Volatility Dynamics in African Equity Markets during Financial Crises

by

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Abstract

The focus of this paper is on volatility dynamics in five African stock markets. Special emphasis is placed on five crisis periods that occur between 1 January 1997 and 22 October 2010. Rolling-window bivariate diagonal-BEKK GARCH models are run between the African markets and markets taken as the sources of the crises from the start of the 14-year period until its end. It is found that while African volatility is persistent and volatility linkages exist between the five markets and the overseas markets, some of the effects of the crises are dominated by non-crisis period volatility dynamics and spillovers as well as domestic influences. This is especially the case for volatility persistence, unconditional volatility and the own- and cross-GARCH effects. The crisis that has the strongest impact on the volatility of the five African markets is the Credit Crisis, thus not providing support for the theory of emerging markets “decoupling” from the U.S.
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1. **Introduction**

African economies and equity markets are said to be the final investment frontier. Stock markets on this continent are increasingly attracting investors who are drawn to the possibility of growing economic and political stability and above-average investment returns. The focus of this paper is African stock market volatility, with particular emphasis on the persistence of volatility and volatility spillovers during crisis periods. Several papers show that stock market volatility and volatility spillovers increase during periods of financial instability. Aggarwal, Inclan, and Leal (1999) report a significant jump in emerging market volatility after the 1987 crash; Nikkinen, Omran, Sahlstrom, and Aijo (2008) find higher stock market volatility after the 11 September 2001 terrorist attacks in America than before; and Beirne, Corporale, Schultze-Ghattas, and Spagnolo (2008), Diebold and Yilmaz (2008), and Yilmaz (2009) report a rise in volatility spillovers between equity markets during periods of financial instability.

Five of Africa’s largest and most important stock markets, namely, Egypt, Kenya, Mauritius, Nigeria, and South Africa, are studied to see how they behaved with respect to volatility during five crisis periods between 1 January 1997 and 22 October 2010. Despite being more sophisticated than the others, South Africa is included because it is the largest and most important market in Africa. Egypt, Kenya and Nigeria were chosen because they are the most influential and largest markets in the North African, East African and West African regions, respectively. Mauritius is included in the study because it is ranked by Canada’s Fraser Institute as the freest economy in Africa and the ninth freest in the world; it has no foreign exchange controls, is one of the most open and liberalised capital markets in Africa, and has attempted to position itself as an offshore financial centre.

The five crises studied are the Asian Crisis of 1997, the Brazilian Crisis of 1998-9, the 1999 Russian/Ruble Crisis, the bursting of the Dot Com Bubble from 2000-2, and the Global Financial/Credit Crisis of 2007-9. A rolling bivariate diagonal BEKK-GARCH model is used to determine the persistence of volatility for each African market and the transmission of volatility to the five markets from the equity markets that are taken as sources of the crises. Each regression is for a 1 000-day period and is moved forward by a day from the start of the 14-year period to the end. Equity markets in Brazil, Hong Kong, Russia and the United States (U.S.) are used as proxies for the source of the crises. A BEKK-GARCH model is used as it is widely applied in the literature.
and has sometimes been proven to give superior results to other GARCH models. Furthermore, a rolling window approach is taken to capture any additional changes that occur in volatility over time.

The average coefficients for cross-volatility innovation and the cross-GARCH effect are obtained from the BEKK-GARCH model and are important in determining the magnitude of the linkages between African and world equity markets. The average coefficients for own-volatility innovation and the own-GARCH effect, and as a result persistence and unconditional volatility are presented for each stock market during crisis and non-crisis periods. The findings for each African market during crises are then compared with each other and with the results for non-crisis periods. In addition, the behaviour of the markets from one crisis to the next are also analysed and compared.

The BEKK-GARCH is used by papers such as Kearney and Patton (2000); Ciffarelli and Paladino (2005); and Beirne, Caporale, Schultzze-Ghattas, and Spagnolo (2008); and as far as is known, this is the first time that a rolling bivariate BEKK-GARCH model is applied to African equity markets. Research originally done on volatility focused on developed markets and only later did emerging markets attract such attention. Even once emerging markets began to be investigated, little was done to include African markets and when they were, the papers mainly focused on South Africa and Egypt.

Studies focusing on African stock markets only came later. The liberalisation of African economies away from central planning and towards the free market after the fall of the Soviet Union in 1989 led to an increase in the number of stock exchanges and revitalised existing markets. Economic liberalisation also led to the implementation of capital market reforms, such as the relaxation or abolishment of exchange controls and the scaling back of restrictions on foreign and domestic investment (Smith, Jefferis, and Ryoo, 2002; Jefferis, K. and Smith, G., 2005), as well as changes in the way stock markets operated. The privatisation of state-owned enterprises gave an added boost to fledgling stock markets.

Nevertheless, the continuing small size, illiquidity, investor restrictions, and relative unsophistication of African stock markets (Smith, Jefferis, and Ryoo, 2002) deter local and foreign investors. Combining these factors with political and economic instability also raises the prospect of a high degree of uncertainty and, as a result, higher-than-normal risk. The result of this additional risk and
illiquidity is most likely increased volatility and if increased volatility does not result in higher returns, investment is further deterred. An additional factor that might raise volatility and hurt investor interest in Africa is capital market liberalisation itself, which may make capital markets more susceptible than before to periods of instability in major equity markets.

This paper finds that volatility is highly persistent for all five African markets in each crisis, with the most volatility persistence recorded during the Credit Crisis period. In contrast, the least volatility persistence is recorded during the Asian Crisis. The finding of strong volatility persistence is consistent with the findings of Schwert (1990) for a developed market such as the United States and of Rao (2008) for emerging Middle Eastern stock markets. However, the strong finding for volatility persistence is the opposite to what is found by Hassan, Maroney, El-Sady, and Telfah (2003) for Kenya and Nigeria; for which they report that volatility is not persistent, and the results of Haque, Hassan, Maroney, and Sackley (2004) for South Africa and Egypt, for which no evidence of volatility persistence is found. A later paper by Ogum, Beer, and Nouyrigat (2005) does, however, support the finding of volatility persistence for Kenya, as the authors report the GARCH parameter to be statistically significant.

Volatility spillovers during the five crises are also found to be quite strong. Cross-volatility innovation and the cross-GARCH effect are strong in all but one crisis, averaging above 0.10 and 0.80 respectively for four crises. Among the crises, cross-volatility innovation is strongest for the Russian/Ruble Crisis. Nevertheless, the weakest cross-GARCH effect for a crisis is found for the Russian Crisis. The strongest cross-GARCH effect occurs during the Credit Crisis, supporting Yilmaz’s (2009) finding that volatility spillovers to East Asian equity markets are at their height during the Credit Crisis. The most unconditional volatility occurs during the Credit Crisis, with the least during the Asian Crisis. Overall, the Credit Crisis is the most severe; it has the largest effect on African volatility, which is not surprising given that the crisis began in the world’s largest economy and quickly took on a global nature. The strong volatility spillovers found during the crises are supported by Diebold and Yilmaz (2008), Rao (2008), and Yilmaz (2009) for emerging markets.

Despite the strength of volatility persistence and the cross-GARCH effect during the five crisis periods, some crisis period coefficients are smaller than during non-crisis periods. Volatility persistence during non-crisis periods is stronger than during crisis periods in three of the five
markets for all the crises, except the Credit Crisis. And the cross-GARCH effect during crisis periods is consistently weaker than during the non-crisis periods for four markets across all five crises. The results are slightly better for unconditional volatility. Only for cross- and own-volatility innovation are the coefficients consistently greater during crisis periods than non-crisis periods for a majority of markets, the exception being own-volatility innovation during the bursting of the Dot Com Bubble period. Cross-volatility innovation and the cross-GARCH effect are also weaker than own-volatility innovation and the own-GARCH effect for a majority of the markets during three out of five crises.

From comparing the cross- and own-volatility coefficients the results suggest that the five crises do not have a strong impact on African volatility. The short-term impact of the crises on future volatility only dominates past domestic innovations during the Brazilian and Russian Crisis periods. The long-term effect of crises on future volatility only dominates past domestic shocks to volatility during the Asian and Credit Crisis periods. However, the long-term impact of the crises may be stronger than their short-term impact, if their long-term effect is interpreted to be felt with a delay, since the cross-GARCH effects between markets taken as the source of the crises and African markets are generally greater during non-crisis periods than crisis periods.

Nevertheless, the findings suggest that African stock market volatility is persistent and is not isolated from events that occur internationally, despite volatility persistence during non-crisis periods being stronger than during crisis periods for the majority of the markets, except during the Credit Crisis. The five markets experience volatility spillovers during all five crises, despite cross-volatility spillovers during non-crisis period sometimes outweighing the effects of the crises.

Considering the strength of volatility persistence and the cross- and own-GARCH effects during crisis and non-crisis periods over the entire fourteen year period, African markets behave no differently than developed and developing equity markets, with the possible exception that volatility persistence, unconditional volatility, and the respective GARCH effects are stronger for non-crisis periods than during crisis periods. Investors might, therefore, do well to invest in African equities during periods of global financial instability, if this is proven true by further investigation. Nevertheless, while investors might obtain higher mean returns by investing in African markets than elsewhere, as is borne out by the raw data; potential investors should remember that African
volatility is still highly persistent and not immune to periods of instability that occur in an increasingly globalised world.

This paper is organised as follows: Section 2 presents a literature review concerning volatility dynamics in developing and emerging stock markets as well as African equity markets. Sections 3 and 4 are focused on the methodology, and the characteristics and descriptive statistics of the data. Section 5 discusses the findings of this study. Finally, a summary of the key points and main findings are presented in the conclusion.

2. Literature Review

Before the Asian Crisis of 1997 emerging markets were of little interest in the study of volatility and its transmission. The majority of work centred on volatility, contagion and volatility spillovers in and between developed stock markets. Such was the importance of the events surrounding the Asian Crisis, however, that it introduced a whole new area of research that focused on the nature, different types and role of volatility in emerging equity markets; that had previously been considered to be of little significance. This new body of literature included important work, such as Bekaert and Harvey (1997) and Aggarwal, Inclan, and Leal (1999), which investigate volatility linkages and volatility transmission among emerging equity markets, as well as between emerging and developed markets.

Nevertheless, while the volume of literature focused on stock market volatility in emerging economies has grown, the studies most often investigated emerging equity markets in South-East Asia, the Middle East, Central and Eastern European Transition economies, and Latin America; while Africa receives little attention. In some cases studies pertaining to the Middle East, such as Nikkinen, Omran, Sahlstrom, and Aijo (2008) and Alkulaib, Najand, and Mashayekh (2009), include stock markets in North Africa but outside of South Africa’s relatively large equity market relatively little attention has been paid to stock market volatility in the rest of Africa. The little attention that is paid to African equity markets is due to a number of reasons, notably their small size, relative youth, low level of development, and lack of international investor attention and knowledge.

The focus of Section 1 is to consider the major work done on volatility in developed stock markets, and linkages between them and volatility spillovers to emerging equity markets. That is followed by a
review of literature focused only on emerging stock markets in South-East Asia, Latin America, and transition economies in Central and Eastern Europe. Finally, studies pertaining to equity markets in Africa are presented.

2.1. The Nature of Volatility in Developed Markets and its transmission from Developed Markets to Emerging Markets

There is plenty of literature about the nature of volatility and its transmission, linkages and spillovers concerning developed stock markets. Developed equity markets in North America, Europe and Japan are the original focus of studies concerned with volatility. The focus on developed world stock markets is because of their sheer dominance and size, high liquidity and ready availability of information. Another reason for that attention is that until the emergence of fast growing economies and viable stock markets in South-East Asia, investors were largely confined to equity markets in North America, Europe and Japan.

The seminal event for the United States and other developed markets is the stock market crash of October 1987 and the importance of that event is supported by the results of prior studies. Schwert (1990) finds that volatility is persistent during the period surrounding the 1987 crash for the Dow Jones Industrial Average and the S&P 500. Hamao, Masulis, and Ng (1990) report that the 1987 crash is an important event in the evolution of volatility transmission between developed markets. The authors use a generalized autoregressive conditional heteroscedastic-in-mean (GARCH-M) model and find evidence of volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London. The importance of the 1987 crash is further demonstrated by the fact that no price volatility spillover effects in other directions are found for the pre-October 1987 period. The findings of Hamao, Masulis and Ng provide mixed support for the results of Eun and Shim (1989), who use a nine-market vector autoregression system and report evidence of volatility transmission but in an earlier pre-1987 period of five years that ends in 1985. The authors find that the more economically and financially integrated two countries are with one another, such as the U.S. and Canada, the greater the effect on stock market correlations and volatility transmission. Overall, innovations in the U.S. are said to be rapidly transmitted to other developed markets but no single foreign market can significantly explain U.S. equity market movements.
Theodossiou and Lee (1993) support Schwert’s findings on the persistence of volatility, Eun and Shim’s (1989) results on the centrality of the U.S. market, and Hamao, Masulis, and Ng (1990) regarding volatility spillovers. Using a GARCH-M model, as do Hamao, Masulis, and Ng, Theodossiou and Lee investigate volatility spillovers across major equity markets from 1980–91, which includes the 1987 crash, and report high levels of own-volatility persistence in four developed markets and the existence of significant volatility spillovers from the U.S. to Canada, the U.K., Germany and Japan, and from the U.K. to Canada, and from Germany to Japan.

Further support for Hamao, Masulis, and Ng (1990) and the importance of the 1987 crash for volatility spillovers is provided by Hassan and Naka (1996), King, Sentana, and Wadhwani (1994), and Koutmos and Booth (1995). King, Sentana, and Wadhwani find that markets in the developed world exhibit a rise in correlation and move in unison in response to the 1987 crash, and Koutmos and Booth report that after the 1987 crash interactions among the New York, London and Tokyo Stock Exchanges increase substantially, which indicates greater interdependence. In addition, using data from Germany, Japan, the United Kingdom, and the United States, Hassan and Naka (1996) investigate dynamic linkages between markets and show that integration and equilibrium relationships for two sets of three markets increase post the 1987 crash. Hassan and Naka find that the United States leads the other equity markets, both in the short- and long-run.

The effect of the 1987 crash also spread – unsurprisingly – to emerging markets. Arshanapalli, Doukas, and Lang (1995) report more co-integration between Asian equity markets and the U.S. post-1987 than before. Pre-1987 the authors find no significant co-integration between the U.S. and Asia. Chaudry (1996) investigates the impact of the 1987 crash on stock market volatility in six emerging markets, including Zimbabwe, and reports changes in the ARCH parameter, risk premia and volatility persistence before and after the crash. However, the changes are not uniform and are dependent on individual markets, with the ARCH effect disappearing in India and Mexico after the crash and appearing post the crash in Zimbabwe. In addition, the persistence of shocks to volatility is permanent before the crash in Thailand and Mexico, but the reverse is found for India and Greece.

In addition, Ng (2000) reports results along these lines in her investigation into volatility spillover effects from Japan and the U.S. to Pacific-Basin equity markets. Ng uses a volatility spillover model
incorporating a bivariate GARCH(1,1) model for the U.S. and Japan and a univariate volatility spillover model to capture innovations in Japan and the U.S. that might influence the returns of Pacific-Basin markets. Korean stock market variance is found by the author to increase sharply in response to U.S. innovations during the 1987 crash, and equity market volatility in Malaysia is reported to be strongly affected by U.S. stock market volatility post the 1987 crash, until mid-1989.

