Evidence of increasing integration between international markets.

ALEXANDRE COSTA
Business Management Post Graduate Program
Universidade Federal de Santa Maria
Av. Roraima n. 1000, Centro de Ciências Sociais e Humanas Prédio 74 C - Sala 430,
Santa Maria/RS – 97105-900
BRAZIL

PAULO SÉRGIO CERETTA
Business Management Post Graduate Program
Universidade Federal de Santa Maria
Av. Roraima n. 1000, Centro de Ciências Sociais e Humanas Prédio 74 C - Sala 430,
Santa Maria/RS – zip code 97105-900
BRAZIL

ALEXANDER SOUZA BLOCK
Academic Coordination
Universidade Federal do Pampa
Rua Luiz Joaquim de Sá Britto, s/n – Itaqui/RS – zip code 97650-000
BRAZIL

Abstract: Since the origins of modern finance theory, interdependence between assets is an issue as the search for diversification ends with a better portfolio. Many studies and many approaches have been given to answer to the questions of correlation, covariance and interdependence but the subprime crises and the almost meltdown of financial markets throughout the globe, proved that portfolios were not efficiently diversified. The concept of diversification and the risk measures did not prevent from hundreds of companies worldwide to go belly up. This paper focuses its attention to a bewildering fact: interdependence is increasing along the years and the task of diversification is becoming tougher. Utilizing the Quantile Regression and including a volatility measure of the American market regressed with other international major players grouped by their geographic region it brings up strong evidence of increasing integration. It comprises stock market data from the year 2000 to 2012, going through four major events: the Nasdaq burst, the 9/11, the Subprime and the European crises.

Key-words: Quantile Regression, GARCH, interdependence, volatility, diversification

1 Introduction

During the last decade financial markets have grown their concern with interdependence, especially after the near meltdown during the Subprime era. Correlations, covariance's and interdependence have been studied heavily since its development by the early work of Harry Markowitz in Portfolio Selection and Bill Sharpe CAPM (Sharpe, 1964), but the recent failure of the financial system in 2007/2008 brought up an old concern – when the sea level goes down, everything on it goes down with it. Therefore, the preoccupation with a diversified portfolio should become more concerning as we display evidence in this paper that integration on international markets are rising.

Markowitz said himself in a recent lecture that the idea of diversification is not from him nor is new; he quoted Shakespeare who has mentioned it on a play back in the seventeenth century. He also quoted the book Treasure Island where pirate Long John Silver says about the results of his piracy "I put it all away, some here, some there. By the reason of suspicion!" Evidencing that the quest for diversification is not recent. This work brings an alternative approach to interdependence and diversification, but more importantly it shows that diversification is becoming tougher as many markets are growing more codependent to the American market.

This work studies interdependence of 15 indexes from major markets around the globe and the S&P 500, from the year 2000 to 2012 using quantile regression. The return series of each index is paired up with of the American index, so is the volatility series as per the GARCH model. We started off trying to find some relationship between the volatility in the United States and returns else where, but we did not. S&P500 returns were known to be significantly correlated as many works such as Baur (2012) also using quantile regression, proved. But we ended up finding something else, the relationship of many markets with the American market is growing and this can be a serious hazard.

We selected initially 18 markets by volume and geographic position; some have to be discarded by lack of data, as they do not go back as far as the year 2000. Some have to be taken off by long periods of inactivity such as Egypt because of the civil war. In the end these are the remaining countries and their respective indexes grouped by their geographic position. Americas: Mexico (IPC), Canada (S&P/TSX Composite Index), Brazil (Ibovespa), Argentina (Merval); Europe: Germany (DAX), United Kingdom (FTSE 100), Spain (IBEX 35), Switzerland (SMI), France (CAC 40); Asia: Russia (RSTI), Japan (Nikkei 225), China (Hang Seng), India (Sensex 30), Israel (TA-100) e Turkey (XU100). We chose to go back as far as 2000 because the sample period would comprise four major events – the Nasdaq burst, the 9/11, the Subprime and the European debt crises.

This work wishes to 1) Prove that the relationship between stock market returns in the US and the rest of the world is growing stronger; 2) Prove that the relationship between stock market volatility in the US is affecting returns elsewhere and this relationship is also growing stronger; 3) Prove that countries geographically close to the US have a higher degree of dependence; 4) Replicate that returns and volatility are more correlated in extreme events (extreme quantiles).

2 Review of Literature

The foundations for interdependence and diversification were laid in the sixties and have been widely studied. Originally long term was the focus but nowadays; short-term and extreme events have drives scholars and professional traders. Longin and Solnik (1995) analyze long-term relationships between the G7 (group of countries with seven bigger GDPs) major indexes.

There are many ways to approach interdependence, Righi and Ceretta (2011) use copula functions to analyze shocks in the US market and their repercussion in Brazil, Mexico and Argentina. Engle e Manganelli (2004) develop a method of quantile regression for Value-at-risk estimation. Ma and Pohlman (2008) introduce quantile momentum for portfolio construction. Chuang *et al.*, (2009) examine the dynamic relation of quantiles in stock market returns and traded volume. Campbell et al., (2008) demonstrate that returns correlation vary systematically in different quantiles.

Quantile regression was initially proposed by Koenker and Basset (1978) and its advantage is to offer results for different states, not only one measurement such as most of the other ways even as refined as Copulas. Koenker (2005) points out that the quantile regression has many advantages over other linear methods. It produces a more complete stochastic relationship between two any random variables. Buchinsky (1998) commends the quantile regression because it brings results from outliers or fat tails that other linear methods do not pick up.

Costinot, Roncalli and Teiletche (2000) propose the use of Copula functions to measure interdependence of South East Asian countries. Baur (2003) tells that in recent years many crises have occurred and this periods are associated with some synchrony, and points out that during these periods no portfolio can be diversified enough.

Bartram and Dufay (2001) in their book International Portfolio Investment: Theory, Evidence and Institutional Framework defend international diversification but alert against pitfalls such as transaction costs. Gallo e Velucchi, (2009) study interdepended of Asian markets from 1990 to 2005 showing volatility spillovers in several markets especially Hong Kong and Korea.

Hamao et al. (1990), study interdependence of returns and volatility in London, Tokyo and New York, proving that a spike in volatility in Wall Street and London affects Tokyo. More recently Kiviaho et al., 2012 study the comovements of European stock markets and the US, proving dynamic relationships along time and point out Lithuania as having the highest degree of correlation with the US.

