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Abstract

This paper investigates the degree and structure of interdependence between emerging (Asian and Latin American) and developed (USA and Japan) stock markets through the study of volatility spillovers for the period spanning from January 1, 1993 to October 13, 2010. Using both standard GARCH model and quantile regression approach, we find the evidence of significant interdependence between financial markets which may give evidence of volatility transmission existence. The volatility transmission is closely associated with geographical proximity as well as with crisis periods which confirm the presence of contagion. The analysis of upper and lower quantiles allows observing that the interdependence increases during bullish markets while decreases during bearish markets. Accordingly, the structure of interdependence is asymmetric for both Asian and Latin American emerging markets. These findings open up new insights for government policy makers and for managerial purposes.

Keywords: Market interdependence, volatility spillovers, asymmetric interdependence, contagion, quantile regression.

JEL Classifications: F15, F36, G01, G15.

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1. Introduction

The financial crises that have shaken the current synchronized world economy were more frequent and more insistent especially for the emerging economies. A number of studies show that the sustainable international financial integration (IFI) in addition to the synchronization of economic sectors are essentially the basis of these financial turbulences. Econometric tests in studies of Phylaktis (1999) and Phylaktis and Ravazzolo (2002) show that financial openness made the integrated financial markets more sensitive to external or common shocks. Other studies, including that of Calvo and Reinhart (1996) show that financial interdependencies between stock markets results frequently in volatility spillovers and amplifies the transmission of crises from one country to another.

The financial literature has recently focused on the study of stock markets interdependence and especially volatility spillover, particularly after the multiplicity of financial crises such as Mexico1994, Asia1997, Brazil 1998, Turkey 2001, and the recent 2008 subprime crisis as the mostly affecting on emerging markets. Empirical results provided by previous works made use of several methodologies to deal with the concept of volatility transmission, including VAR and cointegration models, known as traditional measurement techniques of interdependencies and conditional variance modeling, regime switching models and stochastic volatility (SV) models, which represent the most robust and relevant techniques in terms of estimation. Recently, the VAR-GARCH approach of Ling and McAleer (2003) considers dynamic return links and volatility transmission through conditional first and second moments respectively. This methodology made success to capture interdependencies and spillover mechanisms either in bivariate or in multivariate system. It is worth mentioning that the majority of previous studies have led to the existence of unidirectional and sometimes bidirectional spillovers between international stock markets more amplified in times of financial crises and variant depending on the degree of integration (Gilenko and Fedorova, 2014; Bekiros, 2014; Arouri et al., 2011; Li, 2007; Choudhry, 2004; Darrat and Benkato, 2003; Xu and Fung, 2002; Caporale et al., 2002; Kasch-Haroutounian and Price, 2001; Forbes and Rigobon, 2001, 2002).

Certainly, the increase in the volatility of financial asset prices results in spreads from one country to another during turbulence periods through a mechanism of contagion worries of emerging market governments that are most affected by these crises. This leads us to believe that a rigorous study of financial markets interdependencies in terms of volatility would be useful for governmental policy regulators and portfolio manager.

In this framework, we focus first on the issue of volatility transmission between emerging and developed markets and second on the contagion effects that occurred during the recent financial crises. Our main objective is to look at the interdependencies in terms of volatility transmission between emerging and developed financial markets during both normal and turmoil periods. To achieve our objective, we adopt a more appropriate methodology which is generally characterized by its stability and is suitable for non-standard shaped distributions and by a non linear behavior, contrary to the conventional least squares which, in our view, has not been yet used in this context. It's the Quantile Regression (QR) model, which has been previously used in the financial literature to study the value-at-risk (Engle and Manganelli, 2004; Rubia and Sanchis-Marco, 2013), the systemic risk (Adrian and Brunnermeier, 2011) the prediction of failure (Li and Miu, 2010) and also the modeling of dependence between financial variables (Bassett and Chen, 2001; Chuang et al., 2009; Baur et al., 2012;. Lee and Li, 2012; Tsai, 2012; Ciner et al., 2013; Gebka and Wohar, 2013). This approach seems to be more robust because it uses different measures of central tendency and dispersion statistics for a further detailed analysis of the relationship between variables.

In our study, we use the QR model since it allows considering the conditional dependence of specific quantile for each stock market while respecting the conditioning variables. The QR approach gives also an accurate overview of the interdependencies between stock markets in different market circumstances, namely: Bearish markets (lower quantile), balanced markets (average quantile) and bullish markets (upper quantile). In addition, the QR approach is suitable to capture additional marginal effects derived from various stock markets, particularly where financial crises are considered. In this context, we used time-varying crises indices to take into account the evolutionary characteristics of emerging stock markets. The remaining of this article is organized as follows: The second section presents a review of literature on the transmission of volatility and contagion. The third section is devoted to the presentation of methodology. The fourth section describes the data used and their statistical properties. The fifth section reports results of both the conditional volatility and the quantile regression models. The sixth section discusses the policy implications and concludes.

2. Literature review

Studies on volatility spillovers have involved the interest of many researchers for a long time. During the last decades, several studies in empirical finance and financial economics have focused on the analysis of volatility transmission between emerging markets with regard to the increase in their degree of financial integration after their liberalization process (Gilenko and Fedorova, 2014; Bekiros, 2013; Bensafta and Samedo, 2011; Kearney, 2000; Leachman and Francis, 1996; Karolyi, 1995; Hamao et al., 1990). By reviewing the financial literature, we can remark that several methods were applied to investigate the interdependencies between financial markets in terms of volatility. In the following, we present an overview on the pioneering studies on this subject by reference to their methodologies.

Since the introduction of conditional variance models, several ARCH/GARCH specifications have been widely applied to study the relationship between financial markets and especially of international volatility transmission.

Li (2007) examines the volatility relationships eventually existing between two emerging stock markets (mainland China and Hong Kong) and the US market using a multivariate GARCH model identical to the BEKK approach developed by Engle and Kroner (1995) in order to take into account the regularities which characterize stock indices. Results show evidence of unidirectional transmission of volatility from Hong Kong stock market to those of Shanghai and Shenzhen. However, no evidence of link was found between stock markets in the mainland China and the United States. In addition, a weak dependence between volatility in the Hong Kong and the China markets is verified. The author attributes this weak dependency to the weak degree of market integration.

Darrat and Benkato (2003) used a GARCH model and a multivariate co-integration specification to test the interdependence between return and volatility between Istanbul Stock Exchange (ISE) and the world market represented by the stock markets of the United States, United Kingdom, Japan and Germany. Results suggest that the ISE has become significantly integrated into the global market after the liberalization process towards the end of 1989. Results further show that both the US and the UK markets are the principal sources of volatility spillovers for the ISE. Aggarwal et al. (1999) use a model that combines GARCH and regime switching models. In particular, they use the heteroscedastic ICSS algorithm of Inclan and Tiao (1994) to determine the changing points of volatility and examine local and global events that took place. These changes are introduced as dummy variables in the variance equation of GARCH model. Results suggest that, on emerging markets, the most changes in volatility derive from local factors.

More recently, Gilenko and Fedorova (2014) use the four-dimensional BEKK-GARCH-in mean model to investigate the external and the internal links eventually existing between the BRIC and the global stock markets. During the pre-crisis period, they conclude the existence of some lagged mean-to-mean spillovers between the BRIC stock markets, and find as well that the volatility-to-volatility spillovers are largely present. After the crisis, the volatility-to-volatility spillovers almost disappear while the volatility-to-mean spillovers have not been identified for any period. Furthermore, the influence of external spillovers from developed stock markets to the rest of emerging markets is analyzed before and since the crisis. The authors suggest that the linkages between the developed and the BRICs stock markets have significantly changed after the crisis.

Bekiros (2013) uses vector autoregressions and various multivariate GARCH representations to analyze the volatility spillovers among the U.S., the EU and the BRIC markets and finds that the BRICs have become more internationally integrated and that contagion is further substantiated since the U.S. financial crisis. Bensafta and Semedo (2011) study the multivariate dynamics of returns for various national financial markets. Conditional mean of market returns are modeled using a VAR specification while their conditional variances are modeled by a multivariate GARCH specification. This study aims at proving the existence of multiple regimes in the variance. In addition, this model estimates transmissions variance and test contagion based on the stability of cross-correlations. Authors consider a sample of 11 stock market indices in Europe, North America and Asia between 1985 and 2006. Results on mean transmission confirm the significant effect of American stock prices on other stock markets prices. In addition, there is almost unidirectional transmission of volatility from the American market to other markets. There exist also regional transmissions in Europe and Asia. Moreover, Bensafta and Semedo (2011) argue that the acceleration of the stock markets interdependence is no stranger to the financial liberalization process introduced in the 90s.

The SV models are another alternative for analyzing volatility transmission between financial markets. Although these models they have not been as popular as GARCH models, several studies affirmed the relevance of this type of modeling in detecting interdependencies between markets. We cite, in this framework, the study of So et al. (1997), which adopt a SV model to examine volatility transmission between equity markets in seven Asian countries. Their findings provide evidence in favor of volatility transmission between financial markets in Asia. Wongswan (2006) applies the SV model for high-frequency data, more precisely, for the returns of the following stock markets: USA, Japan, Korea and Thailand. In particular, he focuses on the effect of macroeconomic announcements in the United States and Japan on volatility and trading volume in Korea and Thailand. This paper provides evidence of transmission of information from the U.S. and Japan to Korean and Thai equity markets during the period from 1995 through 2000. Lopes and Migon (2003) combine the factorial models with SV models. They analyze the dependence between stock market indices in Latin

America and USA. According to these authors, the multivariate SV models may be the solution to dimensionality problems and computation.

Finally, Markov switching regime models are used to analyze both mean and volatility equations. Indeed, Edwards and Susmel (2001) apply a bivariate SWARCH model and conclude that high volatility tends to be linked to international crises. Their results show interdependence rather than contagion. Also, Edwards and Susmel (2003) use a switching regime model to analyze the volatility of interest rates in emerging markets. The SWARCH model allows researchers to locate and to date the periods of high volatility, and it is found that, on emerging markets, they tend to be similar in geographically separated regions.

QR has been as well used by a range of recent studies in order to analyze interdependence between financial markets. For instance, Baur (2013) recommended the use of the QR to study the degree and structure of dependence as it is able to disclose information on the asymmetric and non-linear effects of conditional variables on the dependent variables. This technique allows the effects to vary across quantiles representing different states of nature and let for multivariate asymmetry in the studied relationship while linear extant models examines the average influence by assuming a symmetric impact of exogenous factors on the endogenous one. The QR modeling is then offering outsized flexibility and provides new insights for this class of particular issues.

To that end, previous literature review shows the evidence of miscellaneous used methodologies in the analysis of volatility spillover. This paper attempts to explore the dynamics of volatility spillovers between emerging and developed markets in normal times (transmission) and in times of financial crises (contagion) using the quantile regression methodology which has been newly used in this framework.

3. Econometric methodology

Many critics were addressed to the correlation coefficients technique, especially in its ability to measure the degree of dependence between variables. As known, this technique considers only symmetric linear links between variables and cannot provide distinction between dependence during up and down markets or between large and small stock price movements. Therefore, a more robust and pertinent tool is required in order to capture the multifaceted dependence between financial time series.