Nevertheless, despite the importance and severity of the 1987 crash on global stock markets, views differ on whether volatile periods, including the October crash, amount to “contagion”, which is defined by Forbes and Rigobon (2002) as a significant increase in cross-market linkages after a shock to one or many countries. King and Wadhwani (1990) provide evidence for contagion effects during the 1987 crash. Their study finds that contagion coefficients increase during and immediately after the crash and then fall to previous levels afterwards, thereby supporting the contagion hypothesis. However, after adjusting for changes in market volatility, Forbes and Rigobon (2002) report no contagion from the U.S. to other markets for the crash of 1987. Overall, Forbes and Rigobon find evidence of comovement and interdependence, but not of contagion.

Other important events emanating from developed stock markets are 11 September 2001 attacks on New York and the Global Credit/Financial Crisis of 2007-9. Hon, Strauss, and Yong (2004) investigate the impact of the September 11 attacks and find that while daily comovement increases internationally, European stock markets respond more closely to shocks to U.S. equities in the three to six months after the attacks than before. Fernandez (2006) reports that September 11 has a stronger impact on volatility in developed markets than in emerging markets. Nikkinen, Omran, Sahlstrom, and Aijo (2008) support the findings of Hon, Strauss, and Yong, and Fernandez (2006). The authors confirm a significant increase in volatility worldwide but the impact of the September 11 attacks varies widely across regions. In the post-September 11 period European and other developed markets show significantly higher volatility than other regions shortly after the attacks, whereas in the Middle East and North Africa (MENA) region volatility increases, but not by as much. The reason for this is said to be the MENA region’s lack of integration with the international economy, leading to MENA stock markets having less exposure to global shocks.

The impact on world stock market volatility of the Global Financial/Credit Crisis of 2007-9 seems to be no different from previous crises, barring the timing of the impact across regions. Emerging
markets, for instance, may only be fully affected by what happened in the U.S. later than developed countries. Frank and Hesse (2009), and Yilmaz (2009) write that emerging markets are only fully affected by the subprime crisis after the collapse of Lehman Brothers on 15 September 2008, when, according to the authors, a full-blown systemic crisis begins. The Lehman collapse leads to a rise in uncertainty across markets, and Frank and Hesse present evidence of structural breaks in the VIX Index (a measure of U.S. equity market volatility) and other implied volatility stock indices as a result of the bank’s failure. Ramlall (2010) finds the sub-prime crisis leads to an upsurge in volatility clustering in stock markets in China, France, Germany, Hong Kong, India, Japan, South Africa, the U.S. and the U.K, with Mauritius being the only exception. Ramlall also shows that, except for the Indian market, volatility is higher post the sub-prime crisis than before, and is also more persistent.

Volatility linkages and stock market correlations in general are strong and may be strengthening. Berben and Jansen (2005) find correlations among the German, U.K., and U.S. markets double between 1980 and 2000. However, the rise in correlation is uneven, as Japanese market correlation with Germany, the U.K. and U.S remaining constant. Beirne, Corporale, Schultze-Ghattas, and Spagnolo (2008) use a tri-variate BEKK-GARCH model to show that three quarters of emerging equity markets in Asia, Latin America (except Venezuela), and two-thirds of emerging Europe’s markets experience volatility spillovers from mature markets over the period 1993 to 2008. Nevertheless, there is a shift in the transmission of volatility during turbulent periods in mature markets and it is only during unstable episodes that emerging markets appear to be affected by developed market volatility. One reason why volatility spillovers may be becoming more pronounced may be because of increased financial integration. For European Union members, Savva (2009) finds that equity markets become more correlated with each other as countries become more economically integrated and the Euro is introduced.

2.2. Volatility Dynamics in Emerging Markets

As more attention has shifted to emerging markets, studies focusing on their volatility dynamics have become varied, investigating the same issues that are of interest for developed markets. Studies generally find evidence of more volatility in emerging markets than in developed markets; that the Asian Crisis is a seminal event and that emerging market volatility is heavily affected by global crises originating in the developed world, such as the 1987 Stock Market Crash and the Global Financial
Crisis of 2007–9. In addition, volatility spillovers are found not only from developed to emerging stock markets, as discussed above, but between emerging markets themselves.

Bekaert and Harvey (1997), and Aggarwal, Inclan and Leal (1999) undertake important studies on emerging equity market volatility, with Bekeart and Harvey even including the African markets of Nigeria and Zimbabwe. Bekaert and Harvey cover a wide range of issues, especially the wide disparity in the range of unconditional volatility between emerging and developed stock markets, and the effect of capital market liberalization on volatility in emerging markets. The authors find emerging market returns exhibit high unconditional volatility, ranging in over twenty countries from 18 per cent for Jordan to 104 per cent for Argentina, compared to a 1993 study by Harvey in which he reports that volatility in developed markets ranges from 15 per cent for the U.S. to 33 per cent for Hong Kong. Overall, the study finds that the four sources of volatility differences are the degree of asset diversification and concentration, equity market development/economic integration, microstructure effects and macroeconomic influences, and political risks.

The most important conclusion of Bekaert and Harvey is that more open economies experience less stock market volatility. A world factor model shows that only Pakistan’s conditional volatility is much greater after liberalisation, while most of the other 17 countries that opened up their economies saw volatility fall. Dramatic declines in conditional volatility are observed for Brazil, Mexico, Taiwan and Portugal after liberalization. Volatility may even change before the liberalisation date if liberalisation measures are pre-announced or anticipated by the market. Despite finding that more liberalisation leads to lower stock market volatility, Bekaert and Harvey report that the proportion of variance caused by world factors is quite small for emerging markets.

Aggarwal, Inclan, and Leal use the iterated cumulative sums of squares (ICSS) algorithm of Inclan and Tiao (1994) to identify points of sudden change in the variance of returns in emerging markets and the time period for which any shifts last. A GARCH(1,1) model containing no sudden changes and a GARCH(1,1) model incorporating sudden changes obtained from the ICSS algorithm are estimated. The GARCH(1,1) with no sudden changes shows the coefficients that measure the persistence of volatility are significant and high for 16 out of 20 series, whereas much weaker results are reported for a GARCH(1,1) model that includes sudden changes identified by the ICSS algorithm. For a GARCH(1,1) with sudden changes, the GARCH coefficients are significant for
only Taiwan and Japan. The other major findings of Aggarwal, Inclan and Leal are that over a ten-year period from 1985–95 the October 1987 crash is the only global event that causes a significant jump in the volatility of several emerging equity markets and that liberalisation has no discernable impact on emerging market volatility. The results of Aggarwal, Inclan and Leal for liberalisation is at odds with what Bekaert and Harvey report, despite the authors’ agreement that the share of emerging market variance emanating from world factors is quite small.

The other important global event that impacts on emerging market volatility is the Asian Financial Crisis, which began in an emerging market with the devaluation of the Thai baht on 2 July 1997. Baig and Goldfajn (1999) investigate contagion between the financial markets of Thailand, Malaysia, Indonesia, South Korea and the Philippines during the Asian Crisis, and initially find that stock market correlations provide mixed evidence of contagion. However, after controlling for own-country news and other fundamentals, there is support for cross-border contagion.

Wang and Moore (2007) support Aggarwal, Inclan, and Leal’s results with regard to the incorporation of sudden volatility changes when studying volatility. When sudden changes in volatility are included in a GARCH model for emerging Central European stock markets, the authors report a considerable reduction in volatility persistence. The findings of Aggarwal, Inclan, and Leal and Wang and Moore are important because they suggest that volatility persistence may be overstated in emerging markets. However, Bekaert and Harvey’s result that emerging market volatility is higher than developed market volatility is confirmed by Fayyad and Daly (2010). Fayyad and Daly compare volatility in the U.S. and U.K. markets to volatility in the emerging markets of Kuwait and the United Arab Emirates and also find emerging market volatility to be greater than developed market volatility.

The findings of Baig and Goldfajn are not supported by Forbes and Rigobon, who find no evidence of contagion during the Asian Crisis after no increase in unconditional correlation coefficients between equity markets is observed. No evidence of contagion is found for the Mexican devaluation of 1994 either. Forbes and Rigobon do find high a level of comovement among markets during the Asian Crisis, as is found for the 1987 crash, but call this interdependence. Some support is found for both Baig and Goldfajn, and Forbes and Rigobon by Chan-Lau, Mathieson, and Yao (2004). Chan-Lau, Mathieson, and Yao find that the Mexican Peso Crisis of 1994 does not have a major
impact on contagion, but that the 1998 Russian/Ruble Crisis and Brazilian Crisis lead to a global increase in contagion and have a lasting impact on the world’s financial system. However, the Asian Crisis is found by the authors to be only a regional event.

The importance and severity of the Asian Crisis should not be understated though, especially with regard to global volatility spillovers. Caporale, Pittis, and Spagnolo (2006) find that the Asian Crisis causes volatility spillovers between U.S., European, Japanese and South East Asian equities. Raghavan (2008) uses the U.S. and Japan as the world and regional shocks to examine the effect of the Asian Crisis on Malaysia, Singapore and Hong Kong. The author finds that the U.S. and Japan play a significant role in transmitting volatility spillovers in the Pacific-Basin region. While the U.S. is more influential before the crisis, Japan is more influential after the crisis. Wang and Lee (2009) confirm Raghavan’s results and find that Hong Kong, Singapore, Malaysia, Thailand and Japan play important roles in transmitting the Asian Crisis. Spillover effects for volatility among the nine Asian (mostly emerging) markets used in the study are larger after the crisis than before the crisis.

The presence of volatility spillovers and linkages among emerging equity markets is further confirmed by Alkulaib, Najand, and Mashayekh (2009), Diebold and Yilmaz (2008), Rao (2008), Worthington and Higgs (2004), and Yilmaz (2009). (The studies done by Diebold and Yilmaz, and Yilmaz cover for longer time periods.) Diebold and Yilmaz (2008) develop a spillover index to investigate volatility spillovers among the four Latin American stock markets of Argentina, Brazil, Chile and Mexico as well as the United States from 1992 to 2008. The authors find that volatility spillovers just between South American countries alone, at a magnitude of 25 per cent, are sizeable. Volatility spillovers are also impacted by the Brazilian, East Asian, Mexican, and Russian crises as well as the 9/11 terrorist attacks, and the recent Subprime Crisis.

In addition, Diebold and Yilmaz (2008) report that volatility spillovers soar to 50 per cent among South American markets at the outset of the Mexican Crisis and fluctuate between 45 per cent and 60 per cent until the crisis is dropped from the estimation window. Furthermore, Diebold and Yilmaz compare volatility spillover patterns in South America to East Asia and find that the Mexican Crisis has no impact on East Asian volatility spillovers. The findings for the Mexican Crisis mean that while it may not have a worldwide impact (Forbes and Rigobon, 2002), the crisis has a regional impact, as Chan-Lau, Mathieson, and Yao (2004) conclude for the Asian Crisis.
Yilmaz (2009) also examines volatility spillovers among East Asian stock markets and reports that volatility spillovers exhibit significant bursts during major market crises, such as the East Asian Crisis and the Global Financial Crisis of 2007-9. The Brazilian Crisis, the Russian Crisis, the technology bubble in the U.S., and the 9/11 terrorist attacks all affect East Asian volatility spillovers, but none have as significant an impact as the Asian Crisis or the Global Financial Crisis. Yilmaz supports the results of Diebold and Yilmaz (2008) for the Mexican Crisis and finds that the Asian Crisis, while regional and severe, has a smaller impact on East Asian volatility than the recent Global Financial Crisis. The volatility spillover index constructed by Yilmaz hits a high level of 75 per cent by the end of 1997, but reaches 80 per cent at the end of September 2008, following the collapse of Lehman Brothers and the U.S. Treasury’s decision to bail out the insurer AIG.

Rao (2008) analyses volatility persistence in emerging Middle Eastern stock markets from 2003-6 and finds that six Arabian Gulf Cooperation Council markets show significant own and cross volatility spillovers and persistence. However, Rao reports that volatility spillover effects are not as strong as domestic innovation and volatility persistence. Rao’s findings on the predominance of own-volatility effects for emerging Middle Eastern markets is supported by Worthington and Higgs (2004) for emerging equity markets in Asia from 1988 – 2000. Despite innovations in all of the nine Asian markets influencing the volatility of all the other markets, own-volatility spillovers are found to be higher than cross-volatility spillovers for the emerging markets.

Alkulaib, Najand, and Mashayekh (2009) include Egypt, Morocco, and Tunisia in their study of dynamic linkages among stock markets in the Middle East and North Africa and find that linkages exist between markets within the Levant and Gulf Cooperation Council (“GCC”) regions, with the three North African markets and the Levant region influenced by the GCC region. However, the authors report no market causality or spillover among the three North African countries.

2.3. Studies on African Stock Market Volatility

Volatility in African stock markets is affected by their relatively small size, inefficiency, lack of liquidity, and relative isolation due to capital constraints and protectionism. Most studies investigating volatility in African markets have tended to focus on the continent’s largest and most
sophisticated market, South Africa, and stock markets in North Africa, especially Egypt. South Africa, in particular, is almost always included in broader studies of volatility in African stock markets.

The literature on African volatility seems to agree that Southern African stock markets exhibit the most integration and that South Africa is the most globally integrated. However, there is no agreement on two important issues, namely, the persistence of volatility and whether African volatility responds more to bad news than to good news. Two papers disagree as to whether the important African markets of Egypt and South Africa display weak or strong volatility persistence. In addition, while there is agreement that African stock market volatility is asymmetric, it is not clear whether African equities are more volatile when responding to positive or negative shocks.

Lamba and Otchere (2001) use a vector autoregression (VAR) model to investigate volatility linkages among African and world equity markets. The study includes seven African markets and finds that South Africa influences Ghana, Namibia, and Zimbabwe. Namibia is the most endogenous market, followed by Ghana, South Africa, and Zimbabwe. The most exogenous market is Kenya with 90 per cent of its variance coming from its own market innovations. Lamba and Otchere also find that the SADC markets are the most integrated as significant linkages exist between Namibia, South Africa and Zimbabwe. With respect to the effect of major international equity markets on the volatility of African stock markets, Lamba and Otchere find that the U.S. has the most influence on Namibia and South Africa, accounting for around 10 per cent of their forecast error variance, and the U.K. only affects South Africa, contributing around 6 per cent of the JSE’s forecast error variance.

Collins and Biekpe (2003) also investigate contagion and interdependence in African stock markets during the 1997 Asian Crisis. Correlation coefficients between African markets and Hong Kong are used to measure contagion and a simple correlation matrix and Granger causality tests are used to analyse relationships between African markets. The results show no evidence of contagion for any African market except for South Africa and Egypt, contradicting Forbes and Rigobon (2002), who find that no emerging market suffers contagion during the Asian Crisis. However, Collins and Biekpe support Lamba and Otchere’s results of the strongest relationships existing between Southern African markets, namely between South Africa and Botswana, Namibia and South Africa.
and Botswana and Namibia. In total, there are fourteen significant correlation coefficients between African markets, with only Egypt and South Africa displaying a strong inter-regional relationship.

