SUBPRIME CRISIS AND CONTAGION: EVIDENCE FROM THE BRVM

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Abstract

This paper empirically investigates the issue of contagion from the US stock market to the West African Regional Stock Market (BRVM) during the subprime crisis. It carries out aggregate and sectoral level analyses within a modified EGARCH framework. The results are twofold: 1) at the aggregate level, there are contagion effects in the mean and volatility from the US market to the BRVM; 2) at the sectoral level, it appears that all economic sectors have undergone the crisis through either the mean or the volatility or both.

JEL classification: C22; G01; G1

Keywords: Subprime crisis; BRVM; Contagion; EGARCH; West Africa

1. INTRODUCTION

The recent global financial crisis has revealed that the global financial system is intrinsically unstable. It is often hit by crises. Episodes of stability last about ten years (Aka, 2006). In August 2007, after a long and relatively quiet period, a severe financial crisis originating from the US housing market has shaken financial markets around the world. As in many previous credit crises, it was the loosening of credit standards during the lending frenzy that caused the initial set of losses (Kodres, 2008). The crisis, which occurred during a period of strong world macroeconomic growth and low interest rates, has surprised and unnerved many investors and regulators. The turbulence was triggered by a sudden and widespread loss of confidence in securitization and financial engineering, and the manifest failure of respect-

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ed statistical models for assessing and pricing credit risk (Caprio et al., 2008). The crisis spread quickly; first, from Wall Street to mature markets, and then to emerging markets. None of the stock markets around the world seems to have evaded the subprime financial turbulence due to financial globalization and the acceleration of information transmission.

Since the 1994 Mexican peso collapse, the 1997 East Asian crises, and the 1998 Russian financial collapse, there has been a growth in research into how shocks are transmitted internationally from one market to another, and why they have such intensity. The contagion process has been attributed to several factors. Although there is now a large body of empirical studies testing for the existence of financial contagion during financial crises, there exists no consensus among researchers as to what contagion is and how to identify it.

Contagion can broadly be defined as the transmission of market turbulences from one market to another. Its causes can be separated into two categories (Dornbusch et al., 2000). The first type of contagion is caused by a fundamental spillover. In other words, this type of contagion depends on fundamental trade and financial links between economies. The second type of contagion is triggered by "herding behaviour" of investors who sell assets to meet margin calls and/or to rebalance portfolios. While the second type of contagion emphasizes the importance of liquidity in explaining the pattern of contagion, the first points to the importance of macroeconomic fundamentals.

The empirical study of the issue of contagion can be traced back to King and Wadhwani (1990), who find that the correlation in returns between markets increases with the volatility in each market. They interpret this as evidence supporting the 'market contagion' hypothesis. Market volatility is related to underlying information flow, including public information. Public information flows may then be associated with higher volatility and more pronounced comovement, all in the context of a rational approach to asset pricing (Ross, 1989). Early studies on the information transmission across international markets use ARCH-type models (e.g., Bae and Karolyi, 1994; Koutmos and Booth, 1995; Hamao, Masulis, and Ng, 1990). They argue that the phenomenon of volatility spillover results from integration of international markets. Market integration is interpreted as prices in different markets reflecting the same fundamental information; volatility spillover represents a failure of the market to fully process information and may signal a violation of market efficiency (Iwatsubo and Inagaki, 2007). Some studies show a significant increase in cross-country correlations of stock returns and/or volatility during the Asian crisis, and conclude that there was a contagion effect (Sachs et al., 1996; Baig and Goldfajn, 1999). Forbes and Rigobon (2002) stress that, after accounting for heteroskedasticity, there is "no contagion, only interdependence''. However, the existence of contagion effect is supported by Froot et al. (2001) and Basu (2002) who focus on different transmission channels.

As stated above, a striking characteristic of the recent crisis is that the initial shock originated from the US stock market, and has been rapidly transmitted to markets of very different sizes and structures around the globe. This study attempts to shed light on the phenomenon of contagion triggered by the recent subprime crisis. In particular, it empirically investigates contagion effects from the US stock market to the West African Regional Stock Market (BRVM after it French acronym)[2]. To this end, the present paper makes use of the definition of contagion as defined by Baig and Goldfajn (1999), and Forbes and Rigobon (2002). And, it takes advantage of the contagion model proposed by Baur (2003) with a modest modification.

The estimations show that, on the hand, there are significant contagion effects in the mean and volatility from the US stock market to the BRVM at the aggregate level; and, on the other hand, all economic sectors have felt the crisis through either the mean, the volatility or both. Hence, these findings suggest that the BRVM is not immune from contagion before increasing integrated world financial markets, and policymakers should pay attention to movements in mature markets, since contagion effects could impair their ability to raise funds from the domestic market.

The paper is outlined as follows. Section 2 reviews previous literature after the introduction section. Section 3 exposes the methodology. Section 4 describes the data. Section 5 reports empirical results, and section 6 concludes the paper.

2. LITERATURE REVIEW

There is no consensus on what contagion means. Some studies examine changes in the structure of inter-market linkages by analysing changes in the correlation of international stock returns, and define contagion as excessive spillovers from one market onto another during turbulent periods beyond structural linkages between these markets (e.g., Baig and Goldfajn, 1999; Forbes and Rigobon, 2002; Pericoli and Sbracia, 2003). Contagion is described by Park and Song (2000) as the spread of market disturbances from

[2] The West African Economic and Monetary Union member States of Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal and Togo have a common stock market called the *Bourse Régionale des Valeurs Mobilières (BRVM).* The BRVM was set up on 18 December 1996 and is headquartered in Abidjan, Côte d'Ivoire.

one country to another. It is observed through excessive comovement of financial variables of a group of countries during financial crisis. For Fratzscher (2000) contagion is the transmission of a crisis that is not caused by the affected country's fundamentals[3] but by its "proximity" to the country where a crisis has occurred. As suggested by another study, contagion may be evidenced through a simultaneous appearance of extreme stock return shocks across countries (e.g., Longin and Solnik, 2001). In assessing the determinants of a currency crisis, Eichengreen et al. (1996) define contagion as "a systematic effect on the probability of a speculative attack which stems from attacks on the other currency, and is therefore an additional effect above and beyond those of domestic fundamentals".

To summarize, contagion has been commonly defined as a transmission of shocks from a crisis-country to other countries, which can be observed through co-movements of different financial indices (such as exchange rates, stock market prices and interest rates) on multiple markets or rising probabilities of default. In other words, contagion is an excessive transmission of shocks from one crisis market to others, beyond any idiosyncratic disturbances and fundamental links among them.