3 Methodology

The methodology utilized in this work is straightforward. The quantile regression linked the variables: market returns of each country and the US, and the volatility estimated by the GARCH model of the US. We estimated 5 quantiles (0,05; 0,25; 0,50; 0,75; 0,95). The regression estimated 2 betas, one for the volatility and the other for the return. This beta is our measurement of dependency. We can say in advance that we will focus on the beta of returns, as the volatility results did not reveal anything worth telling.

To model volatility, the method chosen was the GARCH (1,1) and since its widespread use in finance has proven its efficiency no further explanation or formula deconstruction will be added, and more details can be extract from the classical work of Bollerslev (1986) and Bollerslev, Engle and Nelson (1994).

The quantile regression is a way to estimate a variable response to a linear model, which allows to a broader view of the relationship between variables (Cade and Noon, 2003). Heteroskedasticity brings more slopes to the regression line and the quantile regression determines different slopes for different quantiles

Normally the quantile regression can be seen as an addend to the natural quantiles in a linear case or if the intent is to determine the relationship in a quantil *Y*, given a *x*, the function can be describe as:

$$Q_\tau\left(Y \,\middle|\, x\right) = x'\beta(\tau)$$

Where $\beta(\tau)$ is a parameter vector, to estimate $\beta(\tau)$ one need only to find $\hat{\hat{\beta}}(\tau)$ that is the solution to the minimizations problem in the linear algorithm:

$$\min_{\beta \in R} \sum_{i=1}^{n} \rho_\tau(y_i - x'_i\beta)$$

The usual regression, the OLS (ordinary least squares) can be written as:

$$y = \beta_0(\tau) + \beta_1 x_1 + \cdots + \beta_p x_p + e$$

Where the error ϵ has mean zero 0 (zero), therefore can be presumed that the conditional mean of the variable $Y \,|\, x$ can be written as:

$$E\left(Y \,\middle|\, x\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p$$

Since our interest is to study varies quantiles of the conditional distribution of the response variable Y, assuming that the linear relationships are:

$$y_1 = \beta_0(\tau) + \beta_1(\tau)x_1 + \cdots + \beta_p(\tau)x_p + u_i$$

Where u_i are random variables, independent and identically distribuited with quantile τ equal to 0 (zero), one can infer that the conditional quantile τ of $Y \,|\, x$ is:

$$Q_\tau(Y \,|\, x) = \beta_0(\tau) + \beta_1(\tau)x_1 + \cdots + \beta_p(\tau)x_p$$

In our model, we need 2 variables to explain interdependence, US returns and volatility, plus the return series of each country done separately.

$$Q_\tau\left(Y \,\middle|\, x\right) = a(\tau) + \beta(\tau)x + GARCH$$

As the GARCH model has been widely used and accepted in modern finance, and it is a proven method to model volatility, no more attention or explanation will be given about.

3.1 Data

The basis for this work are the daily log returns of every market studied, obtained from Thompson Reuters Eikon Software.

As we seek to analyze integration, we calculated in an yearly basis but with daily data, we started off from the first trading day of 2000 and ended on the last year of 2012, excluding days that the American market or any international market have not traded in the same day. Lets say for an example that if there is a holiday in China but America is trading, in a given day, that day is excluded from the roll although if the other markets are running, they will be included in the calculation for the yearly index.

This time spam was chosen for two main reasons: it should not be too long or it would exclude emerging markets; furthermore because it comprehends four main events: the NASDQ burst, the 9/11 terrorist attack, the Subprime and the European debt crises.

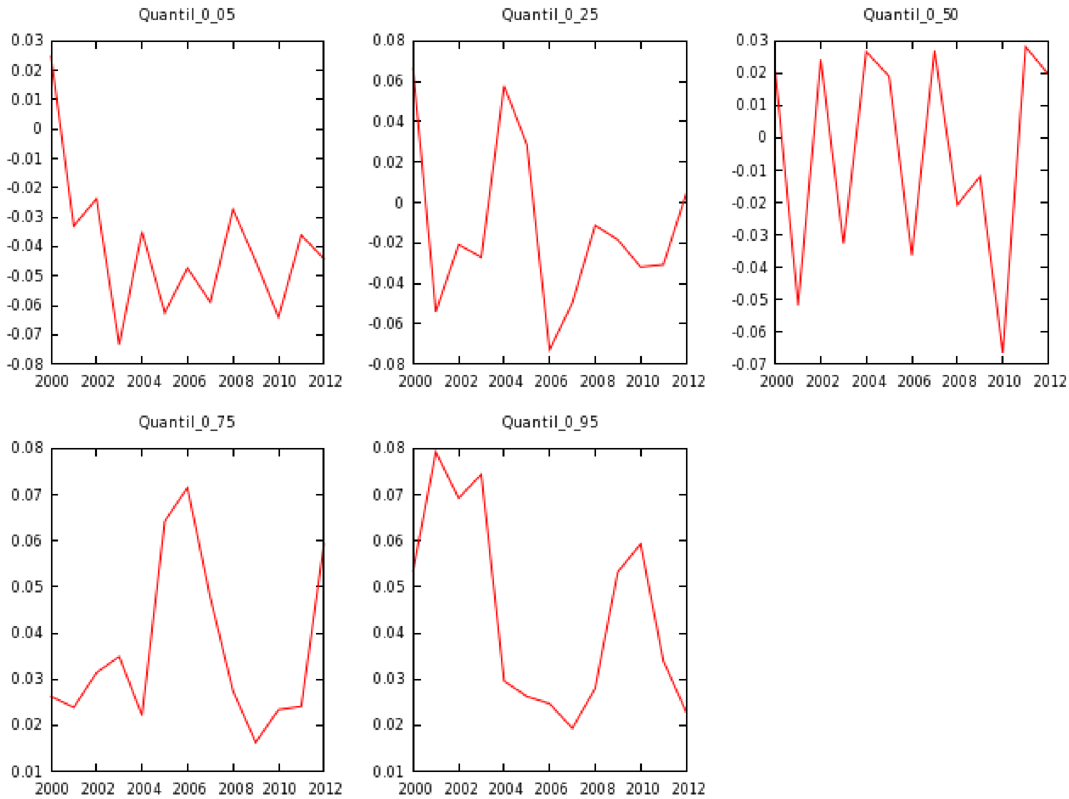
The acronym indicating the index goes as follow: Americas: Mexico (MXX), Canada (GSPTSE), Brazil (BVSP), Argentina (MERV); Europe: Germany (GDAXI), United Kingdom (FTSE), Spain (IBEX), Switzerland (SMI), France (FCHI); Asia: Russia (RTS_RS), Japan (N225), China (HSI), India (BSESN), Israel (TA-100) e Turkey (XU100)

4 Results

We regressed two sets of data, returns and volatility and firstly we will present a figure that defines the role that volatility plays. As we are trying to find an evolution or increment in the relationship of the variables, this set of data did not produce any relevant finding. We could not spot any pattern or trend that could be significant or useful for any forecast or interpretation purposes.