The strong regional relationship for Southern African countries found by Lamba and Otchere and Collins and Biekpe is supported by Collins and Abrahamson (2004). The authors find that countries geographically closer to South Africa exhibit stronger regional than global integration, especially Namibia and Zimbabwe. Kenya is the least globally integrated market and is more regionally integrated, while Egypt and Morocco display higher levels of global rather than regional integration. The authors also find South Africa to be the most globally integrated African market.

Examining country risk and stock market volatility, predictability, and diversification in African and Middle Eastern stock markets, Hassan, Maroney, El-Sady, and Telfah (2003) find that ARCH and GARCH effects exist in all markets, except Morocco. The authors also report that for African markets the political effect is significant for Nigeria and South Africa, financial risks have an impact on the volatility parameters of Kenya, Nigeria, Tunisia and Zimbabwe, and economic risk has an effect on unconditional volatility in Côte d'Ivoire, Nigeria, Tunisia and Zimbabwe. With respect to persistence, the authors find that persistence of volatility is significantly less than one for Côte d'Ivoire, Kenya, Nigeria, and Zimbabwe, with shocks to volatility decaying over time in these four markets. However, the persistence of volatility does not differ significantly from unity in Egypt, Morocco, South Africa and Tunisia. However, the results of the authors regarding the persistence of volatility contradict what Haque, Hassan, Maroney, and Sackley (2004) find. Haque, Hassan, Maroney, and Sackley use a GARCH-M model and find that Egypt, Morocco, and South Africa do not exhibit much volatility persistence, with the sum of the coefficients that measure the persistence of volatility smaller than 0.70. The persistence of volatility for African markets is even less than what is found for Middle Eastern markets. In addition, the authors report that out of four African markets – Egypt, Morocco, Nigeria, and South Africa – Nigeria is the only market that shows no volatility clustering. Hassan, Maroney, El-Sady, and Telfah also report that African equity market volatility increases with good news. The reason why volatility would increase with good news is that African markets are very illiquid and once good news appears investors may flood in, increasing volatility. The authors’ result is not supported by an earlier paper by Ogum (2002), which finds that negative shocks increase African volatility more than positive shocks.
With respect to studies on volatility in individual African countries, Ogum, Beer, and Nouyrigat (2004) report that volatility persistence is present for Kenyan equities in line for most findings on developed equity markets but that the asymmetric volatility found in the U.S. and other developed markets does not apply to Kenya, as positive shocks are found to increase volatility more than negative shocks of equal magnitude. Ogum, Beer, and Nouyrigat's (2005) study on Kenya and Nigeria support the findings of their 2004 study on the persistence and asymmetry of Kenyan volatility. Ogum, Beer, and Nouyrigat (2005) also report that Nigerian volatility is persistent and that it is asymmetric in the same way that volatility is for developed markets.

For Africa’s largest market, Samouilhan (2006) looks at the relationship between international equity market behaviour and South Africa’s JSE using the London Stock Exchange as a proxy for world volatility. The author finds significant evidence exists of a positive relationship between foreign volatility and South African volatility. A one unit rise in the volatility of the FTSE100 is associated with a 0.56 unit increase in the volatility of the JSE’s Top 40 Index. Samouilhan also finds strong evidence that South African volatility reacts more to negative shocks than to positive shocks.

Chinzara and Aziakpono (2008) examine volatility linkages between South Africa and major world stock markets from 1995–2007 in a broader study than Samouilhan, but largely confirm Samouilhan’s finding with respect to the response of South African volatility to international factors, but not to the U.K. itself. The study finds that there are volatility linkages between South Africa and the world’s major markets, with Australia, China and the U.S. having the most influence on the volatility of the JSE. Despite the JSE hosting many significant dual listed companies with the London Stock Exchange, the response of the JSE to innovations from the FTSE 100 seems to be insignificant, with the FTSE 100 responsible for less than 5 per cent of the variations in South African volatility. Chinzara and Aziakpono put the relatively large influence of Australia on South African volatility down to their commodity based economies. Volatility for South Africa is also found to increase during the Asian crisis and to be insignificantly increasing over time. In addition, all the stock markets studied are found to be inherently asymmetric and relatively stable over time.

For Nigeria, Emenike (2010) reports evidence of volatility clustering over the period from 1985–2008 and that volatility is explosive. Emenike, therefore, does not support Ogum, Beer and
Nouyrigat’s (2005) findings that Nigerian volatility is persistent, but supports the authors’ findings that Nigerian volatility responds more to negative shocks than to positive shocks.

3. Methodology

3.1. The Multivariate GARCH Model and its Development

The diagonal BEKK-GARCH evolved from Engle's (1982) ARCH model. The ARCH model was developed to help study volatility in economic and financial time series and was later extended by Bollerslev (1986) into the generalised ARCH (GARCH) model. Initially the ARCH and GARCH models were univariate, with multivariate extensions following later.

Whereas univariate GARCH only allows analysis of individual time series, multivariate GARCH (M-GARCH) models cater for the simultaneous study of multiple time series. Studying multiple time series simultaneously allows for observation of interactions between time series and aids in determining how volatility persistence and innovations in one time series affects another time series (Bauwens, Laurent, and Rombouts, 2006; Silvennoinen and Terasvirta, 2008). M-GARCH models are recognised as a useful development regarding the parameterization of conditional cross-moments (Worthington and Higgs, 2004).

The first multivariate GARCH model was the VEC-H model developed by Bollerslev, Engle, and Wooldridge (1988). The VEC-H model consists of conditional covariance matrices and is a straightforward generalization of the univariate GARCH model, where every conditional variance and covariance is a function of all lagged conditional variances and covariances, lagged squared returns, and the cross products of returns. An important advantage of the VEC-H model is its simplicity but the model has two main disadvantages.

The first disadvantage with the VEC-H model is the large number of parameters to be estimated; the second – and more important – disadvantage is that the positive definiteness of the covariance matrix cannot be assured (Baur, 2004). The first disadvantage was addressed by introducing the diagonal VEC-H model, which reduces the number of parameters by restricting the elements of the
parameter matrices to the diagonals. The second disadvantage remained though, and so the constant conditional correlation (CCC) model was proposed by Bollerslev (1990) and Baba, Engle, Kraft, and Kroner (1991) developed the BEKK model, from which the diagonal-BEKK model emerged.

The CCC model is the second multivariate GARCH model proposed and is a simple multivariate correlation model. The model consists of time-varying covariances but, as its name suggests, the model contains only constant correlations. As Baur highlights, an advantage of the model is that it has a parameter that specifically governs the covariance equation. While the CCC model is viewed as an attractive parameterization, the model's main disadvantage is its restrictive and unrealistic assumption of constant correlation between time series (Silvennoinen and Terasvirta, 2008).

After the CCC model, the next multivariate model developed was the BEKK GARCH model. The BEKK GARCH model improves on the original VEC-H model, as it solves the parameter estimation problem and the issue of positive definiteness of the covariance matrix. The BEKK model makes the improvement by lowering the number of parameters that need to be estimated and by assuring the positive definiteness of the covariance matrix.

While the general BEKK GARCH model solves problems associated with the VEC-H model, it does present drawbacks. Baur (2004) notes that it is difficult to interpret the parameters in the covariance matrix of the general model, since there is no equation that exclusively possesses its own parameters and the statistical significance of the parameters is unclear, due to the combinations of different parameters serving as new coefficients for particular regressors. In answer to these criticisms the diagonal-BEKK model, which is used in this paper, was proposed.

The diagonalised version restricts all the off-diagonal elements of the parameter matrices to zero. As a result, the number of parameters is reduced, while the positive definiteness of the conditional covariance matrix is maintained, which is the main advantage of the general BEKK GARCH model. The diagonal-BEKK model still, however, presents disadvantages: there is still no parameter that particularly applies to a specific covariance equation and the BEKK model is still not very flexible and can, therefore, be misspecified.
The last and final multivariate GARCH model to be developed is Engle’s (2002) DCC model. The DCC model and the earlier CCC model are built on the premise of modelling conditional variances and correlations, whereas the VEC-H and BEKK models rely on the direct modelling of the conditional covariance matrix (Silvennoinen and Terasvirta, 2008). The DCC was developed to overcome its CCC forerunner's main disadvantage of constant correlation between time series.

To overcome the assumption of time-invariant correlation, Engle introduced an estimator called dynamic conditional correlation (DCC) that allows for time-invariant correlation. The DCC model’s other advantages are that it has fewer parameters than the general BEKK model with the same dimension when the size of the parameter matrices is small and the positive definiteness of the covariance matrix is guaranteed at anytime. However, as Nelson (2008) and Su and Huang (2010) highlight, a disadvantage of the DCC model is that all conditional correlations have the same dynamic structure. Another disadvantage is that the numerically simple estimation of the CCC model is lost, as the correlation matrix must be inverted for each iteration (Silvennoinen and Terasvirta, 2008).

Comparing the various multivariate GARCH models and their respective advantages and disadvantages, the diagonal-BEKK GARCH model is chosen. The BEKK GARCH model is widely used in the literature to study volatility and contagion. The BEKK GARCH model is used by Kearney and Patton (2000), Worthington and Higgs (2004), Ciffarelli and Paladino (2005), Caporale, Pittis, and Spagnolo (2006), and Beirne, Caporale, Schultze-Ghattas, and Spagnolo (2008). Su and Huang (2010) compare the DCC model to the BEKK GARCH model and find the parameter estimation of the BEKK model to be more accurate than the estimate given by the DCC model.
### 3.2. GARCH Models and Applied Methodology

#### 3.2.1. Univariate GARCH model

The ARCH\((q)\) model is given by the following mean and variance equations:

\[
\begin{align*}
    r_t &= E(r_t) + \epsilon_t \\
    h_t &= \alpha_0 + \alpha_1 \epsilon^2_{t-1} + \ldots + \alpha_q \epsilon^2_{t-q} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon^2_{t-i}
\end{align*}
\]

(1)

(2)

where the residual term \(\epsilon_t\) is normally distributed and independent with mean zero and variance \(b_t\), i.e. \(\epsilon_t \mid I_{t-1} \sim N(0, b_t)\) with \(I_{t-1}\) the information set, and \(\alpha_0\) a constant, \(\alpha_i > 1\), and \(1 \leq i \leq q\) (Tsay, 2002, and Lutkepol and Kratzig, 2004). Conditional variance, \(b_t\), is the period ahead forecast variance based on past information, and the sum of the squared past error terms, \(\sum_{i=1}^{q} \alpha_i \epsilon^2_{t-i}\), is the ARCH effect, capturing news about volatility from the previous period. Similarly to the ARCH\((q)\) model, the GARCH\((q,p)\) model contains a mean equation from which the residual term \(\epsilon_t\) is obtained for use in the variance equation. The only difference is that the variance equation contains an additional term capturing the GARCH effect, or long-term memory in the volatility process. The variance equation of a model that includes the GARCH effect is written as:

\[
    h_t = c + \sum_{i=1}^{q} \alpha_i \epsilon^2_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-i}
\]

(3)

where \(p > 0, \beta_i > 0, 1 \leq i \leq p\) and \(\alpha_i + \beta_i < 1\). The GARCH effect, which is measured by \(\sum_{i=1}^{p} \beta_i h_{t-i}\), captures the sensitivity of the current estimate for volatility to its past value or the last period’s forecast variance (Tsay, 2002, Lutkepol and Kratzig, 2004). In order to have a weakly stationary GARCH\((q,p)\) process, the coefficients \(\alpha_i\) and \(\beta_i\) must sum to less than 1. If \(\alpha_i\) and \(\beta_i\) sum to more than 1, variance is explosive and the GARCH\((q,p)\) process will not be stationary. The sum of the coefficients \(\alpha_i\) and \(\beta_i\) measure the persistence of volatility. When a univariate GARCH is used, a GARCH\((1,1)\) is usually applied and its performance is adequate relative to higher order models (Cowpertwait and Metcalfe, 2009).

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3.2.2. The BEKK GARCH Model and Applied Methodology

The BEKK GARCH model is multivariate in nature and contains a covariance matrix $H_t$ of equations that is modelled as follows:

\[ H_t = \lambda'\lambda + M'e_t\epsilon_t'M + G'H_{t-1}G \]  

(4)

where $\lambda$, $M$, and $G$ are parameter matrices. Matrix $\lambda$ consists of elements $\lambda_{ij}$ which are constants, matrix $M$ contains elements $m_{ij}$ which measure the sensitivity of own- and cross-market innovations which are measured by $\epsilon_t$, matrix $G$ consists of elements $g_{ij}$ which show the persistence in conditional volatility between markets $i$ and $j$, and the persistence of stock market volatility as a whole is given by the sum of the diagonal elements of matrices $M$ and $G$, i.e. $m_{ii} + g_{ii}$. Furthermore, $\lambda_{1,ii} > 0 \forall i$, $M_{11}^2 > 0$ and $G_{11}^2 > 0$ to achieve the unique identification of $H_t$ and $M_{11}^2 + G_{11}^2 < 1 \forall i$ to ensure covariance stationarity (Engle and Kroner, 1995; Tsiaplias and Chua, 2009).

From equation (4) it can be seen that the positive definiteness of the covariance equation is assured as long as $\lambda'\lambda$ is positive definite. The covariance matrix $H_t$ can be represented by the following equations in bivariate form with $h_{11,t}$ and $h_{22,t}$ denoting the conditional variances of the underlying return series and $b_{i,j}$ their covariance:

\[ b_{12,t} = l_{12}^2 + m_{11}m_{12}s_{1,t-1}^2 + (m_{11}m_{21} + m_{11}m_{22})\epsilon_{1,t-1}\epsilon_{2,t-1} + m_{21}m_{22}\epsilon_{2,t-1}^2 \]

\[ + g_{11}g_{12}b_{11,t-1} + (g_{12}g_{21} + g_{11}g_{22})b_{12,t-1} + g_{21}g_{22}b_{22,t-1} = b_{21,t} \]

\[ b_{21,t} = l_{11}^2 + m_{11}^2s_{1,t-1}^2 + 2m_{11}m_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + m_{21}^2s_{2,t-1}^2 + g_{11}^2b_{11,t-1} + 2g_{11}g_{21}b_{12,t-1} + g_{22}^2b_{22,t-1} \]

\[ b_{11,t} = l_{12}^2 + m_{12}^2s_{2,t-1}^2 + 2m_{12}m_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + m_{22}^2s_{2,t-1}^2 + g_{12}^2b_{11,t-1} + 2g_{12}g_{22}b_{22,t-1} \]

\[ b_{22,t} = l_{22}^2 + m_{22}^2s_{2,t-1}^2 + 2m_{12}m_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + m_{22}^2s_{2,t-1}^2 + g_{12}^2b_{11,t-1} + 2g_{12}g_{22}b_{22,t-1} \]

(5)

where $m_{ii}^2s_{ii,t-1}^2$ is own-volatility innovation or the ARCH effect, $g_{ii}^2b_{ii,t-1}$ is the own-GARCH effect, $2m_{ij}\epsilon_{ij,t-1}\epsilon_{ij,t-1}^2$ is cross-volatility innovation, and $2g_{ij}b_{ij,t-1}$ is the cross-GARCH effect.
3.2.2.1. The Diagonal-BEKK GARCH Model

In modelling the bivariate diagonal-BEKK GARCH model used in this paper a mean return equation is first estimated for an African stock market and an international equity market:

\[ R_t = A_t + U_t \]  \hspace{1cm} (6)

where \( i = 1, 2 \), the parameter vector \( A_t = (a_1, a_2) \) is a constant vector, and the residual vector \( U_t = (\varepsilon_{1,t}, \varepsilon_{2,t}) \) is bivariate and normally distributed \( U_t | I_{t-1} \sim N(0, H_t) \), with the corresponding conditional variance covariance, matrix \( H_t \), given by the general BEKK parameterization as defined in (4) above, but with the elements of both matrices \( M \) and \( G \) now restricted to the diagonals. In addition, as \( M \) and \( G \) have been diagonalized, the variance equation takes the following simpler form:

\[ h_{11,t} = l_{11}^2 + m_{11}^2 \varepsilon_{1,t-1}^2 + g_{11}^2 h_{11,t-1} \]
\[ h_{22,t} = l_{22}^2 + l_{11}^2 + m_{22}^2 \varepsilon_{2,t-1}^2 + g_{22}^2 h_{22,t-1} \]
\[ h_{12,t} = h_{21,t} = l_{11} l_{22} + m_{11} m_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + g_{11} g_{22} h_{11,t-1} h_{22,t-1} \]  \hspace{1cm} (7)

where \( m_{ii}^2 \varepsilon_{ii,t-1}^2 \) is own-volatility innovation or the ARCH effect, \( g_{ii}^2 h_{ii,t-1} \) is the own-GARCH effect, \( m_{ij} m_{ji} \varepsilon_{ij,t-1} \varepsilon_{ji,t-1} \) is cross-volatility innovation and \( g_{ij} g_{ji} h_{ij,t-1} h_{ji,t-1} \) is the cross-GARCH effect.