Economic literature suggests several channels of contagion, namely real interdependence (or trade links), similar initial conditions and financial linkages (Hernandes and Valdès, 2001). For the purposes of the current study, we shall focus on the trade channel and financial linkages related to investor behavior.

Trade links work through the impact of the significant currency devaluation/depreciation associated with crises. A devaluation/depreciation of a domestic currency improves the international competiveness (price effect) of the country in question, and consequently lowers the exports of major trade partners. The negative effects of currency devaluation/depreciation on major trade partners through loss of competitiveness may be reinforced by a fall in demand in the crisis country (income effect) if it experiences economic downturn. The two effects (price and income) worsen the current account balances of trade partners. This, in turn, triggers speculative attacks on the currencies of these countries. Trade links were very much at play during the 1992-1993 European Exchange Rate Mechanism crisis, the 1994 Mexican crisis, the 1997 Asian crisis, and the 1999 Brazilian crisis (Eichengreen and Rose, 1999; Forbes, 2001, 2004; Glick and Rose, 1999). During the recent global financial crisis, trade links work through the decline in commodity prices and exports alongside the global economy's collapse.

[3] The transmission has an impact on the country's fundamentals ex post facto.

The financial links emphasized in this paper result from factors related to Investor behaviour, such as risk aversion, information asymmetries, herding, and principal agent problems.[4] During a crisis period, risk appetite declines, and risk adverse investors rebalance their portfolio composition in order to reduce their exposure to risk. Thus with asymmetric information, investors might shift their assessments about countries even without any change in fundamentals. Investors might react to news revealed in the crisis country by avoiding, and pulling back from, countries that share some characteristics with the crisis country, even if no other news emerged (wake-up call hypothesis) (Eichengreen et al., 1996; Goldstein, 1998). Factors related to reputation and compensation may also provide incentives for managers to follow the herd: financial managers' performance is often assessed by comparison with their peers, rather than on the basis of absolute returns; managers thus have strong incentives to follow others in the industry and would take a big risk if they deviate from their competitors (Rajan, 2005).

3. METHODOLOGY

Existing empirical studies on contagion offer a wide range of methods to measure contagion across markets worldwide during turmoil periods[5]. The most and widely used methodologies are based on cross-market correlation coefficients[6], Logit/probit techniques[7], VAR and VECM approaches[8], and ARCH-type models. In this paper, we take advantage of the fourth methodology. The ARCH model is one of the most popular methods used to modeling the volatility of financial time series data.

In this section, we use a two-stage procedure to investigate the contagion

[4] The financial channel of contagion has received much attention in the last few years. For example, Kaminsky and Reinhart (2000) document the role of banks. Borensztein and Gelos (2003), Kaminsky, Lyons, and Schmukler (2004), and Broner, Gelos, and Reinhart (2006) discuss the role of mutual funds. Allen and Gale (2000), Kodres and Pritsker (2002) provide theoretical analysis of the mechanisms underpinning contagion.

[5] Bodart and Candelon (2009) propose a new measure of contagion based on the frequency analysis.

[6] See, among others, King and Wadhwani (1990), Lee and Kim (1993), Calvo and Reinhart (1996), Baig and Goldfajn (1999).

[7] See, among others, Eichengreen et al. (1996), Glick and Rose (1999), De Gregorio and Valdes (2001), Caramazza et al. (2000, 2004), Van Rijckeghem and Weder (2001), and Kaminsky and Reinhart (2000).

[8] See, among other,s Nagayasu (2000), Masih and Masih (1999), Clare and Lekkos (2001), Sander and Kleimeier (2003).

effect in returns and return volatilities of the daily-traded stocks of BRVM. GARCH model specifications have been proposed in attempts to describe volatility clustering and the asymmetric nature of processes leading to volatility (Bollerslev, 1986). Baur (2003)[9] suggests modified GARCH(1,1) and EGARCH(1,1) models that allow for a change in the transmission mechanism during a crisis period relative to a tranquil period. In addition, in contrast to the others methodologies, this methodology differentiates between mean and volatility contagion. Based on Baur's approach, the paper suggests a modest modification that more closely suits the data. In particular, we allow change in the transmission mechanisms during different phases of the crisis. Therefore, the GARCH (1,1) model to test for contagion is given as follows:

$$r_t = \tilde{\mu}_0 + \tilde{\mu} r^*_{t-1} + \sum_{j=1}^{2} \tilde{\mu}_j r^*_{t-1} D^j_{crisis,t-1} + \sum_{j=1}^{2} \tilde{d}_j D^j_{crisis,t-1} + \varepsilon_t \quad [1]$$

$$h_t = \tilde{c}_0 + \tilde{c}_1 z_{t-1} + \tilde{\beta}_1 h_{t-1} + \tilde{\alpha}_0 r^*_{t-1} + \sum_{j=1}^{2} \tilde{\alpha}_j r^*_{t-1} D^j_{Crisis,t-1} \quad [2]$$

$$\varepsilon_t = z_t + \sqrt{h_t}$$

$$z_t \sim N(0,1),$$

where r_t is BRVM index return; r^*_t is U.S. stock index return; and $D^j_{Crisis,t-1}$ are dummy variables that capture the first phase and the second phase of the crisis.

3.1 Contagion in mean

Equation [1] is the BRVM index return's equation which includes exogenous variables such as U.S. stock return (r^*_{t-1}), interactive variables ($r^*_{t-1} D^j_{crisis,t-1}$) with j = {1,2} the phase of the crisis, and dummy variables D^j that are set to one during the corresponding financial crisis phase.

The parameteris $\tilde{\mu}_0$ is the mean; the parameter $\tilde{\mu}$ captures the normal effect of shocks from U.S. market (r^*) to the BRVM (r); and the parameter $\tilde{\mu}_j$ indicates whether there is an additional effect (beyond what is normally expected) in a particular phase of crisis ($D^j_{Crisis,t-1}$ is a dummy variable that is

[9] The original model suggested by Corsetti et al. (2001) does not capture any change in the transmission mechanism beyond the transmission which is expected in normal times.

equal to one in the phase corresponding of crisis, and zero otherwise). In other words, if $\tilde{\mu}_j$ coefficient is equal to zero, then no structural interaction change occurred.

$\tilde{d}_j$ is an intercept dummy variable. If $\tilde{d}_j$ is not significantly different from zero, no structural intercept change from the crisis phase is indicated. Increased uncertainties resulting from the existence of a crisis should reduce stock returns making the intercept dummy variables negative ($\tilde{d}_j < 0$).