Figure 1 sums up the information we want to pass on, it displays in all quantiles we calculated a total absence of any pattern. It brings and average of all indexes per year in relationship to American volatility. A full chart of all the betas for every market in every quantile can be seen in the Appendix. The quantiles analysed are: 1) 0,050; 2) 0,250; 3) 0,500; 4) 0,750; 5) 0,950.

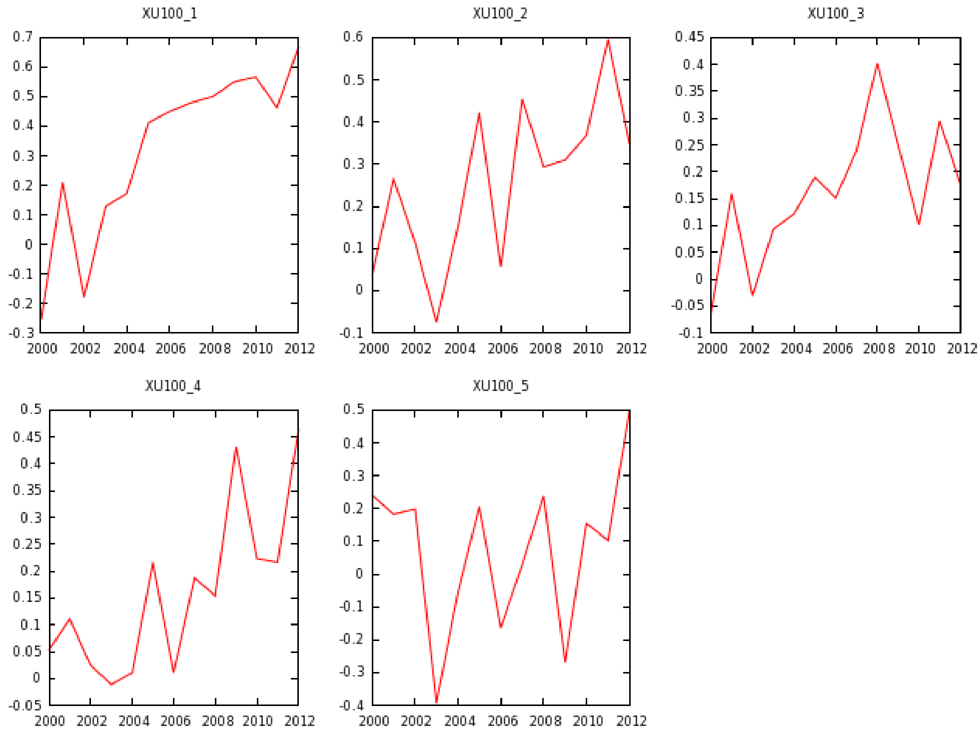
Figure 1 –Average betas of the S&P500 volatility in the returns of the 15 other indexes from 2000 to 2012.



Source: elaborated by the authors.

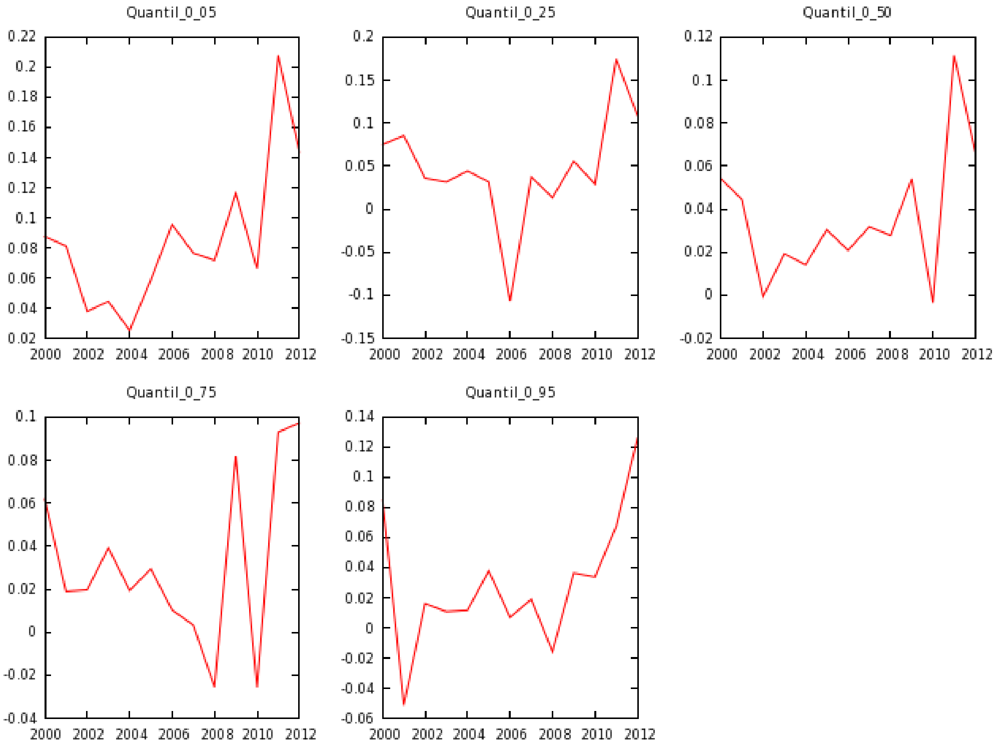
Results on returns are much more interesting. Through Figure 2 it is easily seen that the average beta has been increasing since the beginning of the sample period up to the end. This phenomenon turns up in every quantile studied. Furthermore the integration in most cases peaked in the last year of analysis. This trend is what this study tries to evidence, that integration is becoming stronger with the US market. Not all countries displayed the same characteristics and as can be seen in the figures below, some display strong increase of integration and some do not. The more emblematic case is the Turkey index, which shows clearly not only that an increment in integration but also displays stronger betas.

Figure 2 - Betas of XU100 for all quantiles from 2000 to 2012.



Source: elaborated by the authors.