The estimation of the model in this paper is done with back-casting of 0.7 and Bollerslev-Wooldridge (1992) standard errors. In addition, the Berndt, Hall, Hall and Hausman (BHHH) (1974) algorithm is used to yield the maximum likelihood parameters.

From every estimation the rolling unconditional variance for each African stock market is obtained. Unconditional volatility is defined using the coefficients from the covariance matrix \( H_t \) and is estimated as follows:

\[ \sigma = \frac{l_{11}^2 + l_{22}^2}{1 - m_{22}^2 \varepsilon_{2,t-1}^2 - g_{22}^2 h_{22,t-1}} = \frac{\omega}{1 - m_{22}^2 \varepsilon_{2,t-1}^2 - g_{22}^2 h_{22,t-1}} \]  \hspace{1cm} (8)
with the obvious restriction that the unconditional variance must be greater than zero.

4. **Data**

The data for this research study consists of daily closing index values in local currencies from 1 January 1997 - 22 October 2010 for the five African stock markets and four of the most important international developed and emerging equity markets. The international equity markets used are Brazil, Hong Kong, Russia, and the U.S. These four markets have been chosen as they are taken as the sources of the 1997 Asian Crisis, the 1998 Brazilian and Russian Crises, the 2000-2 Bursting of the Dot Com Bubble, and 2007-9 Credit Crisis, respectively. For each country the major stock index or its closest proxy is used.\(^1\) Daily returns are defined as logarithmic differences of closing index values. Specifically, the return for stock market \(j\) is defined as \(r_{jt} = \ln(P_{jt}/P_{jt-1}) \times 100\), where \(P_{jt}\) is the period \(t\) closing value. The number of observations for each stock market is 3602.\(^2\)

The Asian Crisis is determined as lasting from 2 July 1997 (when the Thai government devalued the Bhat) to 17 November 1997 (when Hong Kong’s stock market reached its trough according to Forbes and Rigobon, 2002). The Brazilian Crisis is defined as the period from 15 April 1998, when the main Brazilian stock market index, the Bovespa, hit a high of 12,299, to 14 January 1999, the day after the Real was devalued. The start of the Russian Ruble Crisis is taken as 17 August 1998, the date on which the Russian Government devalued the Ruble, and its end as 5 October 1998, when the MSCI Russia Index reached its trough. For the Bursting of the Dot Com Bubble, the crisis is defined from 1 September 2000 – 10 October 2002. The S&P 500 reached its highest closing value of 1,520.77 on 1 September 2000, just short of six months after the NASDAQ closed at its all-time high, and hit its lowest closing value of 776.76 on 10 October 2002, the same date as for the NASDAQ. Lastly, the Credit Crisis is defined as lasting from 2 July 2007 – 6 March 2009.

\(^1\) For Egypt the MSCI Egypt Index is used; for Kenya the NSE20 Index (“NSE20”); for Nigeria the Nigerian All Share Index; for Mauritius the Stock Exchange of Mauritius Index (“SEMDEX”); for South Africa the JSE/FTSE All Share Index (“JSE”); for Brazil the Bovespa; for Hong Kong the Hang Seng; for Russia the MSCI Russia Index; and for the United States the S&P 500. The data is from Bloomberg, Profile Media and INET Bridge.

\(^2\) This is an average number.
Descriptive statistics in Table 4.1 for daily market returns show that besides Kenya, African markets have higher mean returns than the developed markets of Hong Kong and the U.S. Compared to the emerging markets of Brazil and Russia, the picture is more mixed, with Brazil having a higher mean return than all five African markets, and Russia having a lower mean return than Egypt and South Africa. Overall, though, all nine markets have mean returns that are very close to zero.

**TABLE 4.1: Descriptive statistics for all Stock Markets from 1997-2010**

<table>
<thead>
<tr>
<th>Variable</th>
<th>BRAZIL</th>
<th>EGYPT</th>
<th>H.K.</th>
<th>S. AFRICA</th>
<th>NIGERIA</th>
<th>KENYA</th>
<th>RUSSIA</th>
<th>MAURITIUS</th>
<th>U.S.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.064</td>
<td>0.060</td>
<td>0.016</td>
<td>0.042</td>
<td>0.035</td>
<td>0.011</td>
<td>0.041</td>
<td>0.046</td>
<td>0.013</td>
</tr>
<tr>
<td>Median</td>
<td>0.029</td>
<td>0.000</td>
<td>0.000</td>
<td>0.023</td>
<td>0.000</td>
<td>0.000</td>
<td>0.099</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Std Dev</td>
<td>2.246</td>
<td>1.707</td>
<td>1.817</td>
<td>1.311</td>
<td>0.995</td>
<td>0.928</td>
<td>3.198</td>
<td>0.862</td>
<td>1.392</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.243</td>
<td>-0.264</td>
<td>0.132</td>
<td>-0.467</td>
<td>-0.072</td>
<td>0.590</td>
<td>-0.484</td>
<td>-0.408</td>
<td>-0.300</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>26882.300</td>
<td>5968.700</td>
<td>14083.200</td>
<td>4768.200</td>
<td>34151.800</td>
<td>98729.900</td>
<td>20544.400</td>
<td>5000000.000</td>
<td>18847.500</td>
</tr>
<tr>
<td>Sum</td>
<td>230.222</td>
<td>215.705</td>
<td>55.869</td>
<td>150.931</td>
<td>127.326</td>
<td>40.244</td>
<td>148.794</td>
<td>164.900</td>
<td>46.823</td>
</tr>
<tr>
<td>Sum Sq Dev</td>
<td>18160.000</td>
<td>10496.000</td>
<td>11894.800</td>
<td>6187.540</td>
<td>35669.940</td>
<td>31030.010</td>
<td>36835.900</td>
<td>2674.900</td>
<td>6974.030</td>
</tr>
<tr>
<td>Obs</td>
<td>3601</td>
<td>3602</td>
<td>3602</td>
<td>3602</td>
<td>3602</td>
<td>3601</td>
<td>3602</td>
<td>3599</td>
<td>3602</td>
</tr>
</tbody>
</table>

The descriptive data suggests the most volatile market is Russia and the least volatile is Mauritius. The most volatile African market is Egypt. The standard deviation for African markets is less than for the emerging markets of Brazil and Russia and except for Egypt, is less than both Hong Kong and the U.S. Four of the African markets are skewed to the right with only Kenya skewed to the left, and all the markets are leptokurtic and have non-normal distributions.

The figures for standard deviation from Table 4.1 indicate that the most volatile market is Russia, with a variance of 10.23. The most volatile African market is the Egyptian market, with a variance of 2.91, which also has the highest mean return of African markets. Egypt has the fourth highest level of volatility of the nine equity markets. In addition, Brazil’s Bovespa and Hong Kong’s Hang Seng have higher overall levels of volatility than the five African markets.

The least volatile market is Mauritius, with a variance of 0.74. For the remaining African markets, the variances are: 1.72 for South Africa, 0.99 for Nigeria, and 0.86 for Kenya. According to this data then, with the exception of Egypt, African markets are not especially volatile. The S&P 500 is, for instance, more volatile than South Africa’s JSE, the second most volatile African market. The least...
volatile market outside Africa is the S&P 500. Variance for African markets over the 14 year period averages 1.44, lower than the averages of 7.64 for the two non-African emerging markets and 2.62 for the two developed markets. The volatility for each market over the entire 14-year period is shown in Figure 4.1 and for African markets during the five crises in Figure 4.2. Volatility is calculated as \( r_{jt}^2 \), where \( r_{jt} \) is the daily return as defined above. Using this proxy for volatility, the graphs confirm that Mauritius is the least volatile market, Russia the most volatile, and that all markets exhibit volatility clustering.

**Figure 4.1. Volatility for all Stock Markets from 1997 - 2010**

![Volatility Graphs](image)

However, analysis of African volatility during the five individual crises from Figure 4.2 reveals marked differences in behaviour. For the Asian Crisis, Figure 4.2(a) shows that Nigeria and South...
Africa are relatively calm before the crisis and quickly return to low levels of volatility after the end of the crisis. Egypt, Kenya, and Mauritius experience brief periods of rising but low volatility throughout the crisis. Some volatility clustering is also evident for all the indices around the Asian Crisis. Figure 4.2(b) also shows that four of the five markets (Nigeria excluded) reach higher levels of volatility more frequently and maintain those elevated levels for longer time periods during the Brazilian Crisis than during the Asian Crisis. There is also more evidence of volatility clustering for the Brazilian Crisis than during the Asian Crisis.

Figure 4.2. Volatility in African Equity Markets during the five Crises

(a) The Asian Crisis

(b) The Brazilian Crisis

(c) The Russian Crisis

(d) The Bursting of the Dot Com Bubble

(e) The Credit Crisis
For the Russian Crisis, Figure 4.2(c) shows that maximum volatility levels in Mauritius and Nigeria are lower than during the Asian or Brazilian Crises. For Kenya and South Africa volatility reaches the same levels that it does during the Brazilian Crisis. However, compared to the Asian Crisis, Kenya sees higher levels of volatility, whereas South Africa reaches lower maximum volatility levels. For Egypt, peak volatility is lower than during the Asian Crisis, but higher than during the Brazilian Crisis. There is also less evidence of volatility clustering than during either the Asian or Brazilian Crises. For the Dot Com Bubble, Figure 4.2(d) shows volatility for four markets, except South Africa, reach higher maximum levels than during the Asian, Brazilian or Russian Crises. Volatility clustering is also present, but there is no common point when maximum volatility levels are reached.

Figure 4.2(e) shows that all five African markets exhibit volatility clustering during the Credit Crisis, and reach their peak volatility levels after the Lehman Brothers bankruptcy of 15 September 2008. All five markets also tend to become more volatile after July 2008. Except for South Africa, the markets reach higher maximum levels of volatility during the Credit Crisis than during the other crises. For the Credit Crisis, Egypt reaches the highest maximum volatility level of any African market during any crisis.

Analysing the data for mean returns and standard deviation produces inconsistencies with commonly held investor assumptions. Usually one would expect higher returns to be associated with more risk, i.e. higher volatility. However, the data suggests that while the highest returns are from African markets, African equities have the lowest average volatility over the entire period. The higher mean returns for African markets may be explained as market inefficiency by the fact that all of the mean returns are essentially zero when transaction costs are considered, higher commodity prices of late with regard to Nigeria and South Africa, and African countries’ sometimes recent superior growth rates and, therefore, rising stock prices coming off a very low base.

These initial observations of lower volatility in African markets compared to developed markets are supported by Chukwuogor (2008) for some African markets and by Nikkinen, Omran, Sahlstrom, and Aijo (2008) for Middle Eastern and North African markets following the 11 September 2001 terrorist attacks, but are the opposite to what most other studies find with respect to emerging markets. African stock markets are emerging markets and are characterised more so than others by political and economic risks, small size, capital controls, and market inefficiency. Therefore, one
would expect African equity markets to display more volatility. However, three of the five African countries, Kenya, Nigeria, and South Africa, experience major political, currency and/or economic crises during the 14-year study period, and would be expected to display higher levels of volatility than the Hang Seng and the S&P 500, which Kenya and Nigeria do not.

Furthermore, capital controls and their effect on volatility may be the most contradictory area regarding African volatility. Focusing on the effect of liberalisation on stock market volatility, Bekaert and Harvey (1997) find that the more open a country’s capital markets are, the lower the level of volatility. Considering the standard deviations of the five African markets, there is no strong support for either theory. Mauritius has a very open capital market and has the lowest volatility overall, but South Africa’s JSE, which is Africa’s largest market, is the second most volatile African market. Kenya and Nigeria, which are less sophisticated than the JSE, have lower levels of volatility.

As for skewness, kurtosis and, ultimately, the normality of the return series, six of the nine markets — the S&P 500, Egypt, Mauritius, Nigeria, Russia, and South Africa — are skewed to the right. Kenya is the only African market skewed to the left. The descriptive statistics show that concerning kurtosis, all the markets are leptokurtic. Mauritius, with a value of 179.73, is the most leptokurtic; more than six times the magnitude of 28.62 for kurtosis for the next stock market, Kenya. In addition, the results of the Jarque-Bera test for normality show that the return series for all the equity markets have non-normal distributions at the 5 per cent level of significance.

5. **Results**

Section 5 presents the results of the GARCH analysis for each African stock market during five crises, from 1 January 1997 to 22 October 2011. The section is divided into five sub-sections, namely, the Asian Crisis, the Brazilian Crisis, the Russian Crisis, the Bursting of the Dot Com Bubble and the Credit/Global Financial Crisis. Each sub-section consists of findings obtained from the rolling-window bivariate diagonal-BEKK GARCH models that are run for the five markets pertaining to a specific economic/financial crisis and related non-crisis period.
As a rolling-window regression is used, the results for the crises are given in terms of “crisis periods.” This is because a whole crisis or parts of a crisis are contained in many data points, with one data point containing 1000 days. Therefore, to capture the full effect of a crisis, all data points that contain a part of a crisis must be included in the analysis of the results. A full description of how crisis periods and the resulting non-crisis period are defined is in the Appendix.

In addition, when reporting the results, point estimates of coefficients obtained from the rolling regressions that are insignificant are discarded and only significant values are retained. The significant point estimates are then averaged to obtain estimated values of coefficients of bivariate GARCH models during crisis and non-crisis periods. It is, therefore, not possible to use confidence intervals to determine whether the differences between coefficients are statistically significant to one another, as there is no way of determining whether the estimated coefficients, as averages, are significant or not. The estimated coefficients for the five crisis periods and their corresponding non-crisis periods appear in Tables 5.1 to 5.5.