The null hypothesis of a test for contagion is that there is no increased transmission of shocks from the U.S. market to the BRVM in the crisis period: $H_0 : \tilde{\mu}_j \leq 0$ against the alternative hypothesis $H_1 : \tilde{\mu}_j > 0$. A positive parameter $\tilde{\mu}_j$ can be viewed as excess transmission of shocks in the crisis period.

3.2 Contagion in volatility

Equation [2] states that the conditional volatility is assumed to follow a GARCH specification, including two additional exogenous variables such as U.S. stock return (r^*_{t-1}) and interactive variables ($r^*_{t-1}D^j_{crisis,t-1}$). The first regressor captures the volatility spillover commonly observed, and the second regressor reveals any departure from the normal volatility spillover in the phase of crisis ($D^j_{Crisis,t-1}$ is equal to 1 in the phase of crisis, and zero otherwise). The null hypothesis of no volatility contagion $H_0 : \tilde{\alpha}_j \leq 0$ is against the alternative hypothesis $H_1 : \tilde{\alpha}_j > 0$.

To ensure a positive conditional variance h_t, parameters in equation [2] should be positive: $\tilde{c}_0 > 0$, $\tilde{c}_1 > 0$, $\tilde{\beta}_1 > 0$, $\tilde{\alpha}_0 > 0$ and $\tilde{\alpha}_j > 0$. It is possible that volatility does not increase in the crisis period but decreases. However, allowing the parameter $\tilde{\alpha}_j$ to be negative would risk a negative volatility in the estimation process of the GARCH model (Baur, 2003). To avoid this problem, the paper takes advantage of the exponential GARCH (EGARCH) model (see Nelson, 1991). Indeed, unlike ordinary GARCH, the EGARCH model does not require non-negativity constraints on parameters. Thus, the conditional mean and volatility of returns of BRVM are formulated as follows:

$$r_t = \mu_0 + \mu r^*_{t-1} + \sum_{j=1}^{2} \mu_j r^*_{t-1} D^j_{crisis,t-1} + \sum_{j=1}^{2} d_j D^j_{crisis,t-1} + \varepsilon_t \qquad [3]$$

$$\ln(h_t) = c_0 + c_1 \left[|z_{t-1}| - E(|z_{t-1}|) \right]$$

$$+ c_2 z_{t-1} + \beta_1 \ln(h_{t-1}) + \alpha_0 r^*_{t-1} + \sum_{j=1}^{2} \alpha_j r^*_{t-1} D^j_{Crisis,t-1} \qquad [4]$$

On the one hand, the null hypothesis of a test for contagion in mean is $H_0 : \mu_j \leq 0$ against the alternative hypothesis $H_1 : \mu_j > 0$. On the other hand, the null hypothesis of no volatility contagion is $H_0 : \alpha_j \leq 0$ against the alternative hypothesis $H_1 : \alpha_j > 0$.

4. DATA

4.1 Stylized facts

African stock markets are growing rapidly. South Africa, Egypt, Morocco and Zimbabwe seem to be the leaders. Table 1 shows that their market capitalizations as a share of GDP are 280.23; 86.97; 75.47; and 70.26, respectively. The number of listed companies of each of the top four stock markets is higher than other markets. Stock markets in West Africa (Côte d'Ivoire, Ghana, and Nigeria) belong to the intermediate group in terms of development in Africa. Meanwhile, poorly developed stock markets can be found in Uganda, Tanzania, and Swaziland. Moreover, stock markets in Africa as a whole are illiquid. Table 1 shows that only the stock markets of Egypt, Morocco and South Africa are as liquid as stock markets in advanced emerging market countries.

4.2 Descriptive statistics

The period considered in this paper is dictated by the availability of data and the crisis period. Consequently, the period studied spans from January 2, 2007, through January 30, 2009. The data set includes, on the one hand, total market capitalisation of the BRVM as a whole (CAP_BRVMC), and market capitalisation of the ten most active enterprises of the BRVM (CAP_BRVM10). On the other hand, the data set consists of stock indices of the BRVMC and BRVM10, and of the Dow Jones Industrial Average (DJIA). In addition, six sectoral stock indices of BRVM are included. These sectors are agriculture, distribution, finance, industry, public utilities and transportation. All stock indices are in local currency, and are based on daily closing prices in each national market. Every level series is composed of a total of 517 observations. All the data were obtained from the BRVM's website (http://www.brvm.org).

To visualize the market capitalisations for BRVM, the series are depicted in Figure 1. Two different phases of the subprime crisis are identified. The first phase covers the period from August 1, 2007 through August 31, 2008. In this phase, the crisis seemed to be confined to mature markets, and in-

Table 1: Indicators of Stock Markets Development in Africa, 2006

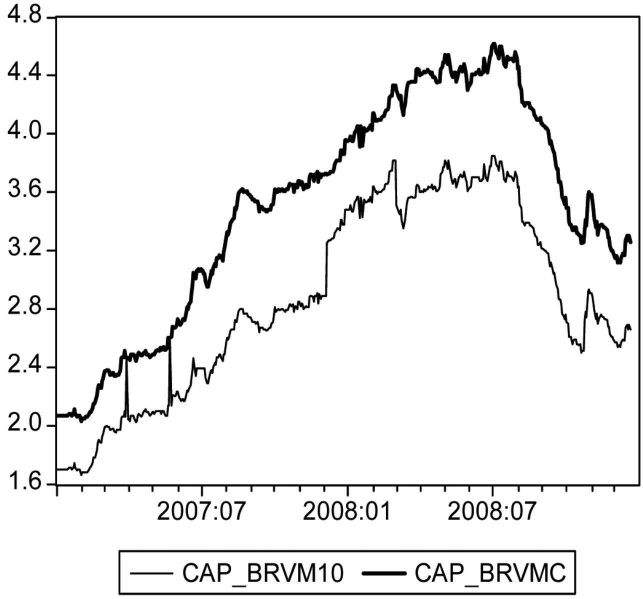
Countries	Number of listed companies	Market capitalization (% of GDP)	Value traded (% of GDP)	Turnover ratio (%)
Botswana	18	37.24	0.68	2.27
Côte d'Ivoire (BRVM)	40	23.67	0.61	3.30
Egypt	603	86.97	44.16	54.82
Ghana	32	25.04	0.41	2.14
Kenya	51	49.95	5.70	14.63
Malawi	10	18.56	0.45	3.49
Mauritius	41	56.70	2.16	4.42
Morocco	65	75.47	20.64	35.26
Nigeria	202	28.45	3.08	13.64
South Africa	401	280.23	122.45	48.80
Swaziland	6	7.55	0.002	0.03
Tanzania	6	4.23	0.09	2.10
Tunisia	48	14.67	1.72	14.26
Uganda	5	1.23	0.06	5.22
Zambia	14	11.04	0.21	2.11
Zimbabwe	80	70.26*	9.70*	6.19
Argentina	103	37.21	2.12	6.42
Brazil	392	66.61	23.84	42.93
Chile	244	119.68	19.71	18.49
Malaysia	1027	156.20	44.40	32.12
Mexico	131	41.51	9.54	27.27
Thailand	518	68.38	48.85	70.75