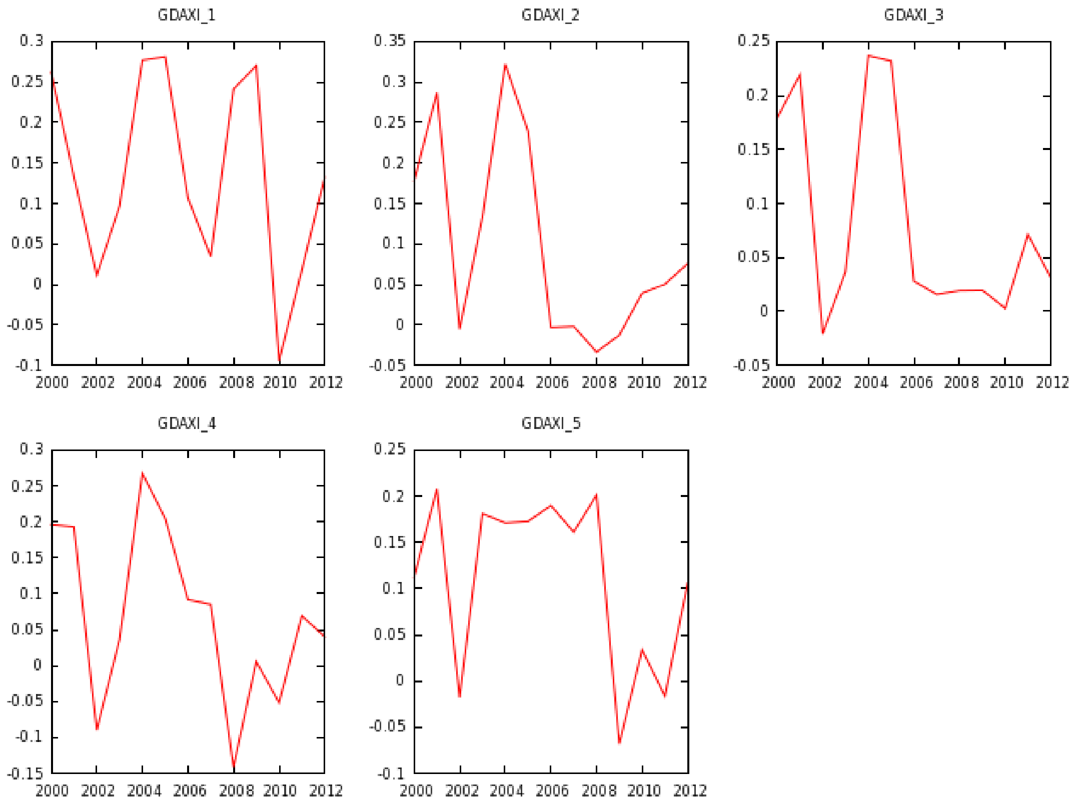
Figure 3 –Average betas of the S&P500 log-returns in the returns of the 15 other indexes from 2000 to 2012.



Source: elaborated by the authors.

Figure 4 shows a different case, the German index, the DAX did not show that evolution in interdependence, although it displayed a high integration average coefficient if considered the whole period. Most of its European peers presented the same characteristics as the Turkish index, increasing integration.

Figure 4 - Betas of the DAX for all quantiles from 2000 to 2012.



Source: elaborated by the authors.

All other indexes can be seen in the Appendix. Among the other countries that have their main indexes increasing in correlation with the American index as it can be spotted in the charts below, England, India, and France.
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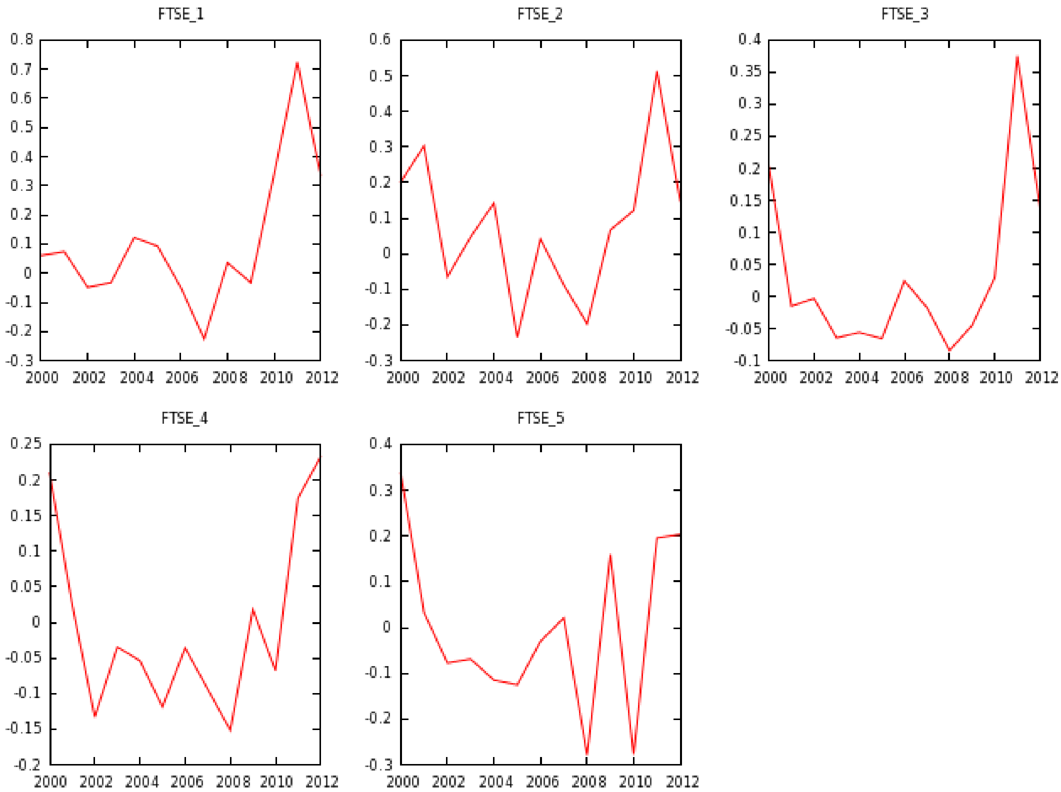
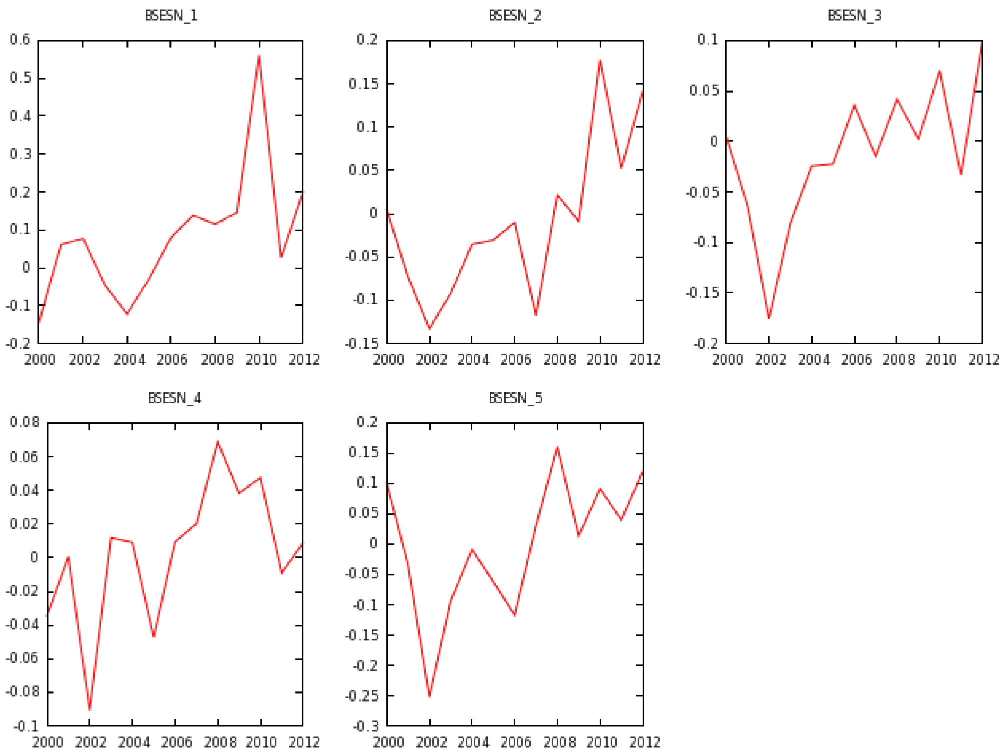
Another fact that can be visualized and it is a stylized fact is that in the lower and upper quantiles the betas are stronger, exteriorizing a greater dependence in extreme market conditions