5.1. The Asian Crisis

The devaluation of the Thai bhat on 2 July 1997 led to huge devaluations in the exchange rates of Indonesia, Korea, Malaysia, and the Phillipines, as well as huge declines in financial markets. As the crisis became more severe, currency and stock market turmoil spread across Asia and, eventually, worldwide, especially to other emerging markets. According to Boorman, Lane, Schultze-Ghattas, Bulir, Ghosh, Hamann, Mourmouras, and Phillips (2002), only by mid-1999 did Asia really begin to recover.

To study the impact of the Asian Crisis, the Hang Seng is taken as its source and is, therefore, the market index used in the bivariate GARCH model that is run for all five African markets. The Hang Seng is used because even though the source of the crisis may be Thailand, Western newspapers only take notice of the crisis when the Hang Seng begins to decline (Forbes and Rigobon, 2002). Figures 5.1 and 5.2 show the behaviour of African volatility during the Asian Crisis and the corresponding non-crisis period.
Beginning with the persistence of volatility, Table 5.1 shows that four of the five African markets exhibited high levels of volatility persistence during the Asian Crisis period. Volatility persistence ranges from an extremely strong average of 0.988 for Egypt, to a still strong 0.822 for Mauritius. For Nigeria, volatility is explosive and incomparable. Figure 5.1(a) shows that volatility persistence during the Asian Crisis period is very close to 1 for Egypt, highly unstable and for around two-thirds immeasurable for Kenya, and never close to 1 for South Africa. If the persistence of volatility during the crisis period is compared to volatility persistence in the non-crisis period, Table 5.1 shows that non-crisis volatility persistence not only averages above 0.94 for all five markets, but is higher than crisis period volatility persistence for Kenya, Mauritius and South Africa, and only lower for Egypt.

**TABLE 5.1: Volatility Dynamics during the Asian Crisis period & the non-crisis period**

<table>
<thead>
<tr>
<th>Market</th>
<th>Cross-innovation</th>
<th>Cross-GARCH</th>
<th>Own-innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nigeria</td>
<td>0.114</td>
<td>0.863</td>
<td>n/a</td>
</tr>
<tr>
<td>Egypt</td>
<td>0.078</td>
<td>0.89</td>
<td>0.087</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.108</td>
<td>0.822</td>
<td>0.1605</td>
</tr>
<tr>
<td>Kenya</td>
<td>0.079</td>
<td>0.791</td>
<td>0.079</td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.111</td>
<td>0.761</td>
<td>0.178</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Market</th>
<th>Own-GARCH</th>
<th>Persist</th>
<th>Unconditional volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nigeria</td>
<td>n/a</td>
<td>Explosive</td>
<td>3.784</td>
</tr>
<tr>
<td>Egypt</td>
<td>0.901</td>
<td>0.985</td>
<td>4.034</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.763</td>
<td>0.924</td>
<td>1.614</td>
</tr>
<tr>
<td>Kenya</td>
<td>0.772</td>
<td>0.951</td>
<td>0.385</td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.644</td>
<td>0.975</td>
<td>0.194</td>
</tr>
</tbody>
</table>

The estimated coefficients, which are averages of the significant rolling-window point estimates, show that the Asian Crisis has a mixed but weak effect on African volatility. The crisis has a weak short-term effect on African volatility, been generally smaller than short-term past domestic innovations, and its long-term impact may only be felt after the crisis has passed. Volatility persistence is explosive in Nigeria and while strong in the remaining markets, it is smaller than during the non-crisis period, except for Egypt.
The results for unconditional volatility are stronger than for volatility persistence when comparing the crisis period to the non-crisis period. Unconditional volatility during the Asian Crisis period for the four markets in which volatility persistence is not explosive is higher than unconditional volatility during the non-crisis period in Egypt and South Africa, and weaker in Kenya and Mauritius. Unconditional volatility during the crisis period is strongest for Egypt and weakest for Mauritius. Figure 5.1(b) shows no overriding trend for unconditional volatility during the crisis period. Unconditional volatility for South Africa during the crisis period is more than double than during the non-crisis period, whereas non-crisis period unconditional volatility for Kenya is more than six times larger than during the crisis period, and more than double the crisis period unconditional volatility for Mauritius.

![Figure 5.1. Volatility dynamics in African Equity Markets during the Asian Crisis period](image-url)
For the first of the cross-volatility coefficients, Table 5.1 shows that past innovations from the Hang Seng have a stronger effect on future volatility in all five African markets during the Asian Crisis period, than during the non-crisis period. Cross-volatility innovation during the crisis period is strong for Mauritius, Nigeria, and South Africa, and weak for Egypt and Kenya. It is highest for Nigeria, averaging 0.114, and weakest for Kenya, averaging 0.078. Non-crisis cross-volatility innovation is below 0.10 and very weak for all five markets. Figure 5.1(c) shows that cross-volatility innovation during the Asian Crisis period is declining in Egypt, Kenya and Nigeria, displays initial instability and ends weaker for South Africa, and only strengthens for Mauritius, despite weakening quite dramatically for the last 20 per cent of the crisis period.

Figure 5.2. Volatility dynamics in African Equity Markets during the non-crisis period when the Hong Kong Market is used in the bivariate analysis

Comparing cross-volatility innovation from the Hang Seng to own-volatility innovation during the Asian Crisis period, it is found that except for Nigeria, whose own-volatility innovation is
incomparable to cross-volatility innovation, and Kenyan own-volatility innovation of 0.079, which is equal to cross-volatility innovation, own-volatility innovation is stronger than cross-volatility innovation from the Hang Seng. For Mauritius and South Africa, own-volatility innovation during the crisis period is very strong, averaging 0.178 and 0.161, respectively. Figure 5.1(e) shows that own-volatility innovation during the Asian Crisis period only strengthens for Mauritius, but weakens throughout the crisis period in Egypt, and ends weaker than where it starts for Kenya and South Africa. Own-volatility innovation during the crisis period for the four markets that allow comparisons to be made is, in turn, stronger than non-crisis own-volatility innovation for Egypt, Mauritius and South Africa. For Kenya though, own-volatility innovation during the non-crisis period averages an extremely high 0.385; more than quadruple own-Kenyan volatility innovation for the crisis period.

The cross-GARCH effect during the Asian crisis period (seen for the markets in Figure 5.1(d)) is above 0.80, and is, therefore, strong in three markets, Egypt, Nigeria and South Africa, and weak in Kenya and Mauritius. The cross-GARCH effect during the crisis period mainly strengthens in Egypt, is insignificant in Kenya for about two-thirds of the crisis period, declines but recovers during the second half of the last quarter in Mauritius and South Africa, and ends slightly stronger in Nigeria. Despite the cross-GARCH effect being strong for three markets during the Asian Crisis period, much weaker results are found when comparing the cross-GARCH effect between the Hang Seng and the five markets during the Asian Crisis period to the non-crisis period than for cross-volatility innovation. The cross-GARCH effect during the non-crisis period is stronger than during the Asian Crisis period for Egypt, Mauritius, Nigeria, and South Africa.

Comparing the cross-GARCH effect and the own-GARCH effect during the Asian Crisis period, it is found that the cross-GARCH effect from Hong Kong is stronger than the own-GARCH effect for three of the five markets, Kenya, Mauritius and South Africa, and incomparable for Nigeria. The crisis period own-GARCH effect is only strong in Egypt, the only market for which it is stronger than the cross-GARCH effect, averaging a slightly larger 0.901 versus 0.890. The own-GARCH effects during the Asian Crisis period for the four comparable markets in Figure 5.1(e) follow the same patterns as the respective cross-GARCH effects.
Lastly, Table 5.1 shows that the own-GARCH effect during the crisis period is weaker than the non-crisis own-GARCH effect for Egypt, Mauritius and South Africa. The non-crisis own-GARCH effect is very strong in four of the five markets, including Nigeria, and ranges from very strong in Egypt to very weak in Kenya. Kenya is, again, the only market for which the non-crisis own-GARCH effect is weaker than the crisis period own-GARCH effect.

The results suggest that past domestic innovations during the Asian Crisis period have a larger impact on future African volatility than Hong Kong has; indicating that the short-term impact of the Asian Crisis is weak. The impact of past volatility shocks in Hong Kong during the non-crisis period generally has a greater effect on future African volatility than during the Asian Crisis period. However, during the Asian Crisis period the influence from Hong Kong dominates past domestic shocks. Overall, the results suggest that the Asian Crisis has a mixed but weak effect on African volatility, supporting Chan-Lau, Mathieson, and Yao’s (2004) notion that the Asian Crisis is more of a regional Asian event. A broader implication is that when the Asian Crisis occurs, African markets are still emerging from years of isolation and overregulation, and are not well integrated with world equity markets. Another possibility is that because the impact of past shocks in Hong Kong on African markets is generally stronger during the non-crisis period than the Asian Crisis period, the effects of the events in Asia are only felt later.

5.2. The Brazilian Crisis

African markets during the Brazilian Crisis display relatively more consistent behaviour than during the Asian Crisis. The crisis leads to relatively stronger volatility persistence and cross-volatility innovation for the five markets than the Asian Crisis, but the cross-GARCH effect is weaker than the own-GARCH effect in four markets, as opposed to three markets during the Asian Crisis period. The Brazilian Crisis, therefore, has a bigger impact on short-term African volatility; whereas the Asian Crisis has more of a long-term impact. Figures 5.3 and 5.4 show the behaviour of volatility in African markets during the crisis and non-crisis periods when the bivariate GARCH model is run for each African market and the Bovespa.

Volatility persistence in Figure 5.3(a) is strong for all the markets during the Brazilian Crisis period as well as the non-crisis period. Table 5.2 shows that the persistence of volatility during the crisis
period and the non-crisis period is strongest in Nigeria, where it averages a very high 0.988 for both. Crisis period volatility persistence is also very strong for Egypt, averaging an extremely high 0.987. The Egyptian market is the only market for which the crisis period’s persistence of volatility is greater than non-crisis volatility persistence. Kenya has the lowest level of persistence, averaging 0.843. Volatility persistence for Nigeria is explosive for just over 92 per cent of the crisis period, for South Africa it is explosive for around 10 per cent, for Kenya it is explosive only once, and for Egypt and Mauritius volatility persistence is never explosive but highly unstable. For Egypt, Kenya and Mauritius non-crisis volatility persistence is greater than the persistence of volatility during the Brazilian Crisis period. Non-crisis volatility persistence averages above 0.940 for all five markets.

**TABLE 5.2: Volatility Dynamics during the Brazilian Crisis period & the non-crisis period**

<table>
<thead>
<tr>
<th>Market</th>
<th>Cross-innovation</th>
<th></th>
<th></th>
<th>Cross-GARCH</th>
<th></th>
<th></th>
<th></th>
<th>Own-innovation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
<td>Non-crisis</td>
<td></td>
</tr>
<tr>
<td>Nigeria</td>
<td>0.149</td>
<td>0.057</td>
<td>0.816</td>
<td>0.893</td>
<td>0.18</td>
<td>0.141</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Egypt</td>
<td>0.099</td>
<td>0.027</td>
<td>0.853</td>
<td>0.899</td>
<td>0.066</td>
<td>0.044</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>0.113</td>
<td>0.046</td>
<td>0.816</td>
<td>0.91</td>
<td>0.093</td>
<td>0.089</td>
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<td></td>
</tr>
<tr>
<td>Kenya</td>
<td>0.086</td>
<td>0.096</td>
<td>0.778</td>
<td>0.727</td>
<td>0.053</td>
<td>0.389</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.134</td>
<td>0.066</td>
<td>0.766</td>
<td>0.851</td>
<td>0.123</td>
<td>0.156</td>
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</table>

<table>
<thead>
<tr>
<th>Market</th>
<th>Own-GARCH</th>
<th>Persistence</th>
<th>Unconditional volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
</tr>
<tr>
<td>Nigeria</td>
<td>0.808</td>
<td>0.846</td>
<td>0.988</td>
</tr>
<tr>
<td>Egypt</td>
<td>0.92</td>
<td>0.902</td>
<td>0.987</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.856</td>
<td>0.885</td>
<td>0.949</td>
</tr>
<tr>
<td>Kenya</td>
<td>0.793</td>
<td>0.565</td>
<td>0.843</td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.747</td>
<td>0.803</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Volatility persistence is strong for all the markets during the Brazilian Crisis period but weaker than during the non-crisis period, except for Egypt and Nigeria. The estimated coefficients, which are averages of the significant rolling-window point estimates, also show that the short-term impact of the crisis is strong, dominating past domestic innovations. However, the long-term effect of the Brazilian Crisis is weak, as the crisis period cross-GARCH effect is generally weaker than during the non-crisis period as well as the crisis period own-GARCH effect.
Unconditional volatility during the Brazilian Crisis period is the lowest average for a crisis for Egypt, Kenya and Mauritius. Figure 5.3(b) shows that it is the most stable for Mauritius during the crisis period and very unstable for Nigeria. Table 5.2 shows that unconditional volatility during the Brazilian Crisis period is weaker than during the non-crisis period in three markets and stronger in two; the same as for volatility persistence. Unconditional volatility during the crisis period is less than non-crisis unconditional volatility for Kenya, Mauritius and Nigeria, and higher for Egypt and South Africa; similar to the Asian Crisis period, except that Nigeria was incomparable due to the explosive nature of its volatility persistence. Nigeria has the highest unconditional volatility during the Brazilian Crisis period, averaging 6.829, and Mauritius the lowest, averaging 0.182. Similarly to crisis period unconditional volatility, non-crisis period unconditional volatility is also highest for Nigeria, averaging 14.736; which is more than double unconditional volatility during the crisis period. Unconditional volatility during the non-crisis period for Kenya is more than seven times greater than during the Brazilian Crisis period and more than double for Mauritius. Furthermore, unconditional volatility during the Brazilian Crisis period is less than unconditional volatility during the Asian Crisis period for Egypt, Kenya and Mauritius, higher for South Africa, and incomparable for Nigeria.
For cross-volatility innovation, Table 5.2 shows that the effect of past innovations from Brazil’s Bovespa during the Brazilian Crisis period is stronger than cross-volatility innovation during the Asian Crisis period for all five markets, despite cross-volatility innovation from the Bovespa weakening for all five markets. Figure 5.3(c) shows that cross-volatility innovation during the crisis period is on a downward path, despite Nigeria and South Africa hitting 14 year highs of 0.185 and 0.176, respectively. Cross-volatility innovation from the Bovespa during the crisis period is strongest for Nigeria, averaging a high 0.149, and weakest for Kenya, averaging 0.086. As with the Asian Crisis, cross-volatility innovation during the crisis period is greater than during the non-crisis period, except for Kenya.
Comparing cross-volatility innovation to own-volatility innovation during the Brazilian Crisis period, cross-volatility innovation is found to be stronger in four markets, with Nigeria the exception. Nigeria has the strongest crisis period own-volatility innovation, averaging 0.18, and Kenya the weakest, averaging 0.053. In addition to Kenya, crisis period own-volatility innovation is also weak for Egypt and South Africa. Nevertheless, own-volatility innovation during the Brazilian Crisis period shown in Figure 5.3(e) does not decline for all five markets as it does for cross-volatility innovation, with only Mauritius and Nigeria weakening during the crisis period.

