.03419	0.04420	−0.08916	−0.04150
	(0.0174)	(0.0342)	(0.0264)	(0.0111)
γ	0.3306	0.3467	0.3745	0.2269
	(0.0462)	(0.0681)	(0.0529)	(0.0344)
ψ_1	−0.2492	0.1459	−0.5313	0.4044
	(0.579)	(0.237)	(0.170)	(0.404)
ϕ_1	0.5478	0.8337	0.7830	0.4916
	(0.462)	(0.182)	(0.0967)	(0.211)
d	0.5500	0.2936	0.4128	0.4903
	(0.105)	(0.214)	(0.0550)	(0.0449)
Q_{10}	246.30^{**}	64.69^{**}	196.07^{**}	171.42^{**}
Q_{100}	364.82^{**}	217.47^{**}	316.00^{**}	275.56^{**}
Q^A_{10}	49.79^{**}	15.79	13.03	17.34
Q^A_{100}	258.51^{**}	117.23	106.15	124.04

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to Kth order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$ re denoted Q_K and Q^A_K respectively. As in (8), λ_1 represents the risk premium for the 1997 Asian financial crisis. * and ** indicate significance level of 5% and 1% respectively.

Table 10: FIEGARCH-M$(1, d, 1)$ model of daily major market indices returns for country-specific crisis

Parameter	Argentina	Brazil	Chile	Japan	Mexico
$\mu_0 \times 10^{-3}$	0.8212	1.182	0.6305	0.4158	0.7332
	(0.328)	(0.395)	(0.104)	(0.0724)	(0.242)
$\lambda_0 \times 10^{-3}$	−3.224	−3.496	2.217	0.6569	−16.27
	(2.95)	(5.15)	(0.848)	(0.909)	(2.54)
$\lambda_1 \times 10^{-3}$	0.8774	1.990	−0.4461	1.300	12.10
	(3.35)	(5.97)	(0.720)	(1.089)	(26.2)
ω	−7.514	−6.154	−8.232	−8.614	−7.059
	(0.196)	(0.448)	(0.540)	(0.212)	(0.522)
δ	0.1693	0.01993	0.06362	0.3302	0.1443
	(0.0478)	(0.0315)	(0.0355)	(0.0475)	(0.0456)
θ	−0.1077	−0.05873	0.04377	−0.1163	−0.1492
	(0.0237)	(0.0173)	(0.0185)	(0.0279)	(0.0190)
γ	0.2558	0.2059	0.5059	0.3341	0.2704
	(0.0372)	(0.0365)	(0.0629)	(0.0511)	(0.0325)
ψ_1	−0.3636	0.4764	0.07840	−0.3705	0.2828
	(0.277)	(0.471)	(0.562)	(0.166)	(0.273)
ϕ_1	0.6983	0.3040	0.1060	0.6493	0.1500
	(0.183)	(0.189)	(0.387)	(0.0989)	(0.178)
d	0.4434	0.6196	0.5775	0.4904	0.5545
	(0.0891)	(0.0489)	(0.0426)	(0.0323)	(0.0509)
Q_{10}	37.85**	53.70**	707.74**	154.92**	78.38**
Q_{100}	126.96**	240.32**	835.58**	263.07**	186.93**
Q^A_{10}	19.72*	29.44**	12.16	28.81**	18.49*
Q^A_{100}	89.55	143.63**	91.27	131.78*	100.76

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to Kth order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$ re denoted Q_K and Q^A_K respectively. As in (8), λ_1 represents the risk premium for the country-specific crisis. * and ** indicate significance level of 5% and 1% respectively.

Table 10 (Cont): FIEGARCH-M$(1, d, 1)$ model for daily market indices returns for country-specific crisis

Parameter	Peru	Russia	South Africa	Venezuela
$\mu_0 \times 10^{-3}$	1.116 (0.159)	2.046 (0.334)	0.5258 (0.176)	0.9912 (0.242)
$\lambda_0 \times 10^{-3}$	7.962 (1.69)	6.382 (5.80)	−3.049 (2.29)	4.636 (1.94)
$\lambda_1 \times 10^{-3}$	−6.592 (1.70)	−6.183 (5.93)	1.530 (2.19)	−1.880 (2.14)
ω	−8.138 (0.256)	−6.892 (0.287)	−7.846 (0.231)	−7.334 (0.488)
δ	0.07482 (0.0379)	0.1656 (0.0457)	0.05624 (0.0349)	0.2855 (0.0724)
θ	0.03051 (0.0188)	−0.02718 (0.0215)	−0.07365 (0.0208)	0.08978 (0.0284)
γ	0.5182 (0.0551)	0.3884 (0.0523)	0.2813 (0.0530)	0.5128 (0.0634)
ψ_1	0.3014 (0.333)	−0.2738 (0.215)	−0.4114 (0.232)	−0.4624 (0.185)
ϕ_1	−0.03533 (0.338)	0.6829 (0.134)	0.7671 (0.110)	0.8000 (0.116)
d	0.4976 (0.0509)	0.4282 (0.0677)	0.4011 (0.0908)	0.3337 (0.119)
Q_{10}	389.52^{**}	93.68^{**}	98.68^{**}	155.20^{**}
Q_{100}	552.82^{**}	177.71^{**}	180.75^{**}	252.51^{**}
Q_{10}^A	9.67	8.81	7.24	15.56
Q_{100}^A	82.82	81.67	120.71	114.58

Note: Quasi maximum likelihood estimates (QMLE) are reported with robust standard errors in parentheses. The values of the Ljung-Box portmanteau statistic for up to Kth order serial dependence in the standardized residuals, $\widehat{\varepsilon}_t/\widehat{\sigma}_t$, and the absolute standardized residuals, $|\widehat{\varepsilon}_t/\widehat{\sigma}_t|$ re denoted Q_K and Q_K^A respectively. As in (8), λ_1 represents the risk premium for the country-specific crisis. * and ** indicate significance level of 5% and 1% respectively.

Table 11: Wild-Bootstrap results for CRSP value-weighted (dividend included) index (1926.1.2 - 2006.12.31) with crisis risk factors

Parameter	US	Wild-Bootstrap std errors
$\mu_0 \times 10^3$	0.4971 (0.0551)	0.4971 (0.0484)
$\lambda_0 \times 10^3$	-4.585 (0.520)	-4.585 (0.456)
$\lambda_1 \times 10^3$	2.862 (1.02)	2.862 (0.881)
$\lambda_2 \times 10^3$	3.637 (1.42)	3.637 (1.41)
ω	-9.002 (0.146)	-9.002 (0.0666)
δ	0.2371 (0.0389)	0.2371 (4.66×10^{-3})
θ	-0.1327 (0.0132)	-0.1327 (9.87×10^{-3})
γ	0.2058 (0.0138)	0.2058 (0.0102)
ψ_1	-0.4996 (0.133)	-0.4996 (0.0733)
ϕ_1	0.7332 (0.0870)	0.7332 (0.0418)
d	0.5460 (0.0251)	0.5460 (0.0202)

Note: This table reports the standard errors obtained from Wild-Bootstrap procedure for US data as in Table 7. The Wild-Bootstrap algorithm described in Section 5 is conducted for $N = 249$ replications. The parameters are estimated for return series simulated in these replications. The wild-bootstrap standard errors are then calculated for these estimates collected from each replication.

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