Source: World Development Indicators, 2007; and author's calculations. (*) means data of 2005.

vestor trading activities were governed mainly by local (country) information. The second phase spans from September 1, 2008 to January 30, 2009, where we assume that the 2007-2008 financial crisis definitely ended. During this phase the crisis grew in public and government awareness worldwide, and financial markets around the world collapsed. Figure 1 and Table 2 show that aggregate market capitalisation, denoted CAP_BRVMC, experienced a steady increase before and during the first phase of the crisis. During the first phase, CAP_BRVMC grew by 43.32%, and over the whole period preceding the second phase, it grew by 118.48%. These figures correspond to an increase in market capitalisation by CFAF[10] 1365.65 billion (≈ \$3.05 billion) and CFAF 2450.13 billion (≈ \$5.47 billion), respectively. However, the second phase of the crisis is associated with a sharp decline in CAP_BRVMC growth rate by 27.53%, which corresponds to a decrease by CFAF 1238.02 billion (≈ \$2.42 billion). The fall in market capitalisation results from the drop in the stock index as a consequence of the crisis. This fall in market capitalisation may reflect, on the one hand, the deterioration in firms' assets following the decrease in commodity prices and exports, and on the other, a reduction in funds mobilised by the BRVM to finance productive investments.

In other words, the amount of CFAF 1238.02 billion (≈ \$2.42 billion) may represent the loss suffered by the BRVM during the second phase of the crisis spanning from September 1, 2008 to January 30, 2009.

Figure 1: Market Capitalisation of BRVM (billions of CFA franc)



Notes: CAP_BRVMC is the market capitalisation of all securities listed on the BRVM; CAP_BRVM10 is the market capitalisation of the ten most active companies on the BRVM.
Source: BRVM (http://www.brvm.org)

10 CFAF is the currency unit of the WAEMU countries.

Table 2: Market capitalisation of the BRVM (CAP_BRVMC)

Period	Pre-first and first phase of the crisis 01/01/2007-08/29/2008	First phase of the crisis 08/01/2007-08/29/2008	Second phase of the crisis 09/01/2008-01/30/2009
Growth rate	118.48%	43.32%	–27.53%
Variation in CFAF (in $)	+2, 450.13 billion (≈ 5.47 billion)	+1, 365. 65 billion (≈ 3.05 billion)	–1, 238.02 billion (≈ -2.42 billion)

Source: Author's computations.

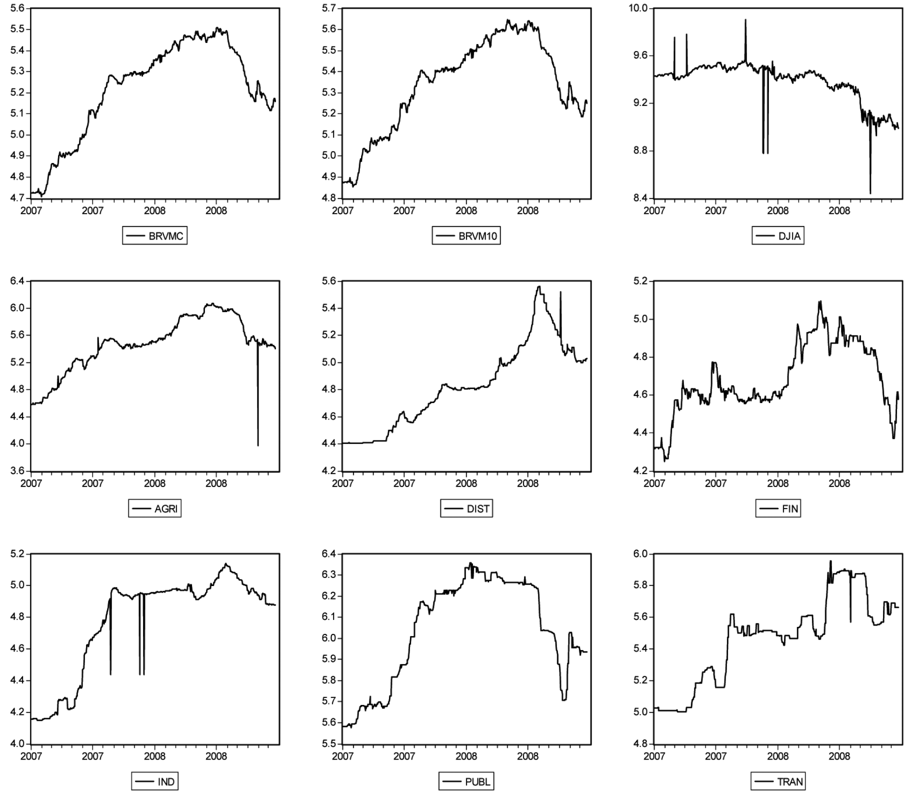
Following the conventional approach, stock returns are calculated as the first difference of the natural logarithm of each stock index, and the returns are expressed as a percentage. Figure 2 shows the development over time of the stock indices in level. This figure indicates that all series experienced an increase during the pre-first phase and first phase, and decreased during the second phase. The return series of the indices are composed by computing $r_{i,t} = 100\times\ln(p_{it}/p_{it-1})$. Here, $r_{i,t}$ denotes the continuously compounded return for index i at time t; $p_{i,t}$ denotes the price level of index i at time t, and $p_{i,t-1}$ denotes the price level of index i at time $t-1$.

To visualize the returns, we depict the series in Figure 3. The plots show a clustering of larger return volatility. This market phenomenon has been widely recognized and successfully captured by GARCH types of models in the finance literature (Bollerslev et al., 1992).

Table A1 in Annex shows basic descriptive statistics for all return series. The mean is 0,084 and -0,086 for DBRVMC and DDJIA, respectively. Looking at the standard deviation (or variance) of the two stock return series, it is clear that they differ somewhat. Specifically, the BRVM shows signs of much lower volatility, with a variance of 0.918 (for the DBRVMC series) compared to U.S. stock market's 77.704. There is a positive skewness in the DBRVMC series, while skewness in the DDJIA is negative. The test for excess kurtosis indicates that all series are significantly leptokurtic. The U.S. stock market shows signs of much more extreme levels of excess kurtosis.