Own-volatility innovation during the Brazilian Crisis period is stronger than non-crisis period own-volatility innovation for three markets; similarly to the Asian Crisis. The three markets for which it is
stronger are Egypt, Nigeria and South Africa. Non-crisis own-volatility innovation is again strongest for Kenya, averaging an extremely high 0.389, more than seven times larger than own-volatility innovation during the Brazilian Crisis period, and more than four times larger than the crisis and non-crisis period average cross-volatility innovation coefficients.

As with the Asian Crisis period, the cross-GARCH effect between the Bovespa and the five markets during the Brazilian Crisis is only stronger than the non-crisis cross-GARCH effect for Kenya. Figure 5.3(d) shows that the cross-GARCH effect between the Bovespa and the five markets only ends higher than its start for Kenya, despite been highly unstable and insignificant for most of the first third of the crisis period. Of the other markets, the Mauritian cross-GARCH effect displays a lot of instability during the second half of the crisis period and is very unstable toward the end of the crisis period for Nigeria and South Africa. The crisis period cross-GARCH effect is strongest for Egypt, averaging a relatively high 0.853, and is weakest for Mauritius, averaging 0.766. Egypt and Mauritius also have the strongest and weakest cross-GARCH effects during the Asian Crisis period.

Whereas cross-volatility innovation is stronger than own-volatility innovation during the Brazilian Crisis period for four of the five markets, excepting Nigeria, the cross-GARCH effect is weaker than the own-GARCH effect for three markets: Egypt, Kenya and South Africa. The individual own-GARCH effect during the Brazilian Crisis period is strongest in Egypt, averaging 0.92, and weakest for Mauritius, with an average of 0.747; as it is for the Asian Crisis period. For three markets as opposed to only one for the cross-GARCH effect, Egypt, Kenya and South Africa, the own-GARCH effect during the Brazilian crisis period ends higher than when it starts, but as Figure 5.3 (f) shows, there is no clear upward path from the beginning. For the two markets that end lower, the crisis period own-GARCH effect follows a downward path for Nigeria and displays much instability during the second half for Mauritius, although it displays an upward trend before a major slump. Overall, the own-GARCH effect during the Brazilian Crisis period is stronger than the own-GARCH effect during the Asian Crisis period. The own-GARCH effect during the Brazilian Crisis period is stronger than the non-crisis own-GARCH effect for two markets, Egypt and Kenya, as opposed to only Kenya when the Hang Seng is used in the bivariate regression. The non-crisis own GARCH effect is above 0.800 for four of the five markets.
The results imply that past volatility innovations from the Bovespa during the Brazilian Crisis period have a stronger general effect on future African volatility than during the non-crisis period as well as past domestic innovations during the crisis period; indicating that the impact of the crisis is very strong in the short-term. However, the effect of past volatility shocks to the Bovespa during the Brazilian Crisis period is generally weaker than during the non-crisis period as well as the impact of past domestic shocks during the crisis period. Therefore, the results suggest that the long-term effect of the Brazilian Crisis on African volatility is weaker than for the Asian Crisis, while the short-term impact of the crisis is strong. Similarly to the Asian Crisis, the long-term effect of the Brazilian Crisis may also be delayed. In addition, the results again suggest that maybe African markets at this point in time are not that well integrated with world markets and, consequently, do not feel the full effects of the crisis.

5.3. The Russian/Ruble Crisis

The Russian or Ruble Crisis, runs concurrently with the Brazilian Crisis, but is of shorter duration and starts and ends within the confines of the Brazilian Crisis. The crisis also has a similar impact on African volatility to the Brazilian Crisis, but has a weaker short-term impact. The behaviour of African volatility during the Russian Crisis and the corresponding non-crisis period can be seen in Figures 5.5 and 5.6.

For the persistence of volatility during the Russian Crisis period, Table 5.3 shows that similarly to the Asian Crisis period, volatility persistence is explosive for Nigeria (in this case for all but two observations), highest in Egypt, and weakest in Mauritius. The persistence of volatility is never explosive for the other four markets. In addition, just as for the Asian and Russian Crisis periods, the persistence of volatility is strong in all the markets. Despite the persistence of volatility been above 0.800 in all four non-explosive markets (see Figure 5.5(a)), volatility persistence is even higher, and above 0.900 for all five markets during the non-crisis period. The persistence of volatility during the non-crisis period is less than volatility persistence during the Russian Crisis period in only one market, Egypt, as it is when comparing the corresponding non-crisis period to both the Asian and Russian Crisis periods.

**TABLE 5.3: Volatility Dynamics during the Russian Crisis period & the non-crisis period**
Volatility persistence is strong during the Russian Crisis period, but lower than during the non-crisis period. The estimated coefficients, which are averages of the significant rolling-window point estimates, also show that the short-term impact of the crisis is strong. Cross-volatility innovation from Russia is only weak for Kenya, but does not dominate the non-crisis period, as did the previous two crises. The long-term impact of the crisis is not that strong, with the crisis period cross-GARCH effect dominated by the non-crisis period cross-GARCH effect and the crisis period own-GARCH effect.

Table 5.3 shows that during the Russian Crisis period, unconditional volatility is incomparable to non-crisis period unconditional volatility for Nigeria; similarly to the Asian Crisis period, and is stronger for Egypt and South Africa, and weaker for Kenya and Mauritius; similarly to the Asian and Brazilian Crisis periods. Figure 5.5(b) shows that crisis period unconditional volatility for the four comparable markets gets weaker in Mauritius and South Africa, is stable in Kenya, only ending higher than its start in Egypt. Unconditional volatility during the Russian Crisis period is the second lowest average for a crisis for Kenya and Mauritius. For South Africa, crisis period unconditional volatility hits a 14-year high of 6.813 for the second observation.
For the four comparable markets, unconditional volatility for Egypt, Kenya and Mauritius during the Russian Crisis period is higher than during the Brazilian Crisis period, with South Africa being the exception. However, unconditional volatility during the Russian Crisis period is lower for Egypt, Kenya and Mauritius, and higher for South Africa than during the Asian Crisis period. Unconditional volatility during the Russian Crisis period is highest in Egypt and lowest in Mauritius. For non-crisis period unconditional volatility, Nigeria has the highest average and Mauritius the lowest. The large differences between unconditional volatility during the crisis period and non-crisis period for Kenya, Mauritius and South Africa are smaller than for the two preceding bivariate GARCH models.
During the Russian Crisis period, average cross-volatility innovation from Russia to the five markets is stronger than cross-volatility innovation during the Asian and Brazilian Crisis periods for all the markets, and only below 0.10 for Kenya. However, just as for the Brazilian Crisis period, Figure 5.5(c) shows that cross-volatility innovation weakens throughout the Russian Crisis period. Cross-volatility innovation during the Russian Crisis period is strongest for Nigeria, as it is during the Asian and Brazilian Crisis periods, and weakest for Kenya, averaging a relatively weak 0.089. However, despite this strength, cross-volatility innovation during the Russian Crisis period is higher than non-crisis volatility innovation for only three markets, as opposed to all the markets for the Asian Crisis period, and four of the five markets during the Brazilian Crisis period. Cross-volatility
innovation is stronger than non-crisis cross-volatility innovation in Nigeria, Egypt and South Africa, and weaker in Kenya and Mauritius.

Comparing cross-volatility innovation to own-volatility innovation during the Russian Crisis period, cross-volatility innovation from Russia to the five markets is stronger than own-volatility innovation for three of the four comparable markets, Egypt, Kenya and South Africa, and weaker for Mauritius. Similarly to the Asian Crisis period, cross-volatility innovation from Russia to Nigeria is incomparable to own-volatility innovation. Own-volatility innovation during the Russian Crisis period ends lower than where it begins in Egypt, Mauritius and South Africa, despite displaying a clearly weakening trend only for Egypt. As Figure 5.5(e) shows, the only market for which crisis period own-volatility innovation strengthens is, therefore, Kenya, but overall, own-volatility innovation is only strong in Mauritius, averaging a very high 0.162. For Kenya, crisis period own-volatility innovation is again smaller than non-crisis own-volatility innovation, as it is when the Hang Seng and the Bovespa are used in the bivariate analysis. Non-crisis own-volatility innovation is less than own-volatility innovation during the Russian crisis period in three markets: Egypt, Mauritius and South Africa; similarly to the Asian Crisis period.

In analysing the average cross-GARCH effect between the Russian market and the five African markets during the Russian Crisis period, the cross-GARCH effect during the crisis period is found to be weaker than the cross-GARCH effect during the non-crisis period in Egypt, Mauritius, Nigeria and South Africa, with Kenya being the only exception. The same is observed for the cross-GARCH effect when the Hang Seng and the Bovespa are used in the bivariate analysis. The cross-GARCH effect during the Russian Crisis period is strong in Nigeria and Egypt, and weak in Kenya, Mauritius and South Africa, compared to three markets, Nigeria, Egypt and South Africa, displaying a strong cross-GARCH effect during the Asian and Brazilian Crisis periods. Overall though, the cross-GARCH effect during the Russian Crisis period is weaker than the corresponding cross-GARCH effect during the Asian Crisis period for all five markets, and weaker than the cross-GARCH effect during the Brazilian Crisis period for four markets, the exception being Kenya. The cross-GARCH effect during the Russian Crisis period is strongest for Egypt, averaging 0.821, and weakest for Mauritius, averaging 0.736, also the same as for the two preceding crisis periods. Studying the individual behaviour of the cross-GARCH effect during the Russian Crisis period for each of the five markets, the cross-GARCH effect strengthens in Figure 5.5(d) for all the markets, despite the
crisis period cross-GARCH effect hitting a 14-year low of 0.737 near the beginning for Egypt, displaying initial instability for Kenya, and not been on a clear upward path for Mauritius.

When comparing the cross- and own-GARCH effects during the Russian Crisis period, the cross-GARCH effect for Egypt, Kenya and South Africa is weaker than the own-GARCH effect. Mauritius is the only market for which the crisis period cross-GARCH effect is larger than the crisis period own-GARCH effect. For Nigeria, though, the crisis period cross- and own-GARCH effects are incomparable, just as it is for the Asian Crisis period due to explosive volatility persistence. This result is similar to when the Bovespa is used in the bivariate GARCH model, with the crisis period cross-GARCH effect for Egypt, Kenya and South Africa being weaker than the corresponding own-GARCH effect, and stronger for Mauritius and Nigeria. The own-GARCH effect for the Russian Crisis period is greater than the own-GARCH effect for the Asian Crisis period for all four comparable markets, but is only stronger than the own-GARCH effect during the Brazilian Crisis period for Kenya and South Africa. The own-GARCH effect during the Russian Crisis period is strongest in Egypt, averaging a high 0.92, and weakest in Mauritius, averaging 0.668. Figure 5.5(f) shows that the own-GARCH effect during the crisis period ends weaker than it starts for Mauritius and South Africa, but ends higher in Kenya. The own-GARCH effect is steady for Egypt, weakens during the second half for Kenya, and is unstable during the last quarter of the crisis period for Mauritius.

Lastly, the own-GARCH effect during the Russian Crisis period is once again, as it is for the Asian and Brazilian Crisis periods, weaker than the non-crisis own-GARCH effect in three markets. The only market for which the crisis period own-GARCH effect is stronger than the non-crisis own-GARCH effect is Kenya, for which it is more than 50 per cent larger. The crisis period own-GARCH effect is weaker than during the non-crisis period for Egypt, Mauritius and South Africa, the same as when the Hang Seng is used in the bivariate analysis.

The results suggest that similarly to the Brazilian Crisis, the short-term impact of the Russian Crisis is generally stronger than past domestic innovations. Also, the effect of past volatility shocks in Russia on future African volatility during the crisis period is weaker than during the non-crisis period. The results again imply that the long-term effect on African volatility of the three crises studied so is not as strong as the impact of past domestic volatility shocks, or that the long-term
effect of the Russian Crisis is felt only with a delay. However, another possibility is that African markets, especially Nigeria and South Africa (as they are large commodity exporters), only mirror movements in resource-rich Brazil and Russia as the commodity boom gains momentum from the early 2000s until the onset of the Credit Crisis in 2007.

5.4. The Bursting of the Dot Com Bubble

The crisis surrounding the Bursting of the Dot Com Bubble has the U.S. at its epicentre and, as such, the S&P 500 is used as the benchmark index. The S&P 500 is used as it is more representative of the U.S. and the world economy in general, rather than the NASDAQ. Nothing is lost by using the S&P 500 as the benchmark index, as the duration of the crisis is measured from peak to trough. The behaviour of African stock market volatility when the S&P 500 is used in the bivariate GARCH model can be seen in Figures 5.7 and 5.8.

During the Dot Com Bubble period, Table 5.4 shows the persistence of volatility is above 0.900 and, therefore, extremely strong for all five markets under consideration. When comparing the persistence of volatility during the Dot Com Bubble period to volatility persistence during the previous three crisis periods, volatility persistence is higher for Kenya and Mauritius than it is during the Asian, Brazilian and Russian Crisis periods. For South Africa the persistence of volatility is higher than during the Asian and Brazilian Crisis periods but weaker than during the Russian Crisis period. Egyptian volatility persistence is weaker than for all three prior crisis periods but for Nigeria the persistence of volatility during the Dot Com Bubble period is weaker than during the Brazilian Crisis period; and is incomparable to the results for the Asian and Russian Crisis periods, due to explosive volatility persistence. Nevertheless, despite Egyptian volatility persistence being weaker than during the three preceding crisis periods, it still averages an extremely high 0.983, the strongest of any of the markets during the Dot Com Bubble period. Mauritian volatility persistence is the lowest, averaging 0.906. Figure 5.7 (a) shows that the behaviour of volatility persistence during the crisis period shows no discernable trend for any of the markets, with Kenya and Mauritius displaying instability at various times, and Nigeria explosive for around one-third of the crisis period. Despite the strength that the persistence of volatility displays for all five markets during the Dot Com Bubble period, it is lower than volatility persistence during the non-crisis period for four markets,
except Egypt; as is the case for three preceding crisis periods (notwithstanding the explosiveness of Nigerian volatility persistence during the Asian and Russian crisis periods).