Figure 5 - Betas of the FTSE100 for all quantiles from 2000 to 2012.



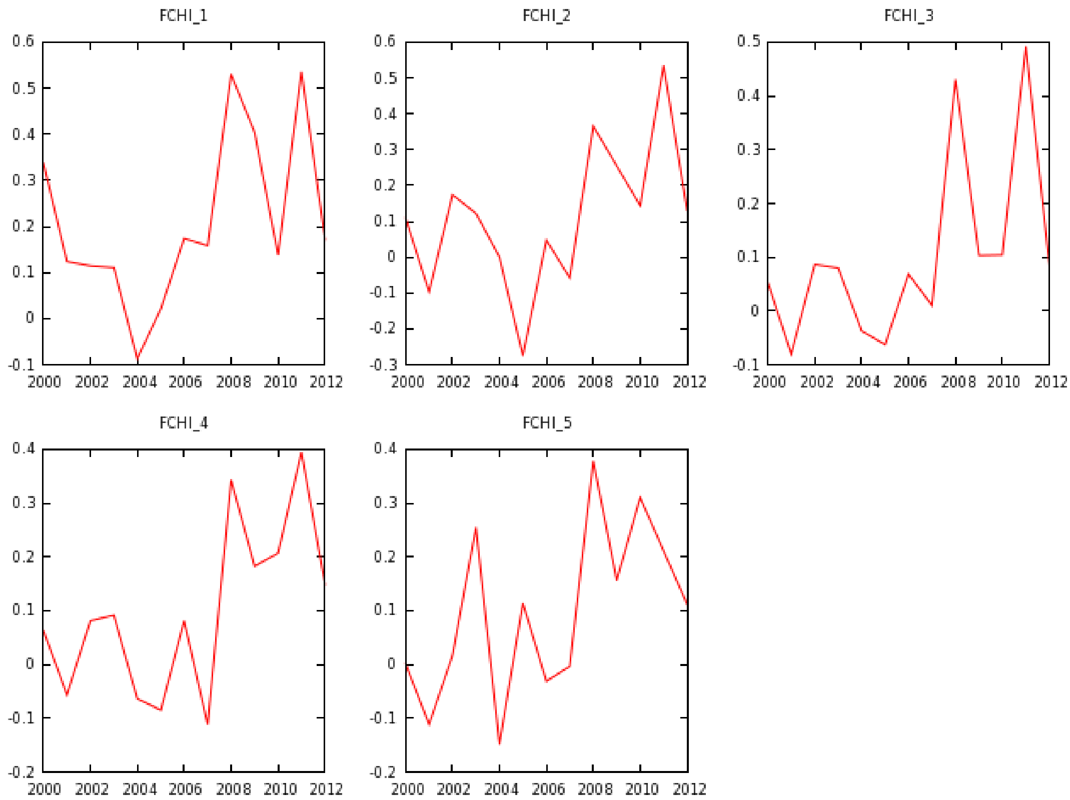
Source: elaborated by the authors.

Figure 6 - Betas of the Sensex for all quantiles from 2000 to 2012.



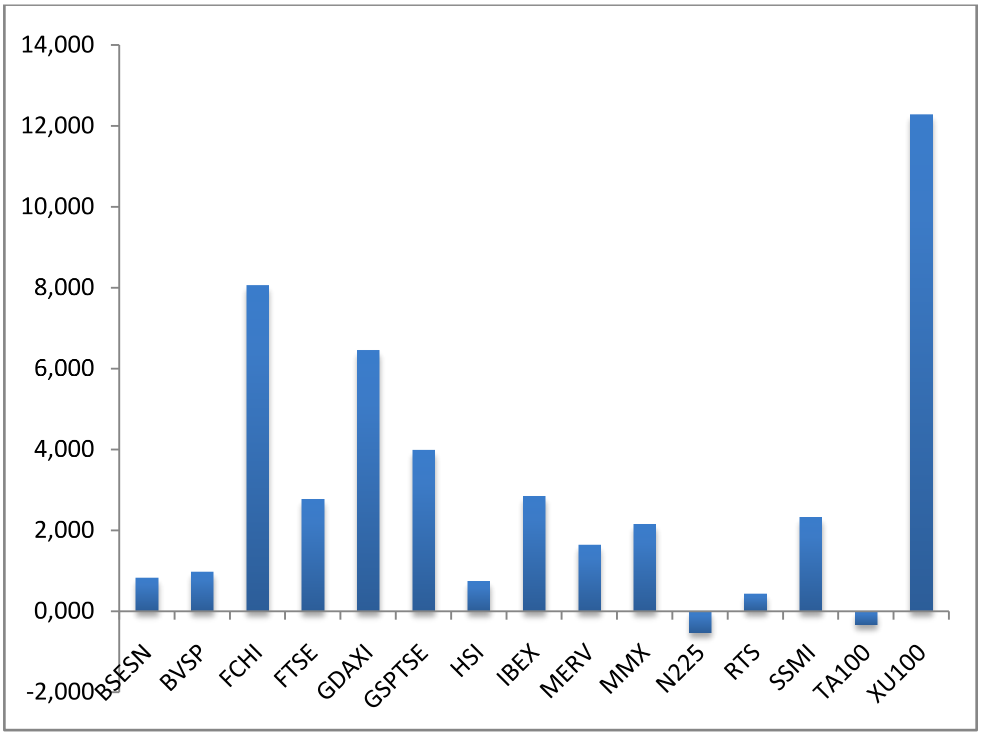
Source: elaborated by the authors.