Overall, the initial descriptive statistics indicate that the BRVM is much more tranquil than the U.S. stock market. This is not a surprising finding, given that the BRVM is a small and burgeoning market. Furthermore, initial descriptive statistics are in favor of a model that incorporates both a mean equation that discards serial correlation, and a volatility equation that acknowledges the strong heteroskedastic features in the data.

Figure 2: Stock indices and sectoral stock indices

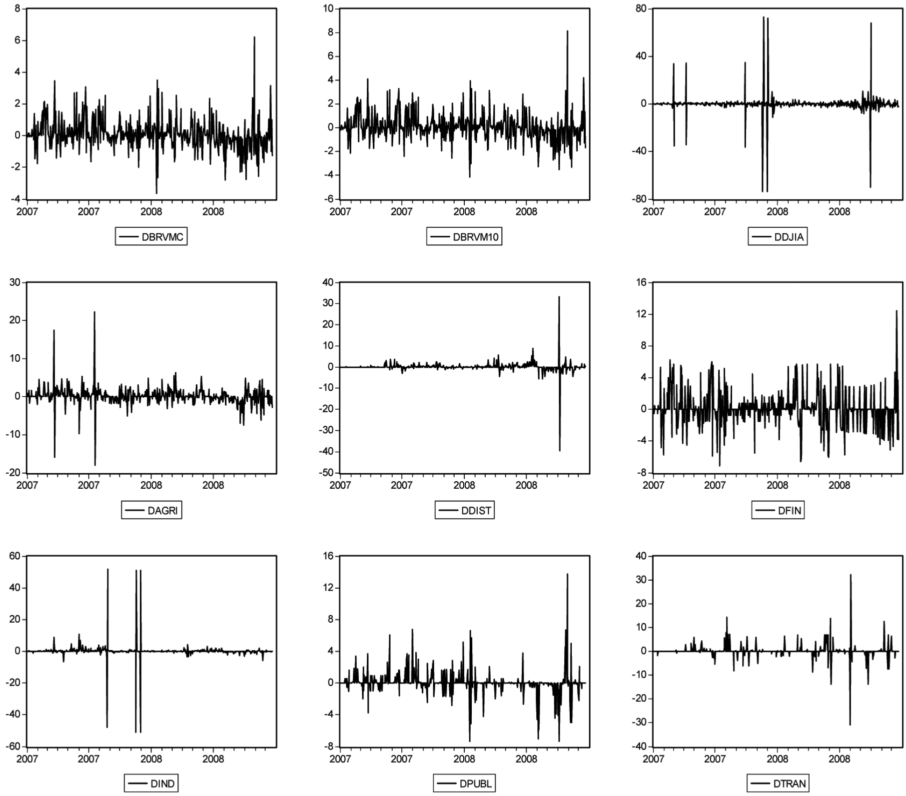


Notes: BRVMC is the BRVM composite index (i.e. the index of all securities listed on the BRVM); BRVM10 is the index of the ten most active companies on the BRVM; DJIA is the Dow Jones Industrial Average Index; AGRI is the agriculture sector index; DIST is the distribution sector index; FIN is the financial sector index; IND is the industry sector index; PUBL is the public utilities sector index; TRAN is the transportation sector index.
Source: BRVM (http://www.brvm.org).

5. EMPIRICAL RESULTS

Table 3 displays empirical results for mean and volatility contagion of the BRVM during the subprime crisis. Let us first focus on contagion of the BRVM as a whole before turning to a consideration of contagion on a sector by sector basis.

Figure 3: Stock-returns and sectoral stock returns (in percentage)



Notes: DBRVMC is the BRVM composite return series; DBRVM10 is the return series for the ten most active companies on the BRVM; DDJIA is the Dow Jones return series; DAGRI is the agriculture sector return series; DDIST is the distribution sector return series; DFIN is the financial sector return series; DIND is the industry sector return series; DPUBL is the public utilities sector return series; DTRAN is the transportation sector return series.

5.1 Aggregate level analysis

Firstly, let us consider the dependant variable DBRVMC. On the one hand, estimation results of mean contagion indicate that the coefficients d_1 and d_2 of intercept dummy variables that capture the phases of the crisis are negative; but only the coefficient of the second phase is statistically significant. This indicates that the context of the crisis has a negative impact on the returns of the BRVM index. This finding shows evidence of structural changes in stock return of the BRVM, reducing stock price returns. This suggests that investors overreacted to the second phase of the crisis. Results show that there is a decreasing transmission mechanism of shocks from the U.S. stock market to the BRVM during the first phase (parameter $\mu_1 < 0$), while the contrary holds during the second phase ($\mu_2 > 0$). Moreover, the total transmission of shocks (*i.e.* $\mu + \mu_1$) during the first phase of the crisis is negative, while it is positive during the second phase ($\mu + \mu_2 > 0$). Both results suggest that there is no evidence of mean contagion from the US stock market to the BRVM during the first phase, while contagion effects are evident during the second phase. On the other hand, the results show volatility transmission to be decreasing during the first phase of the crisis ($\alpha_1 < 0$). In the second phase, however, it is increasing ($\alpha_2 > 0$), suggesting contagion in volatility.

Secondly, if we consider the dependent variable DBRVM10, our evidence shows that contagion in mean occurs during both phases of the crisis ($\mu_1 > 0$ and $\mu_2 > 0$), and contagion in volatility occurs during the second phase of the crisis ($\alpha_2 > 0$). As far as the coefficients d_1 and d_2 of intercept dummy variables are concerned, results are similar to those presented above.

5.2 Sectoral level analysis

Sector-based estimation results[11] of contagion reveals that two sectors, agriculture and finance, experienced a decrease in returns (parameter $d_1 < 0$) during the first phase of the crisis. Returns in other sectors (*i.e.* distribution, industry, public utilities, and transportation) on the other hand experienced an upward trend during the first phase of the crisis (parameter $d_1 > 0$). This was most likely caused by the rise in commodity prices due to speculation during the onset of the financial crisis. However, during the second phase of the crisis, all sectoral stock returns experienced a decrease. This suggests that investors overreacted to the second phase of the crisis.