Quantile regression, developed by Koenker and Bassett (1978), is an extension of the traditional least squares estimation of the conditional mean to a compilation of models for different conditional quantile functions. Compared to a traditional regression model, the QR functions present more specific and accurate results of the impact of conditional variables on the exogenous variables (Koenker, 2005). More precisely, as the median (quantile) regression estimator minimizes the symmetrically weighted sum of absolute errors to estimate the conditional median (quantile) function, other conditional quantile functions are estimated by minimizing an asymmetrically weighted sum of absolute errors, where the weights are functions of the quantile of interest. Moreover, QR technique gives information on the average dependence as well as the upper and lower tail dependence. Thus, quantile regression is robust to the presence of outliers. This technique has been widely used in the past decade in many areas of applied econometrics; applications include investigations of wage structure (Buchinsky and Leslie, 1997), earnings mobility (Eide and Showalter, 1999; Buchinsky and Hunt, 1999), and educational attainment (Eide and Showalter, 1998). This technique has been also used in the financial sector for solving problems related to the Value at Risk and option pricing (Morillo, 2000; Engle and Manganelli, 2004), CoVaR (Adrian and Brunnermeier, 2011), and especially to model the dependence of financial variables and to study the structure and level of dependence (Chuang et al. 2009; Lee and Li, 2012; Baur, 2013).

Generally, the QR fonction can be formulated in the following manner:

$$Q_y(\tau|x) = inf\left\{b\middle|F_y(b|x) \geq \tau\right\} = \sum_k \beta_k(\tau)x_k = x^{'}\beta(\tau) \qquad \text{(Eq.1)}$$

Where *y* is a dependent variable that is assumed to be linearly dependent on *x* and $F_y(b|x)$ is the conditional distribution function of *y* given *x*. $\beta(\tau), \tau \in [0,1]$ represent the QR coefficient, that can determines the dependence relationship between vector *x* and the τ^{th} conditional quantile of *y*. Dependence is unconditional if no exogenous variables are included in *x*. The values of $\beta(\tau)$ determine the complete dependence structure of *y*. The dependence of y based on a specific explanatory variable in vector *x* could be: (a) constant where the values $\beta(\tau)$ do not change for different values of τ ; (b) monotonically increasing (decreasing) where $\beta(\tau)$ increases (decreases) with the value of τ ; and (c) symmetric (asymmetric) where the value of τ is similar (dissimilar) for lower and upper quantiles.

The coefficients $\beta(\tau)$ for a given τ are estimated by minimizing the weighted sum of absolute errors as following:

$$\beta(\tau) = \arg\min \sum_{t=1}^{T}\left(\tau - 1_{\left\{y_t < x_t^{'}\beta(\tau)\right\}}\right)\left|y_t - x_t^{'}\beta(\tau)\right| \qquad \text{(Eq.2)}$$

The solution to this problem is obtained using the linear programming algorithm suggested by Koenker and D'orey (1987). The pair boostrapping procedure introduced by Buchinsky (1995) can be used to obtain the standard errors for the estimated coefficients because it provides asymptotically valid standard errors under misspecifications of the QR function and heteroscedasticity.

As we try to introduce the variable of financial crisis in order to investigate the different effects that the conditioning variables have on the quantile function in the quiet and crises periods. Thus, our empirical model is specified as follows:

$$Q_y(\tau|X) = \alpha(\tau) + \sum_k \beta_k(\tau)X_k + D\left[\gamma(\tau) + \sum_k \theta_k(\tau)X_k\right] \qquad \text{(Eq.3)}$$

Where *D*, is the financial crisis dummy variable. It takes the value "one" if the dependent variable experiences a financial crisis in period *t* and "zero" otherwise. This variable is the combination of currency, banking and twin crises. For each quantile τ, the additional marginal effects of the different conditional variables in the financial crisis sub-periods is given by $\gamma(\tau)$ and $\theta_k(\tau)$ parameters. While the effects in the quiet periods is given by the parameters $\alpha(\tau)$ and $\beta_k(\tau)$. So, the QR model in equation (Eq.3) allows one to first examine the nature of interdependence structure eventually existing between stock market's volatility; then it makes easy to know how the interdependence structure is affected by different regressors; and finally, it allows to identifying how the financial crisis affect the interdependence structure and the co-movement between stock market's volatility.

4. Data and descriptive analysis

With the aim to, empirically, examine the interdependence structure between financial markets in terms of volatility. We use volatility series of ten emerging countries (Argentina, Brazil, Chile, Colombia, India, Malaysia, Mexico, South Korea, Philippines, Thailand) and two developed countries (United States and Japan) obtained by fitting an standard GARCH model. We selected markets whose data on stock indices are available during the period spanning from January 01, 1993 to October 13, 2010, so as to cover several episodes of financial crises. To determine the series of volatility, we used the MSCI market indices for both emerging and developed markets, extracted from DATASTREAM.

For financial crises, we tried to determine a composite index from three types of crises, namely the banking crises, the currency crises, and the twin crises. We identify episodes of financial crises using two types of indicators[1]: the exchange market pressure index (EMPI) for currency crises and the banking sector fragility index (BSFI) proposed by Kibritçioglu (2003)[2] for banking crises. Twin crises are considered as the occurrence of both currency and banking crises during the same month. As shown in Figure 1, we can identify the evidence of a strong dependence between the proliferation of financial crises and the increase in the stock market volatility. Indeed, many break points in volatility indices coincide with the dates of financial crises.

Table 1 presents the descriptive statistics of monthly returns. We note that they are globally similar to the findings of previous studies. First, market returns are significantly departing from normality according to the Jarque-Bera test. Second, the study of stationarity through the Dickey-Fuller unit root test clearly shows that the distributions of market returns are stationary, even at the 1% confidence level, since the ADF calculated value is strictly below the critical threshold. Finally, the Engle's (1982) test for conditional heteroskedasticity rejects the null hypothesis of no ARCH effect in monthly returns. This justifies the use of the GARCH specification.

[Table 1 near here]

5. Empirical results and discussions

In this section we report estimation results for the conditional volatility model (standard GARCH) and quantile regression model designed to analyze the interdependencies between emerging and developed stock markets.

5.1. Results of conditional volatility model

We use the standard GARCH(1,1)[3] model to measure the conditional volatility for all markets. It is worth noting that the choice of the GARCH model is far from being arbitrary. Firstly, many authors argue that the GARCH(1,1) specification model is the most appropriate for predicting volatility given the existence of ARCH effect in returns series (Ramlall, 2010; Nikkinen et al. 2008; Charles and Darne, 2006; Bollerslev et al., 1994). Second, the choice of the GARCH model is made after a comparison with a non-linear EGARCH specification. The criteria used to determine the performance include the information criteria of Akaike and

Schwarz and the log-likelihood value comparison. Result show a strong relevance of the standard GARCH compared to the EGARCH[4].

Table 2 presents the results of parameter estimation of the GARCH(1,1) model for individual markets, and make a detailed analysis of volatility series. We note that the parameters of the conditional variance equation are positive and statistically significant at 1% confidence level and satisfy the conditions of theoretical stability $(\omega > 0, \delta \geq 0 \text{ and } \lambda \geq 0)$. Furthermore, the persistence of conditional volatility is verified for the majority of stock markets, since the risk premium measured by $(\delta + \lambda)$ is superior to 0,9. The diagnostic of standardized residuals presented in Table 2 (part III) suggests that the GARCH(1,1) model seems to be performing to explain the variations of stock market returns since the residuals and squared residuals are not serially correlated. Moreover, we note the absence of ARCH effect among residual series.

[Table 2 near here]

5.2. Results of QR model

It is important to mention that by reference to the financial literature related to application of the quantile regression technique, we proceeded by calculate seven quantile, from the lower $(\tau = 0.05)$ to the higher one $(\tau = 0.95)$. However, we just reported in Tables 3 and 4 the results of three major quantiles $(\tau = 0.05, 0.5 \text{ and } 0.95)$ which relate, most frequently, the maximum of information. Indeed, these three quantiles allows us considering extreme situations inherent to financial markets, respectively bearish movements, mean movements and bullish movements. We report further the standard errors which are obtained using the pairs bootstrapping procedure (Buchinsky, 1995). We illustrate, in Figure 2 and 3, the graphical results for all the quantiles for two markets (Argentina and Brazil)[5].

Our decision rule concerning the existence or no of interdependencies between markets is based on the significance of the estimated coefficients for all the three quantiles and by reference to the analysis of the changes in the quantile regression coefficients obtained by applying the F-test for the equality of coefficients at low and high quantiles. This allows us to judge the nature of co-movement (symmetric or asymmetric).

It is important to remember that, in the analysis of interdependencies between stock markets, we considered a very important factor that typify emerging markets, namely, the financial crises that have been in packet during the last decades in these economies. The incorporation of this factor in our model allows us to test interdependencies in terms of volatility during financial crises (known as the contagion phenomenon).

Note that in order to take into account the effect of geographical proximity; we decomposed the sample into three groups (the Latin American markets, the Asian markets and the developed markets).

[Table 3 near here]

[Table 4 near here]

When reading the Tables 3 and 4, which reports the estimation results of the quantile regression model, we can deduce that the model is able to describe and assess in an appropriate manner, the interdependence of volatility series. Indeed, the explanatory power of the exogenous variables associated with each quantile $(\tau = 0.05, 0.5 \text{ et } 0.95)$ is generally high.

The results show a strong interdependence in terms of volatility between financial markets. With reference to our first judgment criterion (the absolute significance across quantile), we make out 70 significant relationships among 220 (11 x 2 x 10) relationships between emerging markets and developed markets (with a rate of 32%). Among the 70, 20 relationships were identified in financial crises periods, which indicate that financial crises contributes with nearly 29% in the strengthening of interdependence between stock markets. The interdependence in the quiet periods is a sign of the existence of a volatility transmission, while those identified in times of financial crises are significant for the existence of contagion phenomenon (according to the contagion definition provided by the World Bank and described as very restrictive)[6].

In the light of our empirical findings, we clearly identify a strong interdependence in terms of volatility between emerging markets. Similarly, the regional transmission is effective. It has been proven at the two geographical areas for which belong all emerging countries. This transmission varies in the same way from one region to another.

It should be noted that the impact of financial crises seems more effective for markets belonging to both different geographical areas (see Latin America and Asia region). This can be explained by the fact that more the markets are in the same area more they will be affected by the same event (good or bad), this is due to the rapid dissemination of information (informational efficiency).

The whole markets volatility effect on the volatility of Latin American markets, as presented in Table 3, is generally positive and significant for all quantiles. The co-movement between them intensifies from the lower to the upper quantiles, indicating that the interdependence increases during the bullish market and vice versa. Indeed, the trend in correlations among the stock markets is not uniform through time when considering different quantiles. The Fisher test for the equality of coefficients at lower and upper quantiles rejects the null of equality. This evidence confirms that the estimates for the lower and upper quantiles are statistically different. Therefore, the Latin American stock markets display an asymmetric co-movement with all other markets as the intensity of interdependence increases when these markets are booming but interdependence loses intensity when the markets are bearish. However, since the onset of the financial crisis, we have the same results as the calm periods. Indeed, the intensity of dependence increases when these markets are booming and reversely when the markets are bearish. But we find that the crises effect is verified generally for both Asian region markets and developed markets.