Figure 7 - Betas of the Sensex for all quantiles from 2000 to 2012.



Source: elaborated by the authors.

Figure 8 – Sum of all betas of all quantiles for the entire sample period (200-2012) for each inde



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Source: elaborated by the authors.

Figure 8 shows clearly that the Turkey main index was by far the most integrated with the

American index. Another issue that can be seen is that the European index has also trended in sync with the United States.

Table 3 and 4 bring a ranking with the 10 top and least betas in the entire study. The Footsie, in the year 2011 had the highest degree of integration (first quantile), but Turkey has dominated most of the top positions.

Table 1 – Top 10 betas per quantile.

1	FTSE 1 2011	**0,72**	XU100 2 2012	0,67	XU100 3 2011	0,60	XU100 4 2008	**0,40**	XU100 5 2012	0,46
2	BSESN 1 2010	**0,56**	XU100 2 2010	**0,57**	FCHI 3 2011	**0,49**	FCHI 4 2011	**0,39**	XU100 5 2009	0,43
3	BVSP 1 2011	**0,56**	XU100 2 2009	**0,55**	XU100 3 2007	0,45	BVSP 4 2009	**0,38**	FCHI 5 2008	**0,38**
4	FCHI 1 2011	**0,54**	FCHI 2 2011	**0,53**	FCHI 3 2008	**0,43**	FCHI 4 2008	**0,34**	FTSE 5 2000	**0,34**
5	FCHI 1 2008	**0,53**	FTSE 2 2011	**0,51**	MXX 3 2007	**0,43**	GSPTSE 4 2003	0,31	GSPTSE 5 2012	**0,32**
6	GSPTSE 1 2012	**0,42**	XU100 2 2008	**0,50**	XU100 3 2005	**0,42**	XU100 4 2011	0,30	FCHI 5 2010	0,31
7	GSPTSE 1 2011	0,42	XU100 2 2007	**0,48**	BVSP 3 2009	**0,38**	MXX 4 2007	**0,27**	SSMI 5 2003	0,29
8	FCHI 1 2009	**0,40**	MXX 2 2007	**0,47**	FTSE 3 2011	**0,38**	GDAXI 4 2004	**0,27**	BVSP 5 2009	**0,27**
9	MERV 1 2005	**0,36**	XU100 2 2011	0,46	XU100 3 2010	0,37	XU100 4 2009	0,25	MXX 5 2007	**0,27**
10	GSPTSE 1 2003	0,36	XU100 2 2006	0,45	XU100 3 2012	0,35	XU100 4 2007	**0,24**	FCHI 5 2003	0,25

Source: elaborated by the authors. Values in bold displayed significant T-ratio

Table 2 – Bottom 10 betas per quantile.

186	BVSP 1 2007	-0,21	MXX 2 2008	-0,19	TA100 3 2010	-0,10	MXX 4 2010	-0,11	TA100 5 2007	-0,14
187	FTSE 1 2007	-0,23	MERV 2 2008	-0,19	MERV 3 2003	-0,10	HSI 4 2002	-0,11	N225 5 2008	-0,14
188	IBEX 1 2001	-0,23	FTSE 2 2008	-0,20	SSMI 3 2010	-0,11	FTSE 4 2005	-0,12	BVSP 5 2001	-0,14
189	SSMI 1 2008	-0,23	MXX 2 2003	-0,20	N225 3 2009	-0,12	RTS_RS 4 2008	-0,12	FCHI 5 2004	-0,15
190	GSPTSE 1 2007	-0,26	FTSE 2 2005	-0,23	N225 3 2001	-0,13	BVSP 4 2010	-0,13	BVSP 5 2008	-0,15
191	N225 1 2001	-0,27	XU100 2 2000	**-0,25**	GSPTSE 3 2008	-0,13	FTSE 4 2002	-0,13	MXX 5 2010	-0,15
192	N225 1 2008	-0,29	FCHI 2 2005	-0,27	BSESN 3 2002	-0,18	GDAXI 4 2008	-0,14	BSESN 5 2002	**-0,25**
193	RTS_RS 1 2008	-0,30	MXX 2 2009	-0,30	SSMI 3 2007	-0,18	GSPTSE 4 2008	-0,15	FTSE 5 2010	-0,28

194	HSI 1 2008	-0,39	TA100 2 2010	-0,44	MXX 3 2003	-0,19	FTSE 4 2008	-0,15	FTSE 5 2008	-0,28
195	GSPTSE 1 2010	-0,51	BVSP 2 2006	-1,93	HSI 3 2002	-0,23	TA100 4 2002	-0,16	GSPTSE 5 2008	-0,39

Source: elaborated by the authors. Values in bold displayed significant T-ratio

5 CONCLUSIONS

Summing up, we regressed in quantiles the volatility and returns of the American market against returns of 15 different indexes located throughout the world. We did not find any pattern of a dynamic relationship of the first variable, volatility. However, we did find a growing interdependence of returns in many markets like Turkey, India, France, Brazil, England and Israel. The Turkish index is the extreme case; the codependence with the American market is the strongest and is growing. The last, Israel displayed a small interdependence, nevertheless it keeps ascending during our sample. If markets are becoming more closely related, some will loose the benefits that diversification brings and therefore, capital will back out.

It is also noticeable that in extreme quantiles relationships are stronger, this fact is in sync with the work of Forbes and Rigobon (2002). In the core of the European debt crises (2011), the Footsie reached the greatest beta found in all years and in all quantiles, 0,71 denoting a high level of dependence in the lowest quantile. As geography goes, Europe displayed bigger betas, although Turkey alone produced higher coefficients. We also grouped countries by their geographical position and averaging their interdependence was not useful for nothing although results can be seen in the Appendix.