The results also show that the transmission mechanism of shocks varied across sectors during the two periods. The first phase of the crisis was associated with a decreasing transmission mechanism of shocks for distribution, industrial and transportation sectors (parameter $\mu_1 < 0$). This suggests that no contagion in mean occurred in these sectors during the first phase of the

[11] For the sectoral level analysis, due to the lack of data, we use DJIA for the proxy of the US market instead of using a sectoral index.

crisis. However, an increasing transmission mechanism of shocks is found in the case of the agriculture, finance and public utilities sectors (parameter $\mu_1 > 0$), suggesting a contagion in mean during the first phase of the crisis. Furthermore, during the second phase of the crisis contagion in mean is evident in the distribution, finance and transportation sectors (parameter $\mu_2 > 0$) while no evidence of contagion is found for the agriculture, industry and public utilities sectors (parameter $\mu_2 < 0$).

Estimation results of volatility contagion reveal that the agriculture, finance, industry and public utilities sectors experienced contagion during the first phase of the crisis (parameter $\alpha_1 > 0$). Moreover, during the second phase, the contagion phenomenon expanded and hit all economic sectors (parameter $\alpha_2 > 0$). Only the distribution and transportation sectors experienced a decrease in volatility transmission during the first phase of the crisis. However, it is worth noting that this result does not necessarily imply lower volatility.

When testing the normalized residuals, with some minor exceptions, the serial correlations in both the residuals and squared residuals are eliminated. The only exception is in the cases of sectoral stock returns of agriculture (DAGRI) and transportation (DTRAN). For these variables, a correlation in residuals is found. Overall, the models seem to adequately capture the main features of the BRVM market returns.

In sum, the results reveal the existence of contagion in mean and volatility from the US market to the BRVM during the global financial crisis. This observation is supported by the growth of uncertainty in both the US market and the global capital market, and the collapse of the global economy, which have reduced expected returns and risk taking in the BRVM.

6. CONCLUSION

Using a modified EGARCH framework, the paper has taken a closer look at the phenomenon of contagion of the BRVM during the recent financial turmoil that has erupted from a relatively small segment of the US financial market-the subprime residential mortgages.

The findings reveal mean and volatility contagion from the US market to the BRVM. In addition, all sub-indices exhibit contagion effects, either in mean, volatility or both. The findings are counter to view expressed by many policymakers that African financial markets were not likely to experience contagion effects during the recent global financial crisis on the basis that they are not considered to be integrated into the global financial system.

Table 3: Mean and volatility contagion

Dependant variables	DBRVMC	DBRVM10	DAGRI	DDIST	DFIN	DIND	DPUBL	DTRAN
Parameters	Mean Equation: coefficient x10^{-2}							
μ_0	11.54 (0.008)	11.53 (0.030)	38.13 (0.035)	12.35 (0.051)	18.48 (0.395)	20.42 (0.224)	3.35 (0.451)	-1.99 (0.7665)
μ	1.23 (0.428)	1.01 (0.213)	-1.07 (0.000)	-1.67 (0.025)	0.91 (0.687)	-0.99 (0.008)	1.85 (0.018)	-3.45 (0.247)
μ_1	-1.91 (0.357)	**0.74**^{C} (0.035)	**2.38**^{C} (0.000)	-1.56 (0.199)	**1.02**^{C} (0.000)	-2.39 (0.028)	**1.68**^{C} (0.000)	-0.82 (0.354)
μ_2	**1.06**^{C} (0.034)	**0.87**^{C} (0.009)	-1.25 (0.080)	**0.64**^{C} (0.240)	**1.52**^{C} (0.426)	-2.57 (0.094)	-1.89 (0.088)	**8.52**^{C} (0.038)
d_1	-3.42 (0.651)	-3.12 (0.455)	-19.12 (0.435)	30.42 (0.038)	-1.94 (0.942)	2.79 (0.034)	0.87 (0.832)	24.05 (0.291)
d_2	-63.38 (0.000)	-75.13 (0.008)	-104.02 (0.000)	-42.07 (0.031)	-37.25 (0.142)	-26.51(0.189)	-68.07 (0.031)	-134.17 (0.246)
	Volatility Equation: coefficient x10^{-2}							
c_0	-20.32 (0.015)	-10.43 (0.278)	137.45 (0.000)	-21.28 (0.358)	18.41 (0.268)	138.64 (0.000)	-12.03 (0.041)	27.32 (0.311)
c_1	13.32 (0.032)	11.03 (0.166)	23.76 (0.112)	67.42 (0.002)	25.66 (0.004)	31.40 (0.214)	20.51 (0.002)	41.05 (0.446)
c_2	2.41 (0.036)	2.61 (0.035)	41.23 (0.078)	18.19 (0.042)	4.97 (0.147)	7.42 (0.039)	7.84 (0.035)	20.84 (0.034)
β_1	62.51 (0.002)	64.37 (0.005)	10.38 (0.000)	49.01 (0.001)	63.09 (0.000)	20.40 (0.000)	64.10 (0.000)	56.09 (0.000)
α_0	3.04 (0.122)	2.64 (0.227)	-4.02 (0.005)	-1.51 (0.621)	-7.05 (0.015)	3.45 (0.048)	2.06 (0.241)	1.98 (0.246)
α_1	-1.77 (0.141)	-1.33 (0.632)	**0.24**^{C} (0.970)	-1.46 (0.678)	**11.08**^{C} (0.000)	**18.68**^{C} (0.000)	**1.17**^{C} (0.345)	-6.05 (0.000)
α_2	**5.83**^{C} (0.024)	**6.78**^{C} (0.014)	**5.61**^{C} (0.000)	**6.59**^{C} (0.019)	**4.99**^{C} (0.021)	**1.47**^{C} (0.127)	**8.39**^{C} (0.007)	**0.52**^{C} (0.035)
N	515	515	515	515	515	515	515	515
AIC	1.957	1.897	3.148	2.985	3.257	4.786	3.008	3.321
	Residual diagnostics							
LB(3)	4.613 (0.302)	4.289 (0.204)	18.231 (0.024)	4.132 (0.132)	3.456 (0.355)	2.347 (0.217)	3.673 (0.287)	25.984 (0.025)[a]
LBS(3)	6.321 (0.145)	5.014 (0.178)	1.284 (0.654)	5.486 (0.128)	6.789 (0.247)	1.986 (0.875)	1.489 (0.659)	19.47 (0.217)[b]

Notes: 1/ Model: $r_t = \mu_0 + \mu r^*_{t-1} + \sum_{j=1}^{2} \mu_j r^*_{t-1} Dj_{crisis,t-1} + \sum_{j=1}^{2} d_j Dj_{crisis,t-1} + \varepsilon_t$ and $\ln(h_t) = c_0 + c_1 \, |[z_{t-1}| - E(|z_{t-1}|)] + c_2 z_{t-1} + \beta_1 \ln(h_{t-1}) + \alpha_0 r^*_{t-1} + \sum_{j=1}^{2} \alpha_j r^*_{t-1} Dj_{crisis,t-1}$;