Looking to the Asian region we can make the same conclusions as for the Latin American region. Indeed, the positive and significant dependence between the Asian region stock markets and the entire stock markets (as presented in Table 4) is evident for all quantiles. The corresponding F-test for the equality of coefficients across those quantiles is unable to reject the null hypothesis. Accordingly, the interdependence structure has intensified across quantiles and the whole stock market's volatility movement has a similar impact on the quantiles of the Asian stock markets volatility. In addition, the co-movement increases during the sub-period since the financial crisis.

Estimation results related to the developed markets volatility effects on the Asian and Latin American region stock market's volatility (Table 3 and 4) show strong interdependence at calm periods and at financial crises periods, and exhibit asymmetric co-movement, having lower tail independence and upper tail dependence structure.

Finally, it is worth mentioning that the quantile regression approach has always shown its relevance in the study of interdependencies especially between variables that represent some non-linear trends. This technique gives information on the average dependence as well as the upper and lower tail dependence which proves its empirical pertinence to treat the presence of outliers. In addition, the QR approach is suitable to capture additional marginal effects derived from various treated concepts.

Through the application of this approach for the first time to study financial markets interdependencies in terms of volatility, we confirm the results of previous studies which used different methodologies in order to judge the existence of unidirectional and sometimes bidirectional volatility spillovers between financial markets (Gilenko and Fedorova, 2014; Bekiros, 2014; Li, 2007; Darrat and Kasch-Haroutounian et Price, 2001; Forbes and Rigobon, 2001, 2002; etc…). Our findings support the robustness of this methodology to detect interdependencies between volatility series which represent a non linear history over time. In addition, it has enabled us to detect the effects of financial crises (banking, currency or twin crisis) on the interdependencies among stock markets (emerging and developed markets) by determining a marginal effect, through its ability to integrate a time varying crisis variable.

6. Concluding remarks

This article aims at analyzing financial markets interdependence in terms of volatility (transmission and contagion). It contributes to the finance literature in two points. First, the use of the QR methodology which has a confirmed relevance through the use of different measures of central tendency and dispersion statistics as well as by means of its ability to form an accurate overview of the interdependencies under different market circumstances. Second, the consideration of the evolutionary character of emerging markets through the use of high-frequency data and essentially, financial time-varying indexes.

Throughout this article, we were able to verify the existence of volatility transmission between emerging markets as well as between emerging and developed markets. This evidence can be explained by the reinforcement of financial integration level which strengthens the degree of dependence between emerging and developed markets. We note that several studies examined the interdependence in emerging economies and confirmed that they are stronger after financial integration (Bensafta et Samedo, 2011; Phylaktis and Ravazzolo, 2002; Carrieri et al., 2007; Calvo et Reinhart, 1996). One of the important results of this paper is that the geographical proximity involves a great increase of transmission.

The proliferation of financial crises over the last decades throughout the world and more specifically in emerging economies raises the problem of contagion as a transmission of shocks during financial crises. Several recent studies focused on contagion on emerging markets and verified its effectiveness (Bekaert et al., 2005; Forbes and Rigobon, 2001). Our results confirm the presence of transmission of great shocks during various crises periods which confirm the presence of contagion between emerging markets as well as between emerging and developed markets.

In addition, financial crises seem more effective for markets belonging to the same geographical area (Latin America and Asia region). The effect of the whole market's volatility on the volatility of Latin American markets is generally positive and significant for all quantiles. The co-movement between them intensifies from the lower to the upper quantiles, indicating that the interdependence increases during the bullish market and vice versa. Therefore, all stock markets and the Latin American markets display an asymmetric co-movement as the intensity of dependence increases when these markets are booming but decreases when the markets are bearish.

The same conclusions have been observed for the Asian region in so far as the positive and significant dependence with other stock markets is evident for every part of quantiles and the dependence increases at calm periods and during crisis periods and exhibit asymmetric co-movement, having lower tail independence and upper tail dependence structure.

So far, the most frequently useful question for governmental policy makers in emerging economies is: How to avoid volatility transmission and the risk of contagion? In fact, many studies tried to answer this question such as Masson (1999) and Forbes and Rigobon (2001). Given the high fragility of the emerging financial systems, it is necessary to rationalize their economic and financial openness in order to reduce the occurrence of financial crises and consequently the risk of contagion. More precisely, they must undertake some reforms related to exchange rate regimes and interest rates policy, in order to avoid the high devaluation of the national currency which generally results in financial crises (Nguyen, 2005). We note also that international cooperation is generally considered as alternative way to predict and avoid the risk of crises and contagion resulting from international fluctuations. This suggests that emerging countries have to take part in regional and international blocks (World Bank and FMI), which aims at making coordination between them and establishing common prudential rules.

This paper's findings have several economic and financial implications. Firstly, it presents a particular importance for regulators in emerging countries since it provides some answers about the risk management and stock markets stability. Secondly, it informs foreign or domestic investors about financial markets stability in terms of volatility transmission and contagion risk in order to help them to make investment decisions.

Notes

1. For further details about the construction of these crises indexes, see Kibritçioglu (2003, pp. 61–62) and Cartapanis et al. (1998).
2. Kibritçioglu (2003) calculated the BSFI for 22 countries using monthly frequency data with different beginning dates and which ends at December 2002. We have updated this index for the period January 2002– October 2010.
3. The variance equation for the GARCH(1,1) model is: $h_t = \omega + \delta\varepsilon_{t-1}^2 + \lambda h_{t-1}$.
4. For the sake of concision, the test results are not reported here, but they are available under request addressed to the corresponding author.
5. For the sake of concision, the figures for the other markets are not reported here. They are available upon request from the corresponding author.
6. Contagion, as defined by the World Bank, is the transmission of shocks in times of financial crises.

References

Adrian, T. and M. K. Brunnermeier (2011), 'COVAR', Working Paper, NBER, Cambridge.

Aggarwal, R., C. Inclan and R. Leal (1999), 'Volatility in emerging stock markets', *Journal of Financial and Quantitative Analysis*, 34(1): 33-55.

Arouri, M. H., J. Jouini and D. K. Nguyen (2011), 'Volatility spillovers between oil prices and stock sector returns: implications for portfolio management', *Journal of International Money and Finance*, 30(7): 1387-1405.

Bassett, G. and H-L. Chen (2001), 'Quantile style: return-based attribution using regression quantiles', *Empirical Economics*, 26(1): 293-305.

Baur, D. G. (2013), 'The structure and degree of dependence: A quantile regression approach' *Journal of Banking and Finance*, 37(3): 786-798.

Baur, D. G., T. Dimpfl and R. C. Jung (2012), 'Stock return autocorrelations revisited: a quantile regression approach', *Journal of Empirical Finance*, 19(2): 254-265.

Bekiros, S. D. (2013), 'Contagion, decoupling and the spillover effects of the US financial crisis: evidence from the BRIC markets', *International Review of Financial Analysis*, 33: 58-69.

Ben Rejeb, A. (2013), 'Volatility spillovers and contagion: an empirical analysis of structural changes in emerging market volatility', *Economics Bulletin*, 33(1): 56-71.

Bensafta, K. M. and G. Semedo (2011), 'Chocs, chocs de volatilité et contagion entre les marchés boursiers: Application d'un modèle ICSS-MGARCH', *Revue économique*, 62(2): 277-311.

Bollerslev, T., R. F. Engle and D. B. Nelson (1994), 'Arch models', in: R. F. Engle and D. McFadden (eds), Handbook of Econometrics, pp. 2959-3038. Amsterdam: North-Holland.

Buchinsky, M. (1995), 'Estimating the asymptotic covariance matrix for quantile regression models a Monte Carlo study', *Journal of Econometrics*, 68(2): 303-338.

Buchinsky, M. and J. Hunt (1999), 'Wage mobility in the United States', *The Review of Economics and Statistics*, 81(3): 351-368.

Buchinsky, M. and P. Leslie (2010), ‘Educational attainment and the changing U.S. wage structure: dynamic implications on young individuals' choices’, *Journal of Labor Economics*, 28(3): 541-594.

Calvo, G. A., L. Leonardo and C. Reinhart (1996), ‘Inflows of capital to developing countries in 1990s: causes and effects’, *Journal of Economic Perspectives*, 10(2): 123-129.

Calvo, S. and C. Reinhart (1996), ‘Capital flows to Latin America: Is there evidence of contagion effects?’, Working Paper, The World Bank, Policy Research.

Caporale, G., N. Pittis and N. Spagnolo (2002), ‘Testing for causality in variance: an application to the East Asian markets’, *International Journal of Finance and Economics*, 7(3): 235-245.

Carrieri, F., V. Errunza and K. Hogan (2007), ‘Characterizing world market integration through time’, *Journal of Financial and Quantitative Analysis*, 42(4): 915-940.

Charles, A. and O. Darne (2006), ‘Large shocks and the september 11th terrorist attacks on international stock markets’, *Economic Modelling*, 23(4): 683-698.

Choudhry, T. (2004), ‘International transmission of stock returns and volatility’, *Emerging Markets Finance and Trade*, 40(4): 33-52.

Chuang, C. C., C. M. Kuan and H. Y. Lin (2009), ‘Causality in quantiles and dynamic stock return-volume relations’, *Journal of Banking and Finance*, 33: 1351-1360.

Ciner, C., C. Gurdgiev and B. Lucey (2013), ‘Hedges and safe havens: an examination of stocks, bonds, gold, oil and exchange rates’, *International Review of Financial Analysis*, 29(C): 202-211.

Darrat, A. and O. Benkato (2003), ‘Interdependence and volatility spillovers under market liberalization: the case of Istanbul stock exchange’, *Journal of Business Finance and Accounting*, 30(7): 1089-1114.

Edwards, S. and R. Susmel (2001), ‘Volatility dependence and contagion in emerging equity markets’, *Journal of Development Economics*, 66(2): 505-532.

Eide, E. R. and M. H. Showalter (1999), ‘Factors affecting the transmission of earnings across generations:a quantile regression approach’, *Journal of Human Resources*, 34(2): 253-267.

Eide, E. and M. H. Showalter (1998), 'The effect of school quality on student performance: a quantile regression approach', *Economics Letters*, 58(3): 345-350.

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of UK inflation', *Econometrica*, 50(4): 987-1007.

Engle, R. F. and K. Kroner (1995), 'Multivariate simultaneous generalized ARCH' *Econometric theory*, 11(1): 122-150.

Engle, R. F. and S. Manganelli (2004), 'CAViaR: conditional autoregressive value at risk by regression quantiles', *Journal of Business and Economic Statistics*, 22(4): 367-381.

Forbes, K. J. and R. Rigobon (2001), 'Contagion in Latin America: definitions, measurement, and policy implications', *Journal of LACEA Economia*, 1(2): 1-46.