The reasons for Europe be toping the interdependence rank are unknown and that could be left as a suggestion for future studies.

The markets that least related to the US are Japan and Israel and in average they produced negative betas, ideal for a diverse portfolio. The higher coefficients were found in the markets of Turkey, France, Germany, Canada, Spain and Switzerland. Countries bordering geographically the United States have above average interdependence although they did not display an evolution in integration

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APPENDIX

Table 3 – Betas of the relationship between the S&P500 and the international markets per quantile, per year.

	TAO	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
BSESN	0,05	-0,14	0,06	0,08	-0,05	-0,12	-0,03	0,08	0,14	0,12	0,15	**0,56**	0,03	0,20
	0,25	0,00	-0,07	-0,13	-0,09	-0,04	-0,03	-0,01	-0,12	0,02	-0,01	**0,18**	0,05	0,14
	0,50	0,00	-0,06	-0,18	-0,08	-0,02	-0,02	0,04	-0,01	0,04	0,00	0,07	-0,03	**0,10**
	0,75	-0,03	0,00	**-0,09**	0,01	0,01	-0,05	0,01	0,02	0,07	0,04	0,05	-0,01	**0,01**
	0,95	0,10	-0,03	**-0,25**	-0,09	-0,01	-0,06	-0,12	0,03	0,16	0,01	0,09	0,04	0,12
BVSP	0,05	**0,13**	0,05	-0,09	0,11	0,07	**0,09**	-0,13	-0,21	0,11	**0,30**	0,05	**0,56**	-0,10
	0,25	0,05	0,06	0,02	0,04	-0,01	0,04	-1,93	0,02	0,04	**0,34**	0,00	**0,26**	0,08
	0,50	0,03	0,03	0,02	-0,01	-0,02	-0,02	-0,01	0,04	-0,03	**0,38**	-0,04	0,12	0,06
	0,75	0,05	-0,05	0,07	-0,06	-0,01	0,00	-0,06	0,06	-0,05	**0,38**	-0,13	0,14	0,09
	0,95	0,10	-0,14	-0,07	-0,09	0,01	0,04	-0,07	0,05	-0,15	**0,27**	-0,02	0,06	0,12
FCHI	0,05	**0,34**	**0,12**	0,11	0,11	-0,09	0,02	0,17	0,16	**0,53**	**0,40**	**0,14**	**0,54**	0,17
	0,25	0,11	-0,10	**0,17**	0,12	0,00	-0,27	0,05	-0,06	**0,37**	**0,25**	**0,14**	**0,53**	**0,13**
	0,50	0,05	-0,08	0,09	0,08	-0,04	-0,06	0,07	0,01	**0,43**	0,10	**0,10**	**0,49**	**0,09**
	0,75	0,06	-0,06	0,08	0,09	-0,06	-0,08	0,08	-0,11	**0,34**	**0,18**	**0,21**	**0,39**	**0,15**
	0,95	0,00	-0,11	0,02	0,25	-0,15	0,11	-0,03	0,00	**0,38**	0,16	0,31	**0,21**	**0,11**
FTSE	0,05	0,06	0,07	-0,05	-0,03	0,12	0,09	-0,05	-0,23	0,04	-0,03	0,34	**0,72**	**0,34**