2/ p-values are in parenthesis; The p-values are obtained from Bollerslev-Wooldrige (1992) robust standard errors; DBRVMC is the BRVM composite return series; DBRVM10 is the return series for the ten most active companies on the BRVM; DDJIA is the Dow Jones return series; DAGRI is the agriculture sector return series; DDIST is the distribution sector return series; DFIN is the financial sector return series; DIND is the industry sector return series; DPUBL is the public utilities sector return series; DTRAN is the transportation sector return series. N is the number of observations; AIC stands for the Schwarz Information Criterion (a lower value implying a better fit). LB(3): Ljung-Box Q test for the presence of autocorrelation in residuals up to three lags. LBS(3): Ljung-Box Q test for the presence of autocorrelation in squared residuals up to three lags. (a) and (b) stand for LB(15) and LBS(15) respectively. (C) denotes contagion in mean or volatility.

Whatever the degree of integration to the global financial system may be, contagion may take place. In fact, the magnitude of contagion depends on the degree of integration to the global financial system. The greater the extent to which markets are integrated the higher the contagion's magnitude will be, while the lower the extent to which markets are integrated the smaller the magnitude of the contagion will be[12].

The conclusion of this paper suggests that policymakers should pay attention to movements in mature markets, given that contagion effects could impair their ability to raise funds from the domestic market, as well as on international markets.

References

Aka B.E., 2006, "On the Duration of the Financial System Stability under Liberalization", *Emerging Markets Reviews*, Vol. 7, No. 2, pp. 147-161.

Allen F. And D. Gale, 2000, "Financial Contagion", *Journal of Political Economy*, Vol. 108, pp. 1-33.

Bae K.-H. and G. Karolyi, 1994, "Good News, Bad News and International Spillovers of Stock Return Volatility Between Japan and the U.S.", *Pacific-Basin Finance Journal*, Vol. 2, pp. 405-438.

Baig T. and I. Goldfajn, 1999, "Financial Markets Contagion in the Asian crisis", *IMF Staff Papers*, Vol. 46, No. 1, pp. 167-195.

Basu R., 2002, "Financial Contagion and Investor 'Learning': An Empirical Investigation", *IMF working paper*, No. 02/218.

Baur D., 2003, "Testing for Contagion: Mean and Volatility Contagion", *Journal of Multinational Financial Management*, Vol. 13, pp. 405-422.

Bodart V. and B. Candelon, 2009, "Evidence of Interdependence and Contagion Using a Frequency Domain Framework", *Emerging Markets Revi*ew, Vol. 10, pp. 140-150.

Bollerslev T., 1986, "Generalized Autoregressive Conditional Heteroscedasticity", *Journal of Econometrics*, Vol. 31, pp. 307-327.

Borensztein E. and G. Gelos, 2003, "A Panic-Prone Pack? The Behavior of Emerging Market Mutual Funds", *IMF Staff Papers*, Vol. 50, No. 1, pp. 43-63.

Broner F., G. Gelos and C. Reinhart, 2006, "When in Peril, Retrench: Testing the Portfolio Channel of Contagion", *Journal of International Economics*, Vol. 69, No. 1, pp. 203-230.

[12] According to Baur (2003), contagion among financial markets depends on the degree of interdependence (e.g. measured by the correlation coefficient or the transmission mechanism). In particular, the higher the interdependence, the higher the contagious effect and the lower the interdependence, the lower the contagious impact.

Calvo S. and C. Reinhart, 1996, "Capital Flows to Latin America: Is There Evidence of Contagion Effects?", in Calvo G.A., Goldstein M. and E. Hochreittter (Eds.), *Private Capital Flows to Emerging Markets*, Institution for International Economics, Washington, DC.

Caprio G., A. Demirgüç-Kunt and E.J. Kane, 2008, "The 2007 Meltdown in Structured Securitization: Searching for Lessons, Not Scapegoats", *Policy Research Working Paper*s, No. 4756, World Bank.

Caramazza F., L.A. Ricci and R. Salgado, 2000, "Trade and Financial Contagion in Currency Crises", *IMF Working Paper,* No. WP/00/55, Washington, DC: International Monetary Fund.

Caramazza F., L.A. Ricci and R. Salgado, 2004, "International Contagion in Currency Crises", *Journal of International Money and Finance*, Vol. 23, pp. 51-70.

Clare A. and I. Lekkos, 2001, Decomposing the relationship between international bond markets, BIS Central Bank Economists' Meeting, *International Financial Markets and the Implications for Monetary and Financial Stability*, Bank for International Settlements.

Corsetti G., M. Pericoli and M. Sbracia, 2001, "Correlation Analysis of Financial Contagion: What One Should Know Before Running a Test", *Discussion Paper*; No. 822 Economic Growth Center, Yale University.

De Gregorio J. and R. Valdes, 2001, "Crisis Transmission: Evidence from the Debt, Tequila and Asian Flu Crises", *The World Bank Economic Review*, Vol. 15, No. 2, pp. 289-314.

Dornbusch R., Y.C. Park and S. Claessens, 2000, "Contagion: Understanding How it Spreads", *World Bank Research Observer*, Vol. 15, pp. 177-197.

Eichengreen B. and A. Rose, 1999, "Contagious Currency Crises: Channels of Conveyance", in Ito T. and A. Krueger (Eds.), *Changes in Exchange Rates in Rapidly Developing Countries: Theory, Practice and Policy Issues*, University of Chicago Press, Chicago, pp. 29-50.

Eichengreen B., A.K. Rose and C. Wyplosz, 1996, "Contagion Currency Crises: First Tests", *Scandinavian Journal of Economics*", Vol. 98, pp. 463-484.

Forbes K.J. and R. Rigobon, 2002, "No Contagion, Only interdependence: Measuring Stock Market Co-Movements", *Journal of Finance*, Vol. 57, pp. 2223-2261.

Forbes K.J., 2001, "Are Trade Linkages Important Determinants of Country Vulnerability to Crises?", *National Bureau of Economic Research Working Paper*, No. 8194, Cambridge, MA.

Forbes K.J., 2004, "The Asian Flu and Russian Virus: Firm-Level Evidence on How Crises Are Transmitted Internationally", *Journal of International Economics*, Vol. 63, No. 1, pp. 59-92.

Fratzscher M., 2000, "On Currency Crises and Contagion", *Working Paper*, No. 9. Institute for International Economics.