**TABLE 5.4: Volatility Dynamics during the Dot Com Bubble period & the non-crisis period**

<table>
<thead>
<tr>
<th></th>
<th>Cross-innovation</th>
<th>Own-GARCH</th>
<th>Persistence</th>
<th>Unconditional volatility</th>
</tr>
</thead>
<tbody>
<tr>
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<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
<td>Non-crisis</td>
</tr>
<tr>
<td>Nigeria</td>
<td>0.115</td>
<td>-0.032</td>
<td>0.839</td>
<td>0.892</td>
</tr>
<tr>
<td>Egypt</td>
<td>0.08</td>
<td>0.032</td>
<td>0.874</td>
<td>0.911</td>
</tr>
<tr>
<td>South Africa</td>
<td>0.083</td>
<td>0.031</td>
<td>0.868</td>
<td>0.925</td>
</tr>
<tr>
<td>Kenya</td>
<td>0.098</td>
<td>0.063</td>
<td>0.833</td>
<td>0.741</td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.094</td>
<td>-0.054</td>
<td>0.819</td>
<td>0.853</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Crisis</th>
<th>Non-crisis</th>
<th>Crisis</th>
<th>Non-crisis</th>
<th>Crisis</th>
<th>Non-crisis</th>
<th>Crisis</th>
<th>Non-crisis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nigeria</td>
<td>0.842</td>
<td>0.847</td>
<td>0.975</td>
<td>0.988</td>
<td>2.61</td>
<td>4.534</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Egypt</td>
<td>0.925</td>
<td>0.886</td>
<td>0.983</td>
<td>0.934</td>
<td>3.588</td>
<td>2.959</td>
<td></td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>0.8874</td>
<td>0.8876</td>
<td>0.961</td>
<td>0.967</td>
<td>1.329</td>
<td>0.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kenya</td>
<td>0.831</td>
<td>0.57</td>
<td>0.93</td>
<td>0.961</td>
<td>0.724</td>
<td>8.378</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mauritius</td>
<td>0.806</td>
<td>0.853</td>
<td>0.906</td>
<td>0.976</td>
<td>0.22</td>
<td>0.433</td>
<td></td>
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</tr>
</tbody>
</table>

The estimated coefficients obtained from averaging the significant rolling-window point estimates show that cross-volatility innovation during the bubble period is only strong for Nigeria, but that the cross-GARCH effect and volatility persistence are strong in all five markets. The short- and long-term effects of the Dot Com Bubble are generally weaker than past domestic influences. The technology bubble therefore does not have a strong effect on African markets, possibly because outside of South Africa, African countries lack strong high-tech sectors.

Unconditional volatility during the Dot Com Bubble period, as shown in Figure 5.7(b), is stable in Kenya and Nigeria, has no discernable trend but is the most volatile in Egypt, on a slight upward trend for Mauritius, and has a steep initial decline which loses momentum and becomes more unstable during the last quarter for South Africa. Crisis period unconditional volatility is highest in Egypt, averaging 3.588, and is weakest in Mauritius, averaging 0.220. Unconditional volatility during the Dot Com Bubble period is higher for Kenya and Mauritius than during the three preceding crisis periods, lower for South Africa than during all three preceding crisis periods, and weaker for Egypt than during the Asian and Russian Crisis periods but higher than during the Brazilian Crisis period.
For Nigeria, crisis period unconditional volatility is less than during the Brazilian Crisis period but incomparable to the Asian and Russian Crisis periods. In addition, unconditional volatility during the Dot Com Bubble period is higher than for the non-crisis period in Egypt and South Africa, and smaller in Kenya and Mauritius; similarly to the three preceding GARCH models. For Nigeria crisis period unconditional volatility is smaller than non-crisis period unconditional volatility; similarly to the Brazilian Crisis period, the only crisis for which a comparison can be made.

Figure 5.7. Volatility dynamics in African Equity Markets during the Bursting of the Dot Com Bubble period

(a) Persistence of Volatility
(b) Unconditional volatility
(c) Cross-volatility innovation from the U.S. to African equity markets
(d) Cross-GARCH effect between the U.S. and African equity markets
(e) Own-volatility innovation
(f) Own-GARCH effect

For the first time since the Asian Crisis period, Table 5.4 shows that average cross-volatility innovation during the Dot Com Bubble period is stronger than during the non-crisis period for all five markets. However, cross-volatility innovation from the S&P 500 to the five markets during the Dot Com Bubble period is weak for four markets, the most of the four crises so far. Cross-volatility innovation during the Dot Com Bubble period is only strong for Nigeria, where it averages 0.115. Figure 5.7(c) shows that cross-volatility innovation during the Dot Com Bubble period ends weaker than its start for all five markets but has no discernable trend and is unstable for around the final 10
per cent in Kenya, Mauritius and South Africa, and is only on a downward path for Egypt and Nigeria. Despite the general weakness of cross-volatility innovation during the bubble period compared to the three preceding crisis periods, it is more than 400 per cent larger than during the non-crisis period for Nigeria, more than 200 per cent stronger for Mauritius, more than 100 per cent larger for Egypt and South Africa, and more than 50 per cent bigger for Kenya. Non-crisis period cross-volatility innovation from the S&P 500 is, therefore, very weak, averaging below 0.10 for all five markets, and is smallest for Mauritius, averaging an extremely low -0.054.

Comparing cross-volatility innovation to own-volatility innovation during the Dot Com Bubble period, cross-volatility innovation from the S&P 500 to the five markets is stronger than own-volatility innovation for only two markets, Egypt and South Africa, and weaker for the remaining three. This compares to crisis period cross-volatility innovation being higher than crisis period own-
volatility innovation in four markets for the Brazilian Crisis period, three markets for the Russian Crisis period, and no markets for the Asian Crisis period. Own-volatility innovation during the Dot Com Bubble period for Egypt, Mauritius and South Africa is less than own-volatility innovation during the Asian, Brazilian and Russian Crisis periods, but stronger for the Kenyan market than during the preceding crisis periods. Own-volatility innovation during the Dot Com Bubble period is strongest for Nigeria, averaging a very strong 0.132, and is weakest for Egypt, averaging 0.058. Figure 5.7(c) shows that own-volatility innovation during the crisis period only follows an upward trend and ends higher than where it begins in Kenya, ending lower than where it starts in the other four markets.

Own-volatility innovation during the Dot Com Bubble period is smaller than non-crisis period own-volatility innovation for four markets, with Egypt being the only exception, the weakest comparison of any of the five crises studied. Kenyan own-volatility innovation during the non-crisis period is again more than triple crisis period own-volatility innovation.

Analysis of the cross-GARCH effect between the S&P 500 and the five markets during the Dot Com Bubble period shows past volatility shocks to the S&P 500 having a strong effect on future volatility for all markets. For all five markets, Figure 5.7(d) shows that the cross-GARCH effect ends the crisis period higher than where it starts, despite instability at the beginning for Kenya and Nigeria and at the end for Egypt, and no clear upward path for any market. The Dot Com Bubble is the only other crisis period besides the Credit Crisis period for which the cross-GARCH effect is strong for all five markets. Considering the markets individually, the cross-GARCH effect during the Dot Com Bubble period is bigger for Kenya, Mauritius and South Africa than during previous crisis periods, and stronger for Egypt and Nigeria than during the Brazilian and Russian Crisis periods, but weaker than during the Asian Crisis period. The cross-GARCH effect during the Dot Com Bubble period is strongest for Egypt, averaging 0.874, and weakest for Mauritius, averaging a still strong 0.819.

A comparison of the cross-GARCH effect between the S&P 500 and the five markets during the Dot Com Bubble period and the non-crisis period shows that as for the three preceding crisis periods, Kenya is the only market for which the cross-GARCH effect is greater during the crisis period than during the non-crisis period. Just as for the Russian Crisis period, the cross-GARCH
effect during the Dot Com Bubble period is more than 10 per cent larger than during the non-crisis period. The cross-GARCH effect during the non-crisis period is also strong in four of the five markets, with the exception of Kenya.

Nevertheless, despite the cross-GARCH effect during the Dot Com Bubble period been stronger for all five markets than during the Brazilian and Russian Crisis periods, and larger for Kenya, Mauritius and South Africa than during the Asian Crisis period, it is weaker than the own-GARCH effect during the Dot Com Bubble period for three markets, similarly to the Brazilian and Russian Crisis periods. The own-GARCH effect during the Dot Com Bubble period is stronger than the corresponding cross-GARCH effect for Egypt, Nigeria and South Africa, and weaker for Kenya and Mauritius. Overall, just as for the cross-GARCH effect, the own-GARCH effect during the Dot Com Bubble period is strong for all five markets, the only crisis studied – including the Credit Crisis – for which this is the case. The own-GARCH effect during the Dot Com Bubble period is strongest for Egypt, averaging an extremely strong 0.925, and weakest for Mauritius, averaging 0.806. Just as for the cross-GARCH effect, the own-GARCH effect during the Dot Com Bubble period ends higher for the five markets than when it begins, as Figure 5.7(f) indicates. The own-GARCH effect for Egypt follows no discernable trend, for Kenya it ends a period of initial instability higher than when it begins but then embarks on a weakly downward path; for Mauritius it weakens for the first 20 per cent of the crisis period, is unstable for the next 20 per cent and largely stable around a high level for the next 60 per cent, and for Nigeria it is explosive for the first third of the crisis period and thereafter displays no discernable trend. For South Africa the own-GARCH effect has no trend for the first quarter but an upward trend until the end of the crisis period.

The crisis period own-GARCH effect is in turn stronger than the non-crisis period own-GARCH effect for two markets and weaker in the remaining three markets. The own-GARCH effect during the Dot Com Bubble period is greater than the non-crisis period own-GARCH effect in the same two markets as for the Brazilian Crisis, Egypt and Kenya. This compares to the own-GARCH effect during the Asian, Russian and Credit Crisis periods, which is stronger than the non-crisis period own-GARCH effect for only one market. The non-crisis period own-GARCH effect when the S&P 500 is used in the bivariate GARCH model is only weak in Kenya. For Kenya, the own-GARCH effect is more than 40 per cent greater during the crisis period than during the non-crisis period.
The results suggest that as per the Asian Crisis the short-term effect of the Dot Com Bubble generally has a weaker impact on future African volatility than past domestic innovations. Furthermore, the effect of past volatility shocks to the S&P 500 on future African volatility is generally weaker than during the non-crisis period as well as the impact of past domestic volatility shocks during the crisis period, suggesting once again that if the Dot Com Bubble has any effect at all, it is delayed.

One of the reasons why the Dot Com Bubble has a smaller impact on future African volatility in both the short- and long-run than the impact of past domestic influences do, is that, besides South Africa, African countries have only small information technology sectors. If African markets are indeed less affected by crises surrounding the technology industry, investors should be able to gain the benefits of diversification by investing in African equities. This is partly supported by the signs of the coefficients for cross-volatility innovation during the post-crisis period, which suggest that an increase in the volatility of the S&P 500 leads to a decline in future Mauritian and Nigerian volatility.

5.5. The Credit/Global Financial Crisis

The Credit/Global Financial Crisis of 2007-9 began in the United States with the failure of the sub-prime mortgage market in the first quarter of 2007 and reached its climax with the collapse of Lehman Brothers in mid-September 2008 (Yilmaz, 2009). According to Yilmaz, financial markets fluctuated wildly and volatility spread across global markets with unprecedented speed, but Frank and Hesse (2009) claim that the crisis did not initially fully affect emerging markets until the collapse of Lehman Brothers. Both papers view the Lehman Brothers collapse as a key global event, sparking a full-blown systemic crisis characterised by increased risk aversion and falling asset markets.

The severity of the Credit Crisis is born out by the results. The strong results for the Credit Crisis, especially for the persistence of volatility and the cross-GARCH effect, is supported by Yilmaz (2009), who also finds that volatility spillovers for East Asian equity markets are strongest during the Credit Crisis. The graphs in Figure 5.9 show the volatility dynamics in African markets during the Credit Crisis with the S&P 500 used as the source of the crisis in the bivariate GARCH model. As the bivariate GARCH model that is run to determine the impact of the crisis on the five
markets uses the S&P 500, the same index that is used to gauge the impact of the Dot Com Bubble, the comparative non-crisis period is the same for both crisis periods.

### TABLE 5.5: Volatility Dynamics during the Credit Crisis period & the non-crisis period

<table>
<thead>
<tr>
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<th>Cross-innovation</th>
<th></th>
<th></th>
<th>Cross-GARCH</th>
<th></th>
<th></th>
<th>Own-innovation</th>
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<td>Crisis</td>
<td>Non-crisis</td>
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<td>Non-crisis</td>
<td>Crisis</td>
<td>Non-crisis</td>
<td>Crisis</td>
</tr>
<tr>
<td>Nigeria</td>
<td>0.101</td>
<td>-0.032</td>
<td>0.826</td>
<td>0.892</td>
<td>0.198</td>
<td>0.141</td>
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</tr>
<tr>
<td>Egypt</td>
<td>0.049</td>
<td>0.032</td>
<td>0.941</td>
<td>0.911</td>
<td>0.038</td>
<td>0.05</td>
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<td>South Africa</td>
<td>0.076</td>
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<td>0.925</td>
<td>0.107</td>
<td>0.079</td>
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<td>0.149</td>
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<td>0.392</td>
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<td>Mauritius</td>
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<td>0.853</td>
<td>n/a</td>
<td>0.124</td>
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<table>
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<tr>
<th></th>
<th>Own-GARCH</th>
<th>Persistence</th>
<th>Unconditional volatility</th>
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<td>Non-crisis</td>
<td>Crisis</td>
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<td>South Africa</td>
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<td>0.8876</td>
<td>0.978</td>
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<td>0.527</td>
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<td>0.946</td>
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<tr>
<td>Mauritius</td>
<td>n/a</td>
<td>0.853</td>
<td>Explosive</td>
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The estimated coefficients obtained from averaging significant rolling-window point estimates suggest that the Credit Crisis has the strongest impact of any crisis on African volatility. Unconditional volatility during the Credit Crisis period is stronger than during the non-crisis period for a majority of the markets for the first time, and volatility persistence is stronger than during the non-crisis period for two markets for the first time also. In addition, for the first time a crisis has a stronger long-term than short-term impact as the cross-GARCH effect during both the Credit Crisis and non-crisis periods is generally greater than past domestic influences.

The strongest results for persistence of volatility for any of the markets during a crisis period are during the Credit Crisis period. While volatility persistence is explosive for more than 99 per cent of the Credit Crisis period for Mauritius, the persistence of volatility is higher for Egypt, Kenya and South Africa than during any other crisis period. Volatility persistence during the Credit Crisis period is, therefore, only weaker for Nigeria. The persistence of volatility during the Credit Crisis period is one of only two crisis periods, the other is the Dot Com Bubble period, during which volatility persistence for all four comparable markets is above 0.900. Regarding individual market behaviour, Figure 5.9(a) shows that volatility persistence gets stronger as the crisis continues for
Egypt and South Africa and is explosive once towards the end for Nigeria, and briefly on three occasions for Kenya. Crisis period volatility persistence is also very unstable for Kenya. Volatility persistence during the crisis period ranges from an extremely high 0.992 for Egypt, to a still very strong 0.919 for Nigeria.

When comparing the persistence of volatility during the Credit Crisis period to volatility persistence during the non-crisis period, the persistence of volatility is higher for Egypt and South Africa during the crisis period than during the non-crisis period, but smaller for Kenya and Nigeria, and incomparable for Mauritius. This is the first time, though, that volatility persistence during a crisis period is greater than during a non-crisis period for two markets.
Similarly to volatility persistence, the results for unconditional volatility during the Credit Crisis period are stronger than for the preceding crises. Unconditional volatility during the Credit Crisis period may be incomparable for Mauritius, but for Kenya, Nigeria and South Africa it is higher than during all four preceding crisis periods, and for Egypt, it is only weaker than during the initial Asian Crisis period. Also, for the first time, unconditional volatility during the crisis period is higher than non-crisis period unconditional volatility for three markets as opposed to two. Unconditional volatility during the Credit Crisis period for the four comparable markets is greater than unconditional volatility during the non-crisis period for Egypt, Nigeria and South Africa, and only weaker for Kenya. For Nigeria, crisis period unconditional volatility is more than seven times larger than non-crisis period unconditional volatility. Unconditional volatility during the Credit Crisis period is highest in Nigeria, averaging 35.436, and is weakest for South Africa, averaging 2.096. Figure 5.9(b) shows that Egyptian unconditional volatility reaches a 14-year high of 19.32 during the Credit Crisis period.