Forbes, K. J. and R. Rigobon (2002), 'No contagion, only interdependence: measuring stock market comovements', *Journal of Finance*, 57(5): 2223-2261.

Gebka, B. and M. E. Wohar (2013), 'Causality between trading volume and returns: evidence from quantile regressions', *International Review of Economics and Finance*, 27: 144-159.

Gilenko, E. and E. Fedorova (2014), 'Internal and external spillover effects for the BRIC countries: multivariate GARCH-in-mean approach', *Research in International Business and Finance*, 31: 32-45.

Hamao, Y., R. W. Masulis and V. Ng (1990), 'Correlations in price changes and volatility across international stock markets', *Review of Financial Studies*, 3(2): 281-307.

Inclan, C. and G. C. Tiao (1994), 'Use of cumulative sums of squares for retrospective detection of changes of variances', *Journal of the American Statistical Association*, 89: 913-923.

Karolyi, G. A. (1995), 'A Multivariate GARCH model of international transmission of stock returns and volatility: the case of the United States and Canada', *Journal of Business and Economic Statistics*, 13(1): 11-25.

Kasch-Haroutounian, M. and S. Price (2001), 'Volatility in the transition markets of Central Europe', *Applied Financial Economics*, 11(1): 93-105.

Kearney, C. (2000), 'The determination and international transmission of stock market volatility', *Global Finance Journal*, 11(1): 31-52.

Kibritçioglu, A. (2003), 'Monitoring banking sector fragility', *Arab Bank Review*, 5(2): 51-66.

Koenker, R. (2005), 'Quantile Regression', Econometric Society Monograph Series, new York: Cambridge University Press.

Koenker, R. and G. Bassett (1978), 'Regression quantiles', *Econometrica*, 46: 33-50.

Koenker, R. and V. D'Orey (1987), 'Algorithm AS 229: computing regression quantiles' *Journal of the Royal Statistical Society*, 36(3): 383-393.

Leachman, L. and B. Francis (1996), 'Equity market return volatility: dynamics and transmission among the G-7 countries', *Global Finance Journal*, 7(1): 27-52.

Lee, B. S. and M. Y. L. Li (2012), 'Diversification and risk-adjusted performance: a quantile regression approach', *Journal of Banking and Finance*, 36(7): 2157-2173.

Li, H. (2007), 'International linkages of the Chinese stock exchanges: a multivariate GARCH analysis', *Applied Financial Economics*, 17(4): 285-297.

Li, M. Y. L. and P. Miu (2010), 'A hybrid bankruptcy prediction model with dynamic loadings on accounting-ratio-based and market-based information: a binary quantile regression approach', *Journal of Empirical Finance*, 17(4): 818-833.

Ling, S. and M. McAleer (2003), 'Asymptotic theory for a vector ARMA-GARCH model' *Economic Theory*, 19(2): 280-310.

Lopes, H. F. and H. S. Migon (2002), 'Comovements and contagion in emergent markets: Stock indexes volatilities', *Case Studies in Bayesian Statistics*, 6(): 285-300.

Masson, P. (1999), 'Contagion: Macroeconomic models with multiple equilibria', *Journal of International Money and Finance*, 18(4): 587-602.

Morillo, D. (2000), Income mobility with nonparametric quantiles: a comparison of the U.S. and Germany, Preprint.

Nguyen, D. K. (2005), 'Market Deregulations, volatility and spillover effects: Experiences from emerging stock markets', in Governance and Risk in Emerging and Global Markets, (eds), S. Motamen-Samadian, pp. 89-120. Palgrave Macmillan: United Kingdom.

Nikkinen, J., M. M. Omran, P. Sahlstrom and J. Aijo (2008), 'Stock returns and volatility following the september 11 attacks: evidence from 53 equity markets', *International Review of Financial Analysis*, 17(1): 27-46.

Phylaktis, K. (1999), ‘Capital market integration in the Pacific Basin region: an impulse response analysis’, *Journal of International Money and Finance*, 18(2): 267-287.

Phylaktis, K. and F. Ravazzolo (2002), ‘Measuring financial and economic integration with equity prices in emerging markets’, *Journal of International Money and Finance*, 21(6): 879-903.

Ramlall, I. (2010), ‘Has the US Subprime crisis accentuated volatility clustering and leverage effects in major international stock markets?’ *International Research Journal of Finance and Economics*, 39: 157-185.

Rubia, A. and L. Sanchis-Marco (2013), ‘On downside risk predictability through liquidity and trading activity: A dynamic quantile approach’, *International Journal of Forecasting*, 29(1): 202-219.

So, M. K. P., W. K. Li, and K. Lam (1997), ‘Multivariate modelling of the autoregressive random variance process’, *Journal of Time Series Analysis*, 18(4): 429-446.

Tsai, I-C. (2012), ‘The relationship between stock price index and exchange rate in Asian markets: a quantile regression approach’, *Journal of International Financial Markets, Institutions & Money*, 22(3): 609-621.

Wongswan, J. (2006), ‘Transmission of information across international equity markets’, Review of Financial Studies, 19(4): 1157-1189.

Xu, X. and H. Fung (2002), ‘Information flows across markets: Evidence from China-backed stocks dual-listed in Hong Kong and New York’, *Financial Review*, 37: 563-588.

Table 1. Basic statistics of stock markets monthly returns

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	ADF Statistics	Q(6)	Q(12)	ARCH (6)	ARCH (12)
Argentina	0.024	2.359	-1.045	20.520	60176.9^{+++}	-65.480^{+++}	14.950^{++}	43.634^{++}	27.292^{+++}	56.978^{+++}
Brazil	0.058	2.526	-0.117	8.938	6825.6^{+++}	-47.819^{+++}	64.236^{+++}	73.505^{+++}	189.50^{+++}	111.273^{++}
Chile	0.036	1.319	-0.070	14.157	24065.8^{+++}	-57.875^{+++}	135.40^{+++}	152.13^{+++}	238.94^{+++}	141.88^{+++}
Colombia	0.054	1.596	-0.143	13.697	22133.8^{+++}	-55.132^{+++}	229.36^{+++}	255.47^{+++}	185.02^{+++}	104.09^{+++}
India	0.038	1.767	-0.072	9.732	8764.7^{+++}	-61.590^{+++}	61.590^{+++}	107.21^{+++}	55.098^{+++}	34.367^{+++}
Malaysia	0.017	1.828	-0.839	68.207	822412.1^{+++}	-28.603^{+++}	105.94^{+++}	115.91^{+++}	27.829^{+++}	16.554^{+++}
Mexico	0.032	1.992	-0.066	14.620	26101.3^{+++}	-62.453^{+++}	38.917^{++}	52.269^{++}	85.545^{+++}	50.312^{+++}
South Korea	0.025	2.440	0.206	16.679	36202.2^{+++}	**-34.674^{+++}**	85.459^{+++}	131.81^{+++}	169.48^{+++}	114.65^{+++}
Philippines	0.004	1.745	0.484	15.129	28618.5^{+++}	-57.079^{+++}	150.55^{+++}	180.40^{+++}	33.154^{+++}	18.979^{+++}
Thailand	0.001	2.133	0.447	12.912	19145.7^{+++}	-58.697^{+++}	128.78^{+++}	159.39^{+++}	86.358^{+++}	61.306^{+++}
USA	0.022	1.199	-0.221	12.055	15885.2^{+++}	-52.296^{+++}	34.297^{++}	47.321^{+++}	218.07^{+++}	141.03^{+++}
Japan	0.000	1.467	0.113	7.203	3424.4^{+++}	-51.684^{+++}	27.823^{++}	32.070^{++}	103.65^{+++}	59.158^{+++}

Notes: The table presents basic statistics of monthly returns. Columns 1 to 5 are reserved to the mean (%). the standard deviation (%). the skewness. the kurtosis and the Jarque and Bera normality test statistics. Q (6) and Q (12) are statistics of the Ljung-Box autocorrelation test applied on returns with lags between 6 and 12. ARCH (6) and ARCH (12) are the statistics of the conditional heteroskedasticity test proposed by Engle (1982). using the residuals of the AR (1) model. ADF is the statistics of the ADF unit root test proposed by Dickey and Fuller (1981). The ADF test is conducted without time trend or constant. $^{+}$ and $^{++}$ denote that the null hypothesis of tests (no-autocorrelation. normality. no-stationarity and homogeneity) are rejected at. respectively. 5% and 1% levels. The study period is from January 1976 to December 2008.

Table 2. Parameters estimation of GARCH(1,1) and diagnostic tests for conditional volatility

	Argentina	Brazil	Chile	Colombia	India	South Korea	Malaysia	Mexico	Philippines	Thailand	Japan	USA
						Part I: Estimated parameters						
ω	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***	0.000 (0.000)***
δ	0.113 (0.004)***	0.111 (0.006)***	0.121 (0.008)***	0.230 (0.011)***	0.118 (0.007)***	0.067 (0.004)***	0.096 (0.005)***	0.138 (0.005)***	0.113 (0.007)***	0.095 (0.005)***	0.084 (0.006)***	0.067 (0.004)***
λ	0.863 (0.004)***	0.873 (0.007)***	0.848 (0.010)***	0.731 (0.010)**	0.860 (0.007)***	0.929 (0.004)***	0.906 (0.048)***	0.834 (0.006)***	0.861 (0.008)***	0.890 (0.003)***	0.900 (0.007)***	0.927 (0.004)***
$(\delta+\lambda)$	0.976	0.984	0.969	0.961	0.978	0.996	1.002	0.972	0.974	0.985	0.984	0.994
Log-likelihood	11586.77	11265.12	14269.72	13630.47	12781.93	11820.83	14010.76	12434.10	12792.23	12038.59	13427.53	15004.23
						Part II: Basic statistics of conditional volatility						
Mean (%)	0,056	0,065	0,017	0,027	0,032	0,060	0,036	0,040	0,032	0,047	0,022	0,014
Standard deviation (%)	0,084	0,082	0,027	0,050	0,034	0,104	0,099	0,059	0,037	0,059	0,020	0,023
Minimum	0,012	0,010	0,003	0,005	0,007	0,007	0,002	0,009	0,003	0,009	0,003	0,001
Maximum	1,502	0,968	0,633	1,151	0,506	1,395	1,683	0,881	0,562	0,835	0,236	0,249
Jarque-Bera	114203	241560,3^{+++}	6380008^{+++}	3262233^{+++}	203405,3^{+++}	512101,5^{+++}	1508092^{+++}	435560,1^{+++}	421203,3^{+++}	363708,7^{+++}	346780,2^{+++}	400638,4^{+++}
ADF test	-	-6.730^{+++}	-7.364^{+++}	-8.060^{+++}	-7.780^{+++}	-5.628^{+++}	-6.980^{+++}	-5.726^{+++}	-9.051^{+++}	-5.917^{+++}	-5.323^{+++}	-5.158^{+++}
						Part III: Diagnostic of standardized residuals						
Mean	-0.038	-0.035	-0.023	-0.015	-0.029	-0.023	-0.028	-0.050	-0.028	-0.024	-0.018	-0.031
Standard deviation (%)	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.998	0.999	0.999	0.999	0.999
Minimum	-7.996	-5.305	-6.925	-7.540	-6.471	-6.763	-7.325	-8.379	-5.947	-12.598	-5.230	-7.055
Maximum	6.261	4.021	3.935	6.069	6.935	4.840	9.127	5.733	17.003	9.293	5.892	3.458
Skewness	-0.286	-0.330	-0.157	-0.117	-0.095	-0.185	0.081	-0.353	0.930	-0.224	-0.020	-0.469
Kurtosis	6.804	4.436	4.189	5.971	5.767	4.546	7.357	6.049	22.506	11.453	4.294	5.044
Jarque-Bera	2859.9^{+}	483.6^{+++}	292.5^{+++}	1716.9^{+++}	1486.9^{+++}	488.7^{+++}	3673.9^{+++}	1893.6^{+++}	74202.4^{+++}	13849.4^{+++}	324.3^{+++}	977.8^{+++}
Q(12)	22.347^{+}	12.912	24.926^{++}	42.211^{+++}	34.438^{+++}	11.692	24.366^{++}	8.473	18.259	31.855^{+++}	12.458	17.820
$Q^2(12)$	13.105	9.602	7.768	11.562	12.839	11.849	10.597	11.249	1.261	15.056	7.268	12.788
ARCH(12)	1.088	1.254	0.641	0.961	1.054	0.984	0.841	0.904	0.104	1.215	0.609	1.046