	0,25	**0,20**	**0,30**	-0,07	0,05	0,14	-0,23	0,04	-0,09	-0,20	0,07	0,12	**0,51**	**0,15**
	0,50	**0,20**	-0,02	0,00	-0,06	-0,06	-0,07	0,02	-0,02	-0,08	-0,04	0,03	**0,38**	**0,14**
	0,75	**0,21**	0,03	-0,13	-0,03	-0,05	-0,12	-0,04	-0,09	-0,15	0,02	-0,07	**0,17**	**0,23**
	0,95	**0,34**	0,03	-0,08	-0,07	-0,12	-0,13	-0,03	0,02	-0,28	**0,16**	-0,28	**0,20**	0,20
GDAXI	0,05	0,26	0,13	0,01	**0,10**	0,28	0,28	0,11	0,03	**0,24**	0,27	-0,09	0,02	0,13
	0,25	**0,18**	**0,29**	-0,01	**0,13**	**0,32**	**0,24**	0,00	0,00	-0,03	-0,01	0,04	0,05	0,08
	0,50	**0,18**	**0,22**	-0,02	**0,04**	**0,24**	**0,23**	0,03	0,02	0,02	0,02	0,00	0,07	0,03
	0,75	**0,20**	**0,19**	-0,09	**0,04**	**0,27**	**0,20**	0,09	0,09	-0,14	0,01	-0,05	0,07	0,04
	0,95	0,11	**0,21**	-0,02	**0,18**	**0,17**	**0,17**	0,19	0,16	0,20	-0,07	0,03	-0,02	0,11
GSPTSE	0,05	**0,34**	0,01	0,33	0,36	-0,14	-0,06	0,06	-0,26	0,04	-0,14	-0,51	0,42	**0,42**
	0,25	**0,22**	0,17	0,07	0,37	-0,02	0,13	-0,01	0,09	-0,12	0,01	-0,13	**0,33**	**0,18**
	0,50	**0,23**	**0,22**	-0,03	0,16	-0,02	0,03	0,01	0,00	-0,13	0,01	0,03	**0,17**	0,08
	0,75	**0,18**	0,06	0,03	0,31	0,10	0,06	-0,02	-0,10	-0,15	-0,02	-0,03	0,10	0,14
	0,95	0,22	0,07	0,11	0,18	0,06	-0,13	-0,01	-0,10	-0,39	0,00	0,05	0,04	**0,32**
HSI	0,05	-0,02	-0,02	0,15	-0,04	0,09	0,07	0,05	0,21	0,02	0,14	-0,02	0,06	0,08
	0,25	0,09	-0,03	-0,23	-0,07	0,05	0,18	0,01	0,01	-0,02	-0,04	-0,02	-0,04	0,00
	0,50	**0,08**	-0,05	-0,11	-0,01	0,02	-0,01	-0,05	0,01	0,00	0,01	-0,07	0,02	-0,01
	0,75	0,13	-0,08	-0,08	-0,12	0,01	-0,04	-0,05	0,01	-0,04	0,08	-0,07	0,12	-0,05
	0,95	0,09	-0,23	-0,14	0,02	0,08	-0,05	-0,06	0,00	-0,04	0,13	-0,13	0,12	0,03
IBEX	0,05	0,01	**0,21**	**0,24**	-0,09	0,09	-0,02	0,13	0,12	**0,23**	-0,08	0,11	-0,02	**0,17**
	0,25	0,13	**0,23**	**0,19**	-0,02	0,07	-0,06	0,04	0,05	-0,10	0,01	0,00	-0,01	0,06
	0,50	**0,18**	**0,13**	**0,16**	-0,04	0,00	0,08	0,01	0,03	0,02	0,07	0,06	-0,04	0,05
	0,75	0,08	0,06	**0,24**	-0,04	0,03	**0,15**	0,00	0,02	-0,03	-0,02	0,05	0,00	0,09
	0,95	-0,08	-0,10	0,23	-0,02	0,17	**0,36**	-0,04	-0,01	0,06	0,04	0,03	0,01	**0,07**
MERV	0,05	**0,21**	-0,01	0,02	-0,02	-0,02	-0,05	0,09	-0,08	-0,19	0,20	0,20	0,07	0,14
	0,25	**0,07**	0,01	0,04	-0,10	0,05	0,02	0,00	-0,06	-0,04	0,08	0,03	0,00	**0,09**
	0,50	0,02	0,02	0,03	-0,06	0,00	-0,01	0,00	-0,03	0,01	0,00	0,00	0,06	**0,09**
	0,75	0,03	0,00	0,00	-0,01	0,01	0,03	0,01	-0,02	-0,07	0,01	-0,07	0,04	**0,10**
	0,95	0,00	-0,07	-0,08	-0,03	-0,01	-0,10	0,09	-0,05	0,16	**0,11**	0,04	0,04	**0,10**
MXX	0,05	0,06	0,07	0,00	-0,20	0,15	0,08	**0,18**	**0,47**	-0,19	-0,30	-0,05	0,13	0,14
	0,25	0,00	0,02	0,16	-0,19	-0,01	0,05	**0,14**	**0,43**	-0,09	-0,03	-0,02	0,20	0,16
	0,50	-0,01	-0,02	0,03	-0,09	0,02	0,04	**0,06**	**0,27**	-0,07	-0,04	-0,11	0,14	0,02
	0,75	0,01	-0,10	0,11	-0,04	0,07	0,04	**0,06**	**0,27**	-0,11	-0,10	-0,15	0,15	0,15
	0,95	0,01	-0,27	-0,16	-0,13	0,07	0,04	**0,14**	**0,20**	-0,29	0,06	-0,03	0,24	-0,10
N225	0,05	-0,02	-0,05	-0,05	0,05	-0,02	0,05	0,06	-0,12	-0,13	0,05	0,06	0,00	-0,14
	0,25	-0,08	-0,13	**0,16**	-0,02	0,00	0,12	-0,01	-0,02	-0,02	-0,12	0,00	**0,21**	-0,02
	0,50	-0,03	0,05	0,04	-0,02	0,03	0,03	0,01	-0,04	-0,07	-0,04	-0,05	0,05	0,00
	0,75	0,02	0,05	0,13	0,03	-0,01	-0,06	0,02	-0,05	-0,14	0,05	0,00	-0,05	-0,05
	0,95	0,00	0,04	0,19	0,01	-0,01	-0,07	0,08	0,04	-0,30	-0,06	0,23	0,02	0,11
RTS_RS	0,05	**0,10**	-0,04	0,07	-0,02	-0,06	-0,09	0,06	0,07	-0,18	-0,07	0,17	-0,02	0,08
	0,25	0,05	-0,01	0,01	0,02	-0,04	-0,09	-0,01	0,02	-0,03	-0,06	-0,05	-0,08	**0,13**
	0,50	0,05	0,01	0,10	0,01	-0,01	-0,03	-0,02	0,04	-0,12	0,00	-0,08	-0,06	**0,11**
	0,75	**0,07**	-0,01	0,06	0,03	0,01	-0,01	0,00	0,00	-0,05	0,01	-0,11	-0,01	**0,18**
	0,95	**0,12**	-0,09	0,10	0,02	-0,03	-0,09	-0,05	-0,03	-0,23	0,00	-0,17	-0,15	**0,24**
SSMI	0,05	**0,35**	**0,31**	0,00	0,32	-0,06	0,02	0,10	0,10	-0,08	**0,19**	-0,08	0,08	0,05

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	0,25	0,16	0,16	0,14	0,26	0,09	-0,04	0,00	-0,18	0,16	0,04	-0,11	0,00	0,11
	0,50	0,00	0,06	0,05	0,21	-0,02	0,08	-0,01	-0,08	**0,05**	0,04	-0,05	-0,03	0,06
	0,75	-0,04	0,05	0,01	0,29	-0,07	0,06	0,03	-0,09	-0,06	0,11	-0,10	0,01	0,02
	0,95	-0,04	-0,17	0,07	0,24	0,00	0,23	0,23	0,00	0,08	-0,01	0,09	0,08	-0,20
TA100	0,05	-0,11	0,10	-0,07	-0,06	-0,10	0,01	0,07	0,27	0,03	0,10	-0,44	0,08	-0,19
	0,25	-0,10	0,11	-0,10	0,05	-0,09	0,02	0,04	0,02	-0,04	0,00	-0,10	0,01	-0,01
	0,50	-0,09	-0,01	-0,16	0,07	-0,02	0,00	0,00	-0,01	-0,05	0,05	-0,06	0,03	0,00
	0,75	-0,08	0,03	-0,07	0,08	-0,02	0,05	0,01	-0,14	**0,05**	0,05	-0,12	0,05	-0,10
	0,95	0,06	-0,09	0,14	0,08	-0,01	0,04	-0,07	-0,04	**0,16**	0,02	0,12	0,01	0,17
XU100	0,05	**-0,25**	0,21	-0,18	0,13	0,17	0,41	0,45	**0,48**	**0,50**	**0,55**	**0,57**	0,46	0,67
	0,25	**0,04**	**0,26**	0,11	-0,08	0,15	**0,42**	0,06	0,45	0,29	0,31	0,37	0,60	0,35
	0,50	-0,06	0,16	-0,03	0,09	0,12	0,19	0,15	**0,24**	**0,40**	0,25	0,10	0,30	0,18
	0,75	0,05	0,11	0,02	-0,01	0,01	0,22	0,01	0,19	0,15	0,43	0,22	0,22	0,46
	0,95	0,24	0,18	0,20	-0,39	-0,06	0,21	-0,16	0,03	0,24	-0,27	0,15	0,10	0,50

Source: elaborated by the authors. Values in bold displayed significant T-ratio

Figure 9 - Betas of the IBOVESPA for all quantiles from 2000 to 2012.
Source: elaborated by the authors.