The results for cross-volatility innovation during the Credit Crisis period are not as strong as those for volatility persistence when compared to the previous four crisis periods, but are as strong when compared to the non-crisis period. Cross-volatility innovation during the Credit Crisis period is strong in three markets, Nigeria, Kenya and Mauritius, and weak in the remaining two. Credit Crisis period cross-volatility innovation is weaker for Nigeria, Egypt and South Africa than during all four preceding crisis periods, weaker for Mauritius than during the Brazilian and Russian Crisis periods but stronger than during the Asian Crisis and Dot Com Bubble periods. The only market for which cross-volatility innovation from the S&P 500 during the Credit Crisis period is stronger than during the four prior crisis periods is Kenya. Figure 5.9(c) shows that cross-volatility innovation generally strengthens as the Credit Crisis period continues but is initially highly unstable for Nigeria and Mauritius, very unstable for Egypt, starts off insignificantly for South Africa, and is twice briefly insignificant for Kenya. The strongest cross-volatility innovation during the Credit Crisis period is for Kenya, with an average of 0.149, and the lowest average is for Egypt, a weak 0.049. Cross-volatility innovation from the S&P 500 to Kenya during the crisis period hits a 14-year high of 0.184.

Cross-volatility innovation during the Credit Crisis period compared to the corresponding crisis period own-volatility innovation is stronger in only one market, the same as for the Asian Crisis period, but less than the two markets for the Dot Com Bubble period and the four markets for the
Brazilian and Russian Crisis periods. Crisis period cross-volatility innovation is, therefore, stronger than crisis period own-volatility innovation only in Egypt, but weaker for Kenya, Nigeria and South Africa, and incomparable for Mauritius. Credit Crisis period own-volatility innovation is strong in three markets, more than during the four preceding crisis periods. Of the four comparable markets, own-volatility innovation during the Credit Crisis period is stronger than during the Brazilian Crisis period and the Dot Com Bubble period for Nigeria, but incomparable for the other two crisis periods, stronger for South Africa than during three of the four preceding crisis periods, with the Asian Crisis period the exception, and stronger for Kenya than during all four prior crisis periods. The only market for which own-volatility innovation during the Credit Crisis period is weaker than during all four preceding crisis periods is Egypt. Credit Crisis period own volatility innovation is strongest for Kenya, averaging an extremely strong 0.419, more than triple crisis period cross-volatility innovation, and weakest in Egypt, averaging a very low 0.038. Own-volatility innovation strengthens during the crisis period for Nigeria and Kenya, as shown in Figure 5.9(e), and is between 50 to 100 per cent larger than cross-volatility innovation for Nigeria and more than double in magnitude for Kenya, for which it also touches a 14-year high of 0.506.

Own-volatility innovation during the Credit Crisis period is only weaker than non-crisis own-volatility innovation for one market, similarly to the Asian and Russian Crisis periods, but less than two markets for the Brazilian Crisis period and the four markets during the Dot Com Bubble period. Crisis period own-volatility innovation is only weaker than non-crisis own-volatility innovation in Egypt. For the other three comparable markets, own-volatility innovation during the Credit Crisis period is stronger, similarly to the Asian, Brazilian and Russian Crisis periods, but more than the one market for the Dot Com Bubble period.

The cross-GARCH effect between the S&P 500 and the five markets during the Credit Crisis period is strong for four markets, less than all five markets for the Dot Com Bubble period, but more than the two markets for the Russian Crisis period and three markets for the Asian and Brazilian Crisis periods. The cross-GARCH effect during the Credit Crisis period is stronger for Egypt, Mauritius and South Africa than during the four previous crisis periods, stronger for Nigeria than during the Brazilian and Russian Crisis periods, and weaker for Kenya than during all four prior crisis periods. However, the results continue to be the same as for the four preceding crisis periods when comparing the cross-GARCH effect during the Credit Crisis period to the non-crisis period cross-
GARCH effect, with the cross-GARCH effect for four of the five markets smaller during the crisis period than during the non-crisis period. The only difference is that the crisis period cross-GARCH effect is stronger than during the non-crisis period for Egypt instead of Kenya. The cross-GARCH effect strengthens as the Credit Crisis continues for Kenya, Nigeria and Mauritius. However, Figure 5.9(d) shows that the cross-GARCH effect for Mauritius weakens dramatically towards the end of the crisis period, though it still ends much higher than its start at a 14-year low of -0.86. For South Africa the crisis period cross-GARCH effect is briefly insignificant but remains strong for the rest of the crisis period, as does Egypt, which is strong throughout in a narrow range between 0.93 and 0.95. The crisis period cross-GARCH effect is strongest for Egypt, averaging an extremely high 0.941, and weakest for Kenya, averaging 0.702.

The strength of the cross-GARCH effect between the S&P 500 and the five markets during the Credit Crisis period is again observed when making a comparison to the corresponding own-GARCH effect during the Credit Crisis period. The cross-GARCH effect is weaker than the own-GARCH effect during the Credit Crisis period in only one market, Egypt, stronger for Kenya, Nigeria, and South Africa, and incomparable for Mauritius. Results of this strength when comparing the crisis period cross- and own-GARCH effects are not observed for any of the previous crises except for the initial Asian Crisis period, when for four of the five markets the cross-GARCH effect is stronger than the own-GARCH effect.

The crisis period own-GARCH effect for the comparable markets is weak for two markets, Kenya and Nigeria, and strong for two markets, Egypt and South Africa. This compares to the own-GARCH effect been strong in all markets during the Dot Com Bubble period, and weak in three markets during the Asian Crisis period, two markets during the Brazilian Crisis period and one market during the Russian Crisis period. Figure 5.9(f) shows that the own-GARCH effect strengthens as the Credit Crisis continues for Kenya, Nigeria and South Africa, and gets stronger towards the very end for Egypt. The crisis period own-GARCH effect is strongest for Egypt, averaging a very high 0.955, and weakest for Kenya, averaging 0.527, and is weaker than the non-crisis period own-GARCH effect in three markets, similar to the results for the four preceding GARCH models. The own-GARCH effect during the Credit Crisis period is only stronger than during the non-crisis period for Egypt.
The results imply that the impact of own domestic past innovations on future African volatility is generally greater than the impact of past innovations to the S&P 500 during the Credit Crisis period; which suggests that the short-term effect of the Credit Crisis on African volatility is not that strong. Despite past volatility shocks in the US having a generally stronger impact on future African volatility during the non-crisis period than during the crisis period, domestic influences on future African volatility are generally smaller than past U.S. volatility shocks, except for Egypt. Therefore, the Credit Crisis is the first crisis since the Asian Crisis that has more of a long-term than short-term effect on African volatility.

Together with the strong long-term effect of the Credit Crisis on future African volatility and that for the first time volatility persistence is greater in two markets during the crisis period than the non-crisis period and that unconditional volatility is generally greater during the crisis period than the non-crisis period, the results suggest the Credit Crisis has the strongest impact on African volatility of the five crises. The strong impact of the Credit Crisis may not be unexpected due to the fact that the source of the crisis is the world’s largest economy. In addition, the results also provide little support for the theory that emerging markets would be able to “decouple” from events in the U.S.

At this juncture, and leaving the strong impact that the Credit Crisis has on African stock market volatility aside, it is worth discussing possible reasons why the preceding four crises do not have as strong an influence on the volatility of the five African markets. Despite the existence of cross-volatility spillovers, non-crisis period volatility dynamics and domestic factors frequently outweigh crisis period volatility dynamics. This is particularly the case for volatility persistence, the own- and cross-GARCH effects, and unconditional volatility for at least three crisis periods. The reasons for these weak results are complicated and varied but can be explained to a certain extent.

For Egypt, the crisis period cross- and own-GARCH effects may be weaker than during the non-crisis periods because during the non-crisis period the Israel-Lebanon War took place. That war would have led to an increase in certain aspects of Egyptian volatility, as that event was closer to home than any other crisis emanating from a different continent.

For Nigeria, there is political uncertainty during the non-crisis period. During 2007 militants killed a prominent Muslim official and the elections were marred by fraud. In addition, from around 2003 until July 2008, the price of oil (Nigeria’s main export) was strong and rising. These factors may help
explain why the persistence of volatility, unconditional volatility and the cross- and own-GARCH effects for Nigeria during the non-crisis period are stronger than during crisis periods for almost all observations. South Africa, like Nigeria, may also be shielded from the crises by rising commodity prices. As to the reason why the short-term impact of the crises on future African volatility only dominates past domestic innovations during the Brazilian and Russian Crisis periods, that may be explained by local political and economic instability, such as the violence surrounding the Kenyan elections in 2008.

6. Conclusion

This paper uses a rolling bivariate diagonal BEKK-GARCH model to investigate African stock market volatility from 1997 to 2010. Each regression relates to a 1 000-day period, which is consecutively moved forward by a day from the start of the 14-year period, until its end. Special emphasis is placed on five major global crises that do not originate in Africa, but occur during the 14-year period. Five markets are included, namely, Egypt, Kenya, Mauritius, Nigeria and South Africa. The paper has four key findings.

The first important finding concerns volatility persistence. While volatility persistence is strong for crisis and non-crisis periods, it is higher during non-crisis periods. This is the case even for the Credit Crisis, the crisis for which volatility persistence is highest. The results for unconditional volatility are similar, but Credit Crisis period unconditional volatility is higher than during the non-crisis period. This implies that, besides the Credit Crisis, the other crises do not have that strong an impact on volatility persistence and unconditional volatility.

Secondly, cross-volatility spillovers during non-crisis periods are frequently larger than during crisis periods. This is especially the case for the cross-GARCH effect for a majority of the markets. While this situation does occur for cross-volatility innovation, cross-volatility innovation during crisis periods is stronger than for non-crisis periods for a majority of markets across all crises. This suggests that the crises have a strong impact in the short-term. However, their long-term impact is relatively weak, since the impact of shocks to volatility in overseas equity markets on the five African markets during crisis periods is generally smaller than during non-crisis periods.
The third main finding is that the Credit Crisis has the strongest effect on African volatility of the five crises. Volatility persistence, unconditional volatility and the cross-GARCH effect are higher during the Credit Crisis than during the four prior crisis periods. The strength of the results for the Credit Crisis suggests that African markets did not “decouple” from the U.S. during the crisis as some commentators expected to be the case for certain emerging markets. For the other crises, it is difficult to say which has a stronger impact than the other, but cross-volatility innovation is strongest during the Russian Crisis period and weakest during the Dot Com Bubble period, and volatility persistence is lower during the Asian Crisis period than during any other crises.

Finally, while African markets do have volatility linkages with both emerging and developed equity markets, domestic influences on volatility may be more important. Cross-volatility innovation during crisis periods have a stronger impact on future African volatility than past domestic innovations for a majority of markets for only the Brazilian and Russian Crises. Similarly, the crisis period cross-GARCH effect is dominated by past domestic volatility shocks for only two crises, the Asian Crisis and the Credit Crisis. Furthermore, past domestic influences are larger than both the short- and long-term effects of the Dot Com Bubble.

Reasons why non-crisis volatility dynamics and past domestic influences may sometimes be larger than the effects of the crises are the commodities boom for Nigeria and South Africa, events such as the Israel-Lebanon War for Egypt, general political instability, and probably because African markets are still not fully integrated with global markets. The long-term impact of the crises before the Credit Crisis may also be delayed, as the cross-GARCH effect during non-crisis periods is often greater than during crisis periods.

This study contributes to the literature as an all-encompassing investigation of African stock market volatility in an era of globalisation. The results support Diebold and Yilmaz’s (2008) findings on the existence of volatility spillovers between and to emerging markets and Rao’s (2008) results on the strength of volatility persistence in both emerging and developed equity markets. The paper expands on the work of Lamba and Otchere (2001) and Haque, Hassan, Maroney, and Sackley (2004) on African markets, as well as the broader studies on emerging markets of Bekaert and Harvey (1997), and Aggarwal, Inclan, and Leal (1999). The results provide additional understanding to investors on
the behaviour of volatility in African equity markets and the paper can be used as a foundation for further investigation into African markets.

Future work to increase knowledge and understanding of African stock market volatility may include markets such as Botswana, Morocco and Zimbabwe. The analysis of mean returns, as well as extending the time period under study, might also be considered. Different models may also be used, such as a volatility spillover index (as proposed by Diebold and Yilmaz, 2008) and time varying coefficients could be introduced (see, for example, Bollerslev, Engle, and Wooldridge, 1988). African equity markets are likely to attract even more attention going forward as investors look to benefit from unexploited opportunities from international investment and diversification.

Appendix: Determination of Crises and Crisis Periods
**TABLE A.1: Defined Crisis Dates and Crisis Periods**

<table>
<thead>
<tr>
<th>Crisis</th>
<th>Defined Crisis Dates</th>
<th>Crisis Period</th>
</tr>
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<tbody>
<tr>
<td>Asian Crisis</td>
<td>2 July 1997 - 17 November 1997</td>
<td>31 October 2000 - 14 September 2001</td>
</tr>
<tr>
<td>Brazilian Crisis</td>
<td>15 April 1998 - 14 January 1999</td>
<td>31 October 2000 - 13 November 2002</td>
</tr>
<tr>
<td>Credit Crisis</td>
<td>2 July 2007 - 6 March 2009</td>
<td>2 July 2007 - 21 October 2010</td>
</tr>
</tbody>
</table>

In Table A.1 the actual/defined crisis dates for each crisis studied in this paper are provided as well as the corresponding “Crisis Period”. For the purpose of this study it is necessary to distinguish between an actual crisis and a crisis period. A crisis, such as the Asian Crisis, is defined as being from an actual start to an end date. The start or end date is based on a particular event, i.e. a currency devaluation or failure of a financial institution, or the peak or trough of a stock market index. Use of the peak and low values of an index is based on Forbes and Rigobon (2002) and the method is applied to the S&P 500 to determine the duration of the Bursting of the Dot Com Bubble.

A crisis period includes an actual crisis. The dates indicated are as per Figures 5.1 – 5.2 and represent the end dates of one observation point on the graphs. For example, 31 October 2000 represents the results of the first regression that is run from 1 January 1997 - 31 October 2000. As far as is possible, a crisis period is defined as starting from the moment it appears in the observation window, until it disappears. An observation window contains one thousand days, as explained in the methodology. Consequently, the Credit Crisis period which starts on 7 July 2002 and ends on 6 March 2009 has a crisis period that is defined from 7 July 2007 (the last day of the observation point from 2 September 2003) to 21 October 2010 (the last day of the last possible observation point from 22 December 2006).

The non-crisis period for all crises is for the same time period. The corresponding non-crisis period for all the crisis periods has therefore been defined in terms of data points, from 10 August 2006 – 1 July 2007. This has been done for comparative purposes as well as to exclude the possibility that crisis spillovers are transmitted from non-African equity markets to African markets when a crisis does not originate from that specific non-African market.

**References**