Notes: The variance equation for the GARCH(1,1) model is: $h_t = \omega + \delta\varepsilon_{t-1}^2 + \lambda h_{t-1}$. * and ** indicate that coefficients are statistically significant at 5% and 1%, respectively. $^{+}$ and $^{++}$ indicate that the null hypothesis (no autocorrelation, normality, homogeneity and no stationarity) is rejected at 5% and 1% confidence level, respectively.

Table 3. Quantile regression estimates for Latin America region (Markets: Argentina, Brazil, Chile, Mexico and Colombia)

			Latin America region														
		Dependent variables	Argentina			Brazil			Chile			Colombia			Mexico		
		Quantile order	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}
Independent variables	Latin America region	Argentina	β				0.009** (0.003)	-0.001 (0.004)	-0.04*** (0.011)	0.010*** (0.002)	0.021*** (0.007)	0.024 (0.017)	0.000 (0.001)	0.011*** (0.003)	-0.005 (0.011)	0.002 (0.007)	0.122*** (0.018)	1.12*** (0.261)
			θ				0.009 (0.014)	0.409*** (0.087)	0.227** (0.095)	-0.004* (0.002)	-0.011 (0.008)	-0.016 (0.018)	-0.003 (0.007)	-0.024 (0.019)	0.263** (0.123)	-0.001 (0.007)	-0.13*** (0.019)	-1.15*** (0.262)
		Brazil	β	**0.028***** **(0.007)**	**0.142***** **(0.018)**	**0.242***** **(0.060)**				**0.015***** **(0.004)**	**0.067***** **(0.009)**	**0.173***** **(0.020)**	-0.004* (0.002)	-0.008 (0.007)	0.037 (0.052)	**0.045***** **(0.004)**	**0.198***** **(0.013)**	**0.528***** **(0.103)**
			θ	0.141** (0.065)	0.121 (0.083)	-0.541 (0.668)				0.016*** (0.004)	0.001 (0.014)	-0.123* (0.071)	0.012 (0.009)	0.062*** (0.016)	0.415*** (0.138)	-0.001 (0.013)	-0.051 (0.035)	0.838*** (0.280)
		Chile	β	**0.269***** **(0.041)**	**0.727***** **(0.065)**	**0.720***** **(0.264)**	**0.511***** **(0.057)**	**0.984***** **(0.075)**	**3.43***** **(0.464)**				0.058*** (0.008)	0.134*** (0.048)	-0.107 (0.226)	0.232*** (0.035)	0.326*** (0.035)	-0.143 (0.135)
			θ	-0.203 (0.169)	-0.90*** (0.296)	-0.441 (2.268)	0.129 (0.202)	-0.473** (0.202)	-3.70*** (0.612)				0.190*** (0.048)	0.712*** (0.105)	-0.566 (0.419)	0.399*** (0.080)	0.451*** (0.055)	0.499 (0.809)
		Colombia	β	0.022*** (0.007)	0.047*** (0.018)	0.005 (0.025)	0.041** (0.019)	0.084*** (0.016)	0.081 (0154)	**0.022***** **(0.003)**	**0.030***** **(0.010)**	**0.055**** **(0.023)**				0.013** (0.005)	0.041*** (0.010)	-0.041 (0.030)
			θ	0.065** (0.031)	0.323*** (0.101)	0.604 (0.547)	0.002 (0.058)	-0.086 (0.054)	-0.005 (0.203)	-0.007 (0.006)	0.002 (0.019)	0.273** (0.127)				-0.010 (0.034)	-0.09*** (0.023)	-0.096 (0.129)
		Mexico	β	**0.113***** **(0.009)**	**0.196***** **(0.029)**	**0.175***** **(0.029)**	**0.161***** **(0.015)**	**0.321***** **(0.035)**	**0.934***** **(0.137)**	**0.021***** **(0.002)**	**0.056***** **(0.008)**	**0.169***** **(0.035)**	0.003*** (0.001)	0.003 (0.007)	0.010 (0.016)			
			θ	0.184** (0.083)	0.131 (0.111)	0.723 (0.796)	0.059 (0.045)	0.361** (0.160)	1.01*** (0.252)	-0.001 (0.004)	-0.07*** (0.017)	0.232 (0.173)	-0.009 (0.016)	0.038 (0.030)	0.545** (0.238)			
	Asian region markets	India	β	0.039*** (0.008)	0.024 (0.015)	-0.002 (0.685)	0.022 (0.016)	-0.06*** (0.012)	-0.24*** (0.080)	**0.024***** **(0.005)**	**0.049***** **(0.009)**	**0.121***** **(0.028)**	**0.039***** **(0.006)**	**0.128***** **(0.021)**	**0.912***** **(0.175)**	0.008 (0.010)	0.051*** (0.017)	0.143*** (0.048)
			θ	**-0.186**** **(0.076)**	**-0.43***** **(0.128)**	**-2.68***** **(0.940)**	0.039 (0.034)	-0.000 (0.098)	0.133 (0.210)	**-0.021**** **(0.010)**	**-0.05***** **(0.020)**	**-0.21***** **(0.058)**	-0.004 (0.011)	-0.030 (0.037)	1.097** (0.546)	0.050*** (0.018)	0.001 (0.025)	-0.019 (0.176)
		Malaysia	β	**-0.02***** **(0.006)**	**0.036***** **(0.100)**	**0.059**** **(0.023)**	0.053*** (0.011)	0.086*** (0.019)	0.016 (0.037)	0.023*** (0.001)	0.005 (0.004)	-0.01*** (0.004)	0.001 (0.001)	-0.013* (0.007)	-0.027 (0.029)	**0.015**** **(0.007)**	**0.035***** **(0.005)**	**-0.12***** **(0.032)**
			θ	-0.103 (0.219)	0.673 (0.424)	1.032 (2.001)	-0.008 (0.024)	-0.12*** (0.040)	-0.117** (0.049)	-0.02*** (0.002)	-0.02*** (0.008)	-0.002 (0.018)	-0.002 (0.008)	-0.018 (0.016)	-0.004 (0.063)	-0.030** (0.014)	-0.036** (0.015)	0.030 (0.124)
		South Korea	β	0.011*** (0.002)	0.001 (0.001)	-0.02*** (0.007)	**-0051***** **(0.015)**	**-0.03***** **(0.013)**	**-0.04***** **(0.011)**	-0.01*** (0.005)	-0.006 (0.005)	-0.06*** (0.015)	**-0.003***** **(0.001)**	**-0.007***** **(0.001)**	**-0.032***** **(0.007)**	0.001 (0.002)	-0.000 (0.002)	0.101*** (0.023)
			θ	**0.262***** **(0.055)**	**0.917***** **(0.193)**	**13.30***** **(2.544)**	**0.133***** **(0.034)**	**0.278***** **(0.074)**	**0.324***** **(0.117)**	0.015*** (0.005)	0.007 (0.006)	0.053** (0.023)	**-0.020***** **(0.006)**	**-0.016*** **(0.011)**	**-0.377***** **(0.056)**	-0.026 (0.016)	0.061** (0.026)	-0.244* (0.138)
		Thailand	β	-0.02*** (0.006)	-0.04*** (0.009)	-0.039 (0.045)	**-0.027**** **(0.013)**	**-0.03***** **(0.010)**	**0.171**** **(0.084)**	**0.004***** **(0.001)**	**0.011*** **(0.005)**	**0.046*** **(0.026)**	-0.003 (0.002)	-0.017*** (0.005)	-0.066 (0.055)	-0.005 (0.003)	0.004 (0.006)	0.046 (0.031)
			θ	0.125* (0.070)	0.404*** (0.140)	0.319 (1.451)	-0.157** (0.065)	-0.19*** (0.069)	-0.111 (0.193)	0.003* (0.002)	0.007 (0.009)	-0.058* (0.031)	**0.014*** **(0.008)**	**0.075***** **(0.021)**	**-0.144*** **(0.087)**	0.004 (0.014)	-0.037 (0.030)	-0.17*** (0.059)
		Philippines	β	0.062*** (0.006)	0.042*** (0.009)	0.001 (0.028)	0.022*** (0.005)	0.001 (0.009)	-0.148 (0.102)	0.002 (0.003)	0.028 (0.021)	0.007 (0.034)	**0.018***** **(0.005)**	**0.122***** **(0.028)**	**0.385**** **(0.149)**	0.011 (0.012)	0.007 (0.008)	0.086 (0.059)
			θ	-0.141** (0.058)	-0.068 (0.137)	0.049 (1.839)	0.059 (0.066)	0.389*** (0.088)	0.351 (0.493)	-0.006 (0.004)	-0.011 (0.028)	0.083 (0.056)	-0.016*** (0.005)	-0.123*** (0.028)	0.150 (0.181)	0.165*** (0.052)	0.185*** (0.040)	-0.201 (0.466)

(*continued on next page*)

Table 3 (*Continued*)