Froot K., P. O'Connell and M.S. Seasholes, 2001, "The Portfolio Flows of International Investors", *Journal of Financial Economics*, Vol. 59, No. 2, pp. 151-193.

Glick R. and A.K. Rose, 1999, "Contagion and Trade: Why Are Currency Crises Regional?", *Journal of International Money and Finance*, Vol. 18, pp. 603-617.

Goldstein M., 1998, "The Asian Financial Crisis: Causes, Cures, and Systemic Implications", *Policy Analyses in International Economics*, Vol. 55. Washington: Institute for International Economics.

Hamao Y., R.W. Masulis and V. Ng, 1990, "Correlations in Price Changes and Volatility Across International Stock Markets", *The Review of Financial Studies*, Vol. 3, pp. 281-307.

Hernandes L.F. and R.O. Valdès, 2001, "What Drives Contagion: Trade, Neighborhood, or Financial Links?", *IMF Working Paper*s, No. 29.

Iwatsubo K. and K. Inagaki, 2007, "Measuring Financial Market Contagion Using Dually-Traded Stocks of Asian firms", *Journal of Asian Economics*, Vol. 18, pp. 217-236.

Kaminsky G., R. Lyons and S.L. Schmukler, 2004, "Managers, Investors, and Crises: Mutual Fund Strategies in Emerging Markets", *Journal of International Economics*, Vol. 64, No. 1, pp. 113-134.

Kaminsky G.L. and C.M. Reinhart, 2000, "On Crises, Contagion, and Confusion", *Journal of International Economics*, Vol. 51, pp. 145-168.

King M.A. and S. Wadhwani, 1990, "Transmission of Volatility Between Stock Markets", *Review of Financial Studies*, Vol. 3, pp. 5-33.

Kodres L., 2008, "A Crisis of Confidence and a Lot More", *Finance and Development*, Vol. 45, No. 2 (June), IMF.

Kodres L.E. and M. Pritsker, 2002, "A Rational Expectation Model of Financial Contagion", *Journal of Finance*, Vol. 57, pp. 769-799.

Koutmos G. and G. Booth, 1995, "Asymmetric Volatility Transmission in International Stock Markets", *Journal of International Money and Finance*, Vol. 14, pp. 747-762.

Lee S.B. and K.J. Kim, 1993, "Does the October 1986 Crash Strengthen the Co-Movements Among National Stock Markets?", *Review of Financial Economics*, Vol. 3, pp. 89-102.

Longin F. and B. Solnik, 2001, "Extreme Correlation of International Equity Markets", *Journal of Finance*, Vol. 56, pp. 649-676.

Masih A.M. and R. Masih, 1999, "Are Asian Stock Fluctuations Due Mainly to Intra Regional Contagion Effect? Evidence Based on Asian Emerging Stock Markets", *Pacific-Basin Finance Journal*, Vol. 7, pp. 251-282.

Nagayasu J., 2000, "Currency Crisis and Contagion: Evidence from Exchange Rates and Sectoral Stock Indices of the Philippines and Thailand", *IMF Working Papers*, No. WP/00/39.

Park Y.C. and C.-Y. Song, 2000, "Financial Contagion in the East Asian Crisis-With

Special Reference to the Republic of Korea", NBER Project on Exchange Rate Crises in Emerging Market Economies: '*The Korean Currency Crises*', February, Cambridge, MA.

Pericoli M. and M. Sbracia, 2003, "A Primer on Financial Contagion", *Journal of Economic Surveys*, Vol. 17, pp. 571-608.

Rajan R., 2005, "Has Financial Development Made the World Riskier?", *NBER Working Papers*, No. 11728. Cambridge, Massachusetts: National Bureau of Economic Research.

Ross S.A., 1989, "Information and Volatility: The No-Arbitrage Martingale Property to Timing and Resolution Irrelevancy", *Journal of Finance*, Vol. 44, pp. 1-17.

Sachs J., A. Tornell and A. Velasco, 1996, "Financial Crises in Emerging Markets: The Lessons From 1995", *NBER Discussion Papers*, No. 5576.

Sander H. and S. Kleimeier, 2003, "Contagion and Causality: An Empirical Investigation of four Asian Crisis Episodes", *Journal of International Financial Markets, Institutions and Money*, Vol. 13, 171-186.

Van Rijckeghem C. and B. Weder, 2001, "Spillovers Through Banking Centers - A Panel Data Analysis", *Journal of International Economics*, Vol. 54, pp. 293-308.

Annex

Table A1. Descriptive statistics

Aggregate stock returns			
Series	DBRVMC	DBRVM10	DDJIA
Mean	0.084	0.072	-0.086
Standard deviation	0.958	1.158	8.815
Variance	0.918	1.341	77.704
Skewness	0.761	0.868	-0.171
Kurtosis	7.626	8.696	54.320
Autocorr	0.044	0.022	-0.358

Sectoral stock returns						
Series	DAGRI	DDIST	DFIN	DIND	DPUBL	DTRAN
Mean	0.169	0.121	0.049	0.140	0.068	0.123
Standard deviation	2.346	2.543	2.955	5.570	1.541	2.242
Variance	5.504	6.467	8.732	31.025	2.375	5.026
Skweness	0.689	-2.917	0.409	0.254	1.282	0.489
Kurtosis	34.489	171.303	5.830	79.665	21.196	56.875
Autocorr	-0.163	-0.363	0.115	-0.476	-0.040	-0.227

Notes: DBRVMC is the BRVM composite return series; DBRVM10 is the return series for the ten most active companies on the BRVM; DDJIA is the Dow Jones return series; DAGRI is the agriculture sector return series; DDIST is the distribution sector return series; DFIN is the financial sector return series; DIND is the industry sector return series; DPUBL is the public utilities sector return series; DTRAN is the transportation sector return series. Source: Author's computations.

Résumé

Le présent article teste empiriquement la contagion de la Bourse Régionale des Valeurs Mobilières (BRVM) par le marché boursier Américain pendant la crise des subprimes. Il effectue des analyses au niveau agrégé et au niveau sectoriel en utilisant un modèle EGARCH modifié. Deux résultats majeurs se dégagent: 1) au niveau agrégé, il y a des effets de contagion en moyenne et en volatilité du marché boursier américain vers la BRVM; 2) au niveau sectoriel, il apparaît que tous les secteurs d'activité ont subi la crise à travers la moyenne et/ou la volatilité.

JEL: C22; G01; G1

Mots clés: Crise des subprimes; BRVM; Contagion; EGARCH; Afrique de l'Ouest