			Latin America region														
		Dependent variables	Argentina			Brazil			Chile			Colombia			Mexico		
		Quantile order	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}
Independent variables	Developed markets: Japan	β	**0.147***** **(0.023)**	**0.087**** **(0.037)**	**-0.303*** **(0.184)**	0.120** (0.052)	0.539*** (0.068)	-0.008 (0.100)	0.010 (0.010)	0.087*** (0.023)	0.324*** (0.040)	0.020*** (0.007)	0.012 (0.031)	0.167 (0.248)	0.020*** (0.007)	0.012 (0.031)	0.167 (0.248)
		θ	-0.49*** (0.125)	-0.444** (0.210)	-3.137 (3.033)	-0.120 (0.159)	-0.69*** (0.119)	-0.80*** (0.215)	-0.05*** (0.015)	0.020 (0.072)	-0.244* (0.099)	-0.067* (0.036)	-0.024 (0.059)	2.011*** (0.682)	-0.067* (0.036)	-0.024 (0.059)	2.011*** (0.682)
	Developed markets: USA	β	**0.041*** **(0.023)**	**0.328***** **(0.058)**	**1.354***** **(0.218)**	**0.571***** **(0.061)**	**0.724***** **(0.081)**	**0.865***** **(0.168)**	**0.051***** **(0.012)**	**0.062***** **(0.016)**	**-0.088**** **(0.043)**	**0.064***** **(0.012)**	**-0.139***** **(0.025)**	**-0.383***** **(0.109)**	**0.064***** **(0.012)**	**-0.139***** **(0.025)**	**-0.38***** **(0.109)**
		θ	-0.217 (0.140)	-0.528 (0.449)	-15.0*** (3.887)	**0.263**** **(0.112)**	**-0.552**** **(0.243)**	**-0.438*** **(0.264)**	**0.049*** **(0.029)**	**0.447***** **(0.094)**	**0.589**** **(0.256)**	-0.026 (0.033)	-0.345*** (0.053)	-1.815*** (0.259)	-0.026 (0.033)	-0.345*** (0.053)	-1.82*** (0.259)
	α		0.001** (0.000)	0.000*** (0.000)	0.000*** (0000)	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
	γ		0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.00*** (0.000)	-0.00** (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000** (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000** (0.000)	-0.00*** (0.000)
	Pseudo R^2		0.156	0.306	0.548	0.275	0.422	0.643	0.144	0.319	0.728	0.057	0.163	0.452	0.057	0.163	0.452

Notes: This table presents the quantile regression estimates for Latin America region according to the empirical model defined by Eq. (3). The numbers in parentheses are the bootstrapped standard errors. *, ** and *** indicate that coefficients are significant at 10%, 5% and 1% level, respectively. Absolute significance through three quantiles is in bold type. The additional marginal effects of the different conditional variables in the financial crisis sub-periods is given by $\gamma(\tau)$ and $\theta_k(\tau)$ parameters. While the effects in the calm periods is given by the parameters $\alpha(\tau)$ and $\beta_k(\tau)$.

Table 4. Quantile regression estimates for Asian region (Markets: India, Malaysia, South Korea, Thailand and Philippines)

				Asian region														
Dependent variables				India			Malaysia			South Korea			Thailand			Philippines		
Quantile order				$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}
Independent variables	Latin America region	Argentina	β	-0.003* (0.002)	-0.024*** (0.004)	0.003 (0.045)	**-0.013***** **(0.005)**	**-0.030*** **(0.015)**	**-0.041*** **(0.022)**	**0.037***** **(0.003)**	**0.049***** **(0.005)**	**0.198***** **(0.057)**	0.011 (0.009)	0.004 (0.022)	-0.15*** (0.032)	0.029*** (0.008)	0.027* (0.014)	-0.013 (0.030)
			θ	-0.044* (0.026)	0.104*** (0.036)	0.170 (0.162)	-0.006 (0.006)	-0.020 (0.017)	0.006 (0.029)	-0.074** (0.029)	-0.18*** (0.041)	0.070 (0.125)	-0.014 (0.010)	-0.016 (0.022)	0.130*** (0.034)	-0.03*** (0.008)	-0.018 (0.016)	0.007 (0.031)
		Brazil	β	0.009** (0.003)	-0.027*** (0.006)	-0.055* (0.033)	0.004 (0.004)	0.060*** (0.006)	0.174*** (0.024)	-0.005 (0.006)	-0.08*** (0.009)	-0.19*** (0.029)	-0.010 (0.007)	-0.03*** (0.007)	-0.018 (0.046)	0.000 (0.008)	0.012* (0.007)	0.026 (0.032)
			θ	-0.008** (0.012)	-0.012 (0.013)	0.014 (0.065)	**0.013*** **(0.007)**	**-0.078**** **(0.033)**	**1.400***** **(0.490)**	0.083*** (0.031)	0.248*** (0.022)	-0.034 (0.071)	0.028 (0.031)	0.058*** (0.016)	0.213** (0.086)	0.007 (0.011)	0.037** (0.015)	-0.006 (0.048)
		Chile	β	**0.044**** **(0.017)**	**0.387***** **(0.048)**	**0.943***** **(0.248)**	0.072*** (0.015)	0.056 (0.046)	-0.013 (0.087)	-0.056** (0.028)	-0.24*** (0.046)	0.071 (0.198)	**0.072***** **(0.027)**	**0.171***** **(0.055)**	**0.657***** **(0.138)**	**0.061**** **(0.025)**	**0.281***** **(0.033)**	**0.614***** **(0.165)**
			θ	**0.121**** **(0.051)**	**-0.406***** **(0.106)**	**-0.852**** **(0.337)**	-0.094** (0.037)	-0.082 (0.102)	-0.674 (1.031)	**-0.183**** **(0.089)**	**-0.36***** **(0.107)**	**-0.628**** **(0.294)**	**-0.173**** **(0.073)**	**-0.175*** **(0.099)**	**-1.94***** **(0.430)**	0.065** (0.032)	-0.243*** (0.054)	0.081 (0.310)
		Colombia	β	**0.038***** **(0.010)**	**0.169***** **(0.016)**	**0.442***** **(0.123)**	**-0.013***** **(0.004)**	**-0.051***** **(0.006)**	**-0.11***** **(0.026)**	0.007 (0.010)	0.017** (0.006)	-0.039** (0.016)	0.079*** (0.011)	0.069*** (0.017)	-0.012 (0.084)	0.015** (0.007)	0.053*** (0.019)	0.054 (0.108)
			θ	-0.021 (0.015)	-0.030 (0.044)	-0.353*** (0.131)	0.004 (0.012)	-0.057** (0.028)	-0.152 (0.193)	0.034 (0.037)	0.020 (0.023)	-0.122 (0.077)	-0.07*** (0.013)	-0.09*** (0.018)	-0.013 (0.121)	0.010 (0.011)	0.030 (0.028)	-0.020 (0.108)
		Mexico	β	**-0.009***** **(0.003)**	**-0.008***** **(0.003)**	**-0.064***** **(0.012)**	0.031*** (0.007)	0.077*** (0.016)	0.004 (0.022)	0.014*** (0.002)	0.025*** (0.007)	-0.057 (0.059)	-0.002 (0.004)	-0.008* (0.004)	-0.019 (0.032)	0.002 (0.004)	-0.016*** (0.005)	-0.042** (0.018)
			θ	-0.016 (0.016)	-0.055** (0.023)	0.101 (0.192)	-0.001 (0.007)	-0.014 (0.020)	-0.025 (0.301)	0.107*** (0.024)	-0.020 (0.045)	-0.258 (0.187)	0.061 (0.042)	0.098** (0.046)	0.366*** (0.092)	**0.038***** **(0.011)**	**0.053***** **(0.013)**	**0.084**** **(0.034)**
	Asian region markets	India	β				0.022*** (0.007)	0.001 (0.023)	0.456*** (0.075)	0.079*** (0.011)	0.068** (0.029)	0.118 (0.089)	-0.011 (0.032)	0.096*** (0.016)	0.153*** (0.053)	0.016*** (0.004)	-0.005 (0.016)	-0.056* (0.029)
			θ				**-0.066***** **(0.017)**	**-0.147***** **(0.039)**	**-0.79***** **(0.127)**	0.042 (0.047)	0.021 (0.045)	-0.441** (0.188)	0.039 (0.035)	0.005 (0.023)	0.299** (0.129)	-0.09*** (0.015)	-0.078** (0.031)	0.126 (0.125)
		Malaysia	β	-0.007 (0.008)	-0.032** (0.014)	0.018 (0.055)				-0.007 (0.013)	0.507*** (0.039)	1.468*** (0.375)	**0.263***** **(0.039)**	**0.384***** **(0.019)**	**0.304***** **(0.046)**	**0.114***** **(0.016)**	**0.169***** **(0.013)**	**0.266*** **(0.147)**
			θ	0.002 (0.009)	-0.000 (0.016)	-0.062 (0.062)				0.003 (0.015)	-0.55*** (0.039)	-1.49*** (0.418)	-0.22*** (0.039)	-0.32*** (0.028)	-0.112 (0.155)	-0.07*** (0.017)	-0.118*** (0.020)	-0.102 (0.151)
		South Korea	β	**0.044***** **(0.008)**	**0.111***** **(0.015)**	**0.209***** **(0.063)**	**0.054***** **(0.011)**	**0.233***** **(0.077)**	**0.437***** **(0.072)**				**0.153***** **(0.027)**	**0.367***** **(0.030)**	**0.562***** **(0.082)**	0.015** (0.007)	-0.011 (0.015)	0.418*** (0.159)
			θ	**-0.039***** **(0.008)**	**-0.119***** **(0.015)**	**-0.24***** **(0.064)**	0.027* (0.014)	-0.036 (0..083)	-0.36*** (0.082)				**-0.073**** **(0.029)**	**-0.117**** **(0.046)**	**-0.31***** **(0.118)**	-0.000 (0.008)	0.016 (0.018)	-0.46*** (0.162)
		Thailand	β	**0.013***** **(0.004)**	**0.054***** **(0.016)**	**0.204***** **(0.076)**	**0.033**** **(0.013)**	**0.333***** **(0.057)**	**0.761***** **(0.135)**	0.011 (0.008)	0.253*** (0.037)	0.947*** (0.136)				0.004 (0.011)	0.156*** (0.017)	0.255*** (0.091)
			θ	-0.006 (0.014)	-0.007 (0.019)	-0.28*** (0.083)	-0.018 (0.019)	-0.19*** (0.063)	-0.68*** (0.137)	-0.045 (0.043)	0.235** (0.099)	3.026*** (0.556)				**0.021*** **(0.012)**	**0.082**** **(0.037)**	**0.233**** **(0.117)**
		Philippines	β	**0.020***** **(0.003)**	**-0.012*** **(0.006)**	**-0.11***** **(0.011)**	**0.018***** **(0.003)**	**0.164***** **(0.042)**	**0.264***** **(0.067)**	0.012 (0.030)	0.085*** (0.032)	0.080 (0.079)	**0.119***** **(0.025)**	**0.412***** **(0.043)**	**0.768***** **(0.132)**			
			θ	-0.065** (0.020)	-0.004 (0.029)	0.392** (0.163)	**-0.021**** **(0.009)**	**0.408***** **(0.127)**	**1.404***** **(0.241)**	-0.058 (0.304)	0.079* (0.046)	-0.41*** (0.150)	-0.012 (0.027)	-0.23*** (0.061)	0.423* (0.241)			

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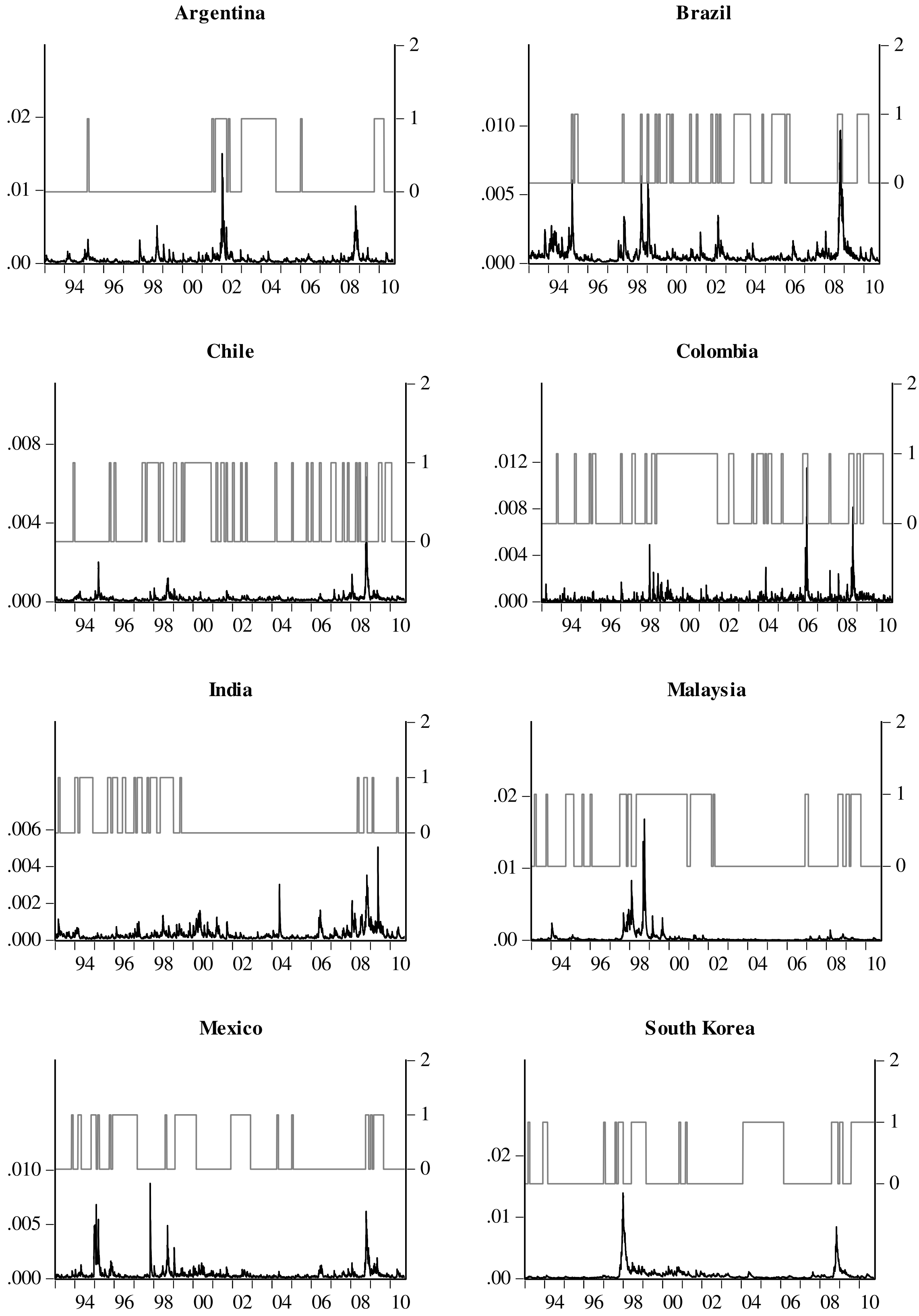
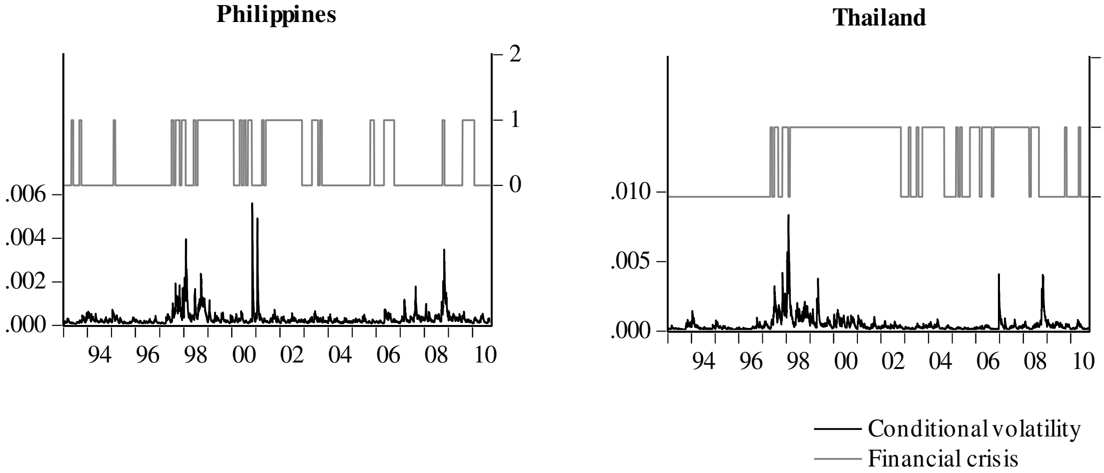
Table 4 (*Continued*)

				Asian region														
Dependent variables				India			Malaysia			South Korea			Thailand			Philippines		
Quantile order				$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}	$Q_{0.05}$	Q_{50}	Q_{95}
Independent variables	Developed markets	Japan	β	**0.058***** **(0.019)**	**0.394***** **(0.034)**	**0.593**** **(0.302)**	**0.034***** **(0.011)**	**-0.057*** **(0.031)**	**0.254*** **(0.138)**	0.141*** (0.039)	0.096** (0.040)	0.045 (0.331)	-0.025 (0.051)	-0.089** (0.038)	-0.044 (0.082)	**-0.12***** **(0.025)**	**-0.117***** **(0.019)**	**-0.28***** **(0.074)**
			θ	0.070* (0.043)	-0.044 (0.071)	-0.243 (0.393)	0.057 (0.062)	1.332*** (0.189)	3.707*** (0.705)	0.069 (0.082)	0.784*** (0.119)	0.597 (0.589)	**0.240***** **(0.056)**	**0.321***** **(0.062)**	**-0.563**** **(0.291)**	0.187*** (0.041)	0.210*** (0.059)	0.131 (0.240)
		USA	β	**-0.053*** **(0.021)**	**0.203***** **(0.054)**	**0.998***** **(0.303)**	**-0.072***** **(0.021)**	**-0.555***** **(0.118)**	**-0.87***** **(0.057)**	**0.759***** **(0.021)**	**1.431***** **(0.044)**	**1.534***** **(0.198)**	**-0.071*** **(0.038)**	**-0.48***** **(0.055)**	**-0.92***** **(0.204)**	**0.172***** **(0.021)**	**0.269***** **(0.033)**	**-0.254*** **(0.153)**
			θ	**0.532***** **(0.053)**	**0.317**** **(0.124)**	**-0.939**** **(0.416)**	0.015 (0.064)	-0.283* (0.168)	-0.833 (0.537)	0.156 (0.138)	-0.080 (0.095)	-0.536 (0.325)	-0.095 (0.063)	0.334*** (0.069)	0.106 (0.252)	-0.13*** (0.034)	-0.354*** (0.046)	-0.086 (0.234)
	α			0.001*** (0.000)	0.000*** (0.000)	0.000* (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
	γ			-0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000** (0.000)	-0.00*** (0.000)	-0.000 (0.000)	-0.00*** (0.000)	-0.00*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
	Pseudo R^2			0.085	0.259	0.439	0.114	0.258	0.673	0.209	0.443	0.680	0.224	0.415	0.576	0.178	0.326	0.522

Notes: This table presents the quantile regression estimates for Latin America region according to the empirical model defined by Eq. (3). The numbers in parentheses are the bootstrapped standard errors. *, ** and *** indicate that coefficients are significant at 10%, 5% and 1% level, respectively. Absolute significance through three quantiles is in bold type. The additional marginal effects of the different conditional variables in the financial crisis sub-periods is given by $\gamma(\tau)$ and $\theta_k(\tau)$ parameters. While the effects in the calm periods is given by the parameters $\alpha(\tau)$ and $\beta_k(\tau)$.

Figure 1. Conditional volatility, banking and currency crisis in selected emerging economies.

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Thailand
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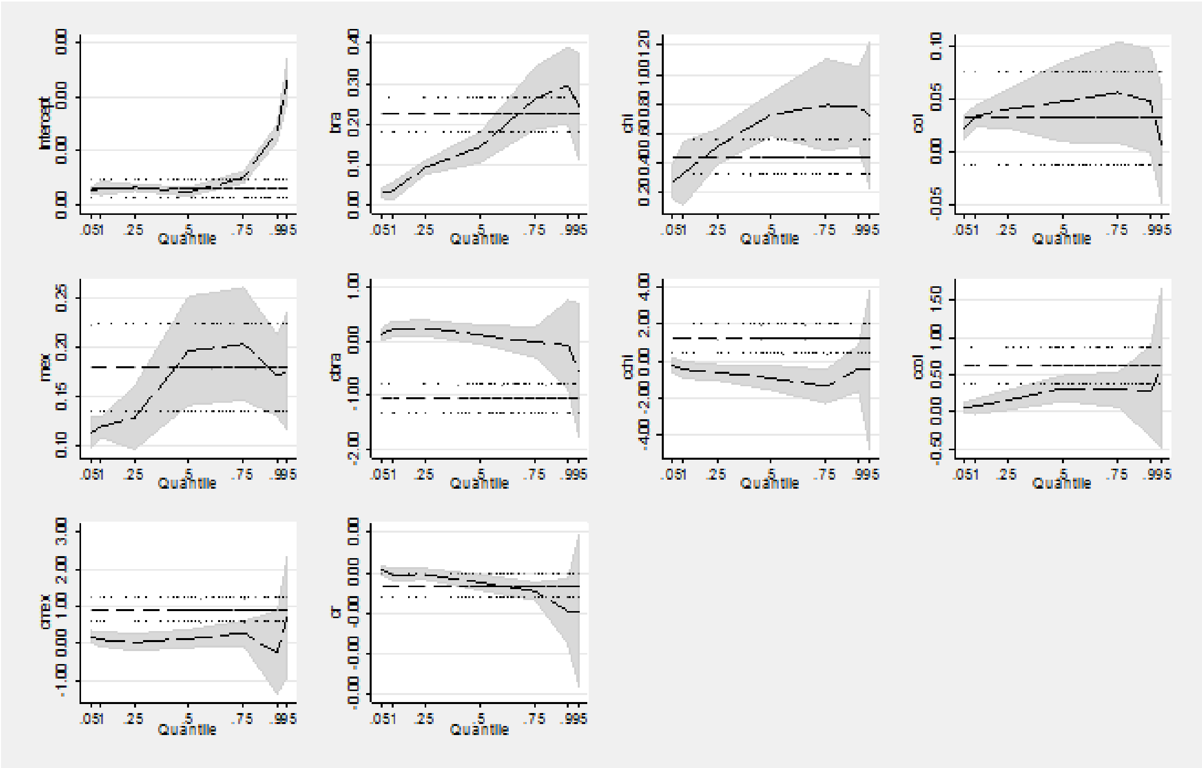
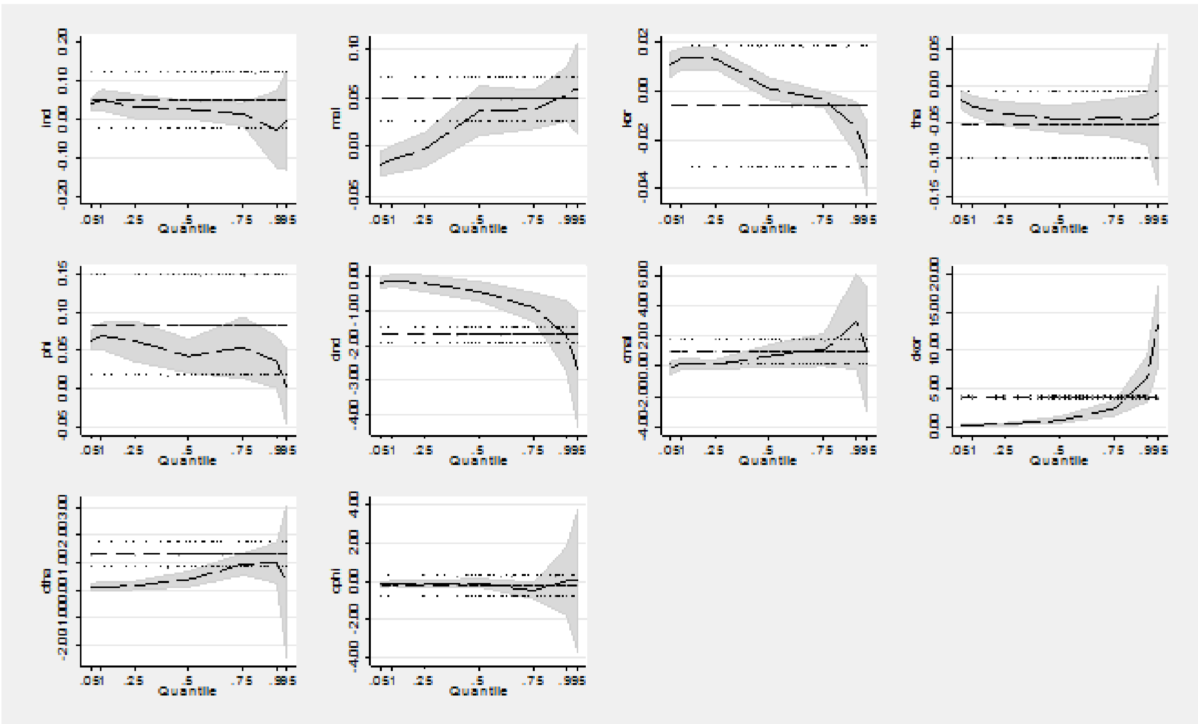
Conditional volatility
Financial crisis

Fig. 2. Changes in the quantile regression coefficients for Argentina

Panel A_1 : Latin America region



Panel A_2 : Asian region



Panel A_3 : Developed markets

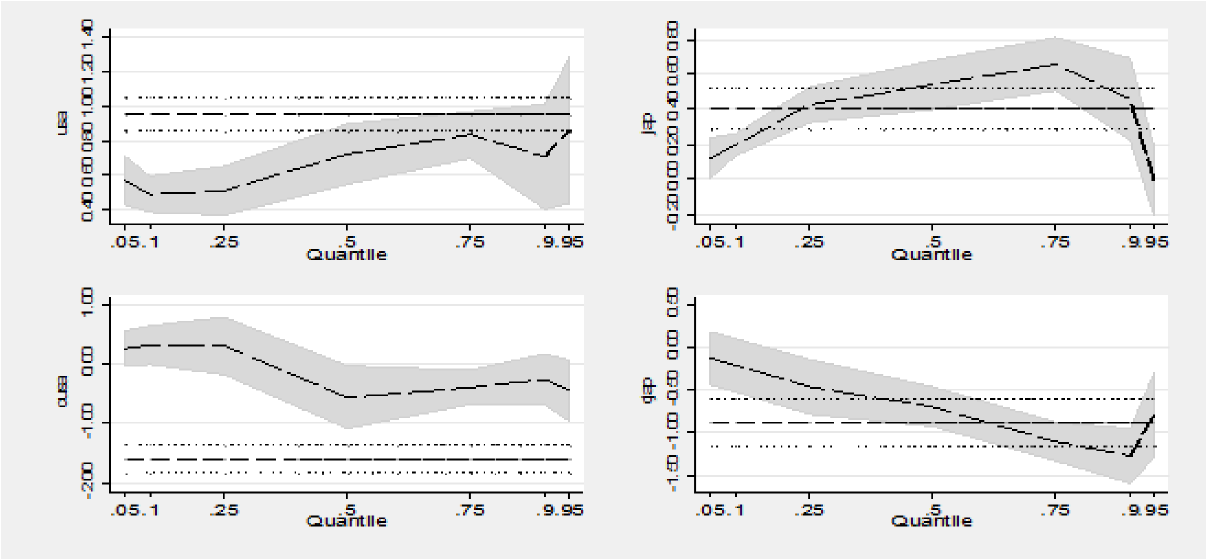
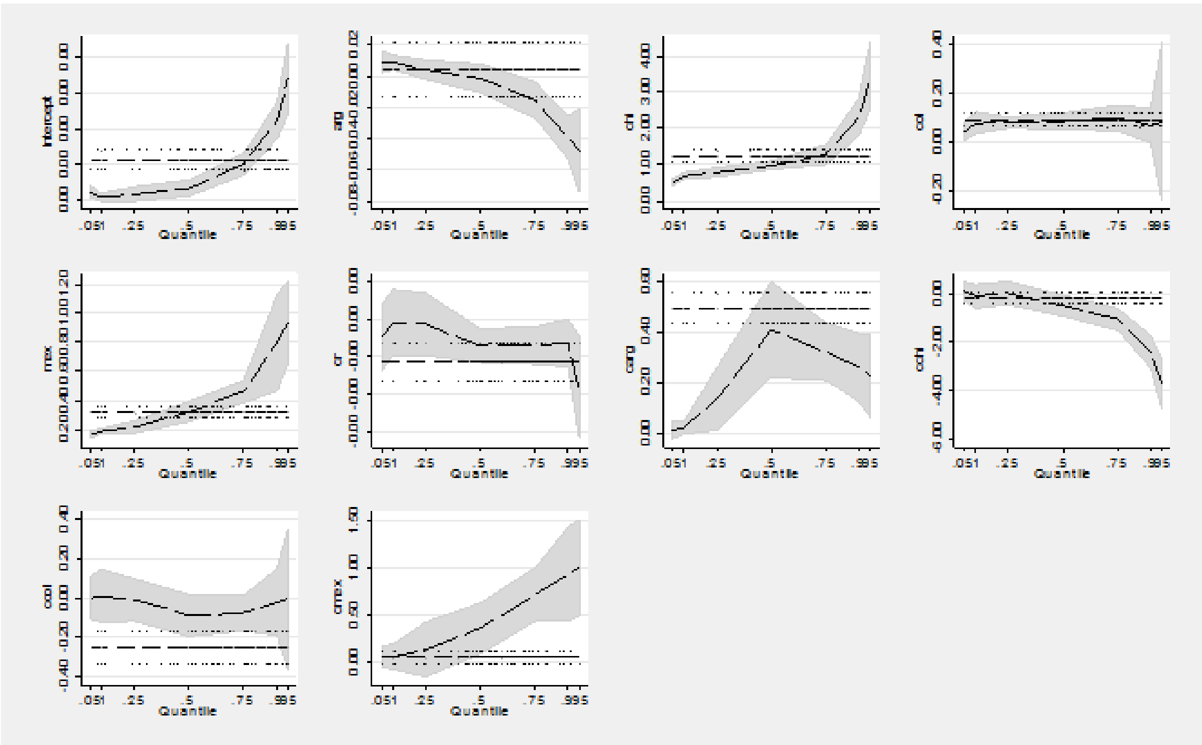
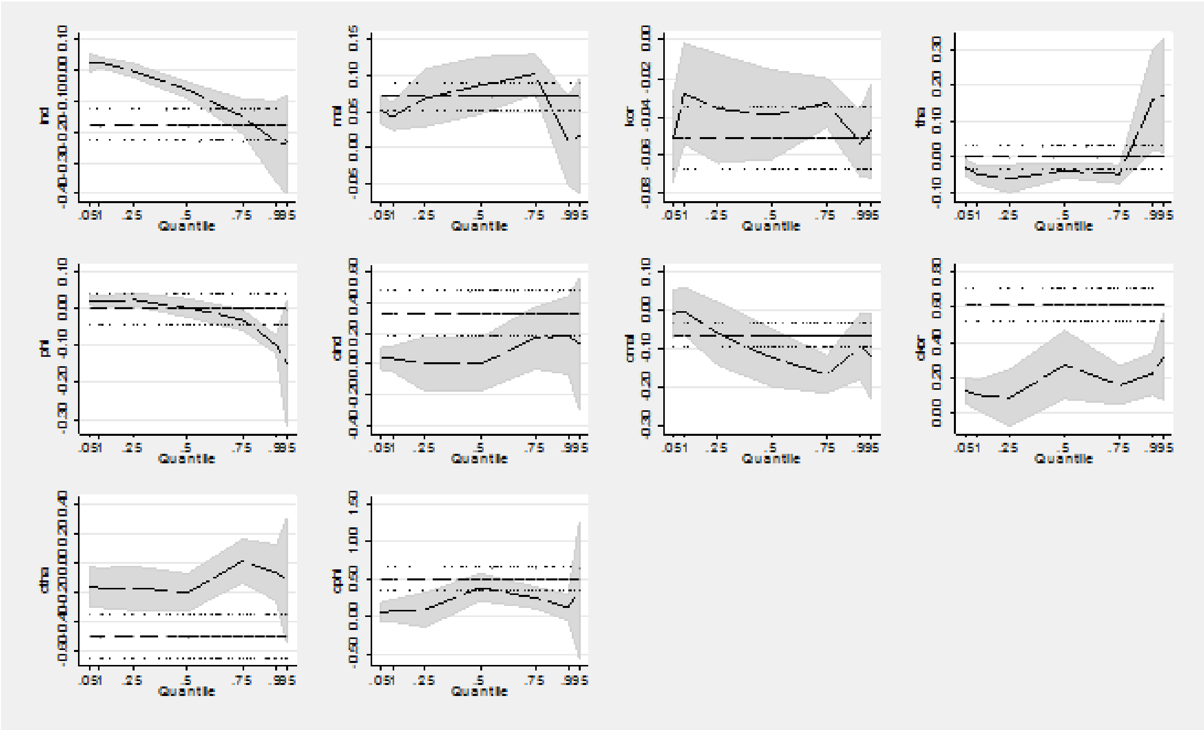


Fig. 3. Changes in the quantile regression coefficients for Brazil

Panel A_1 : Latin America region



Panel A_2 : Asian region



Panel A_3: Developed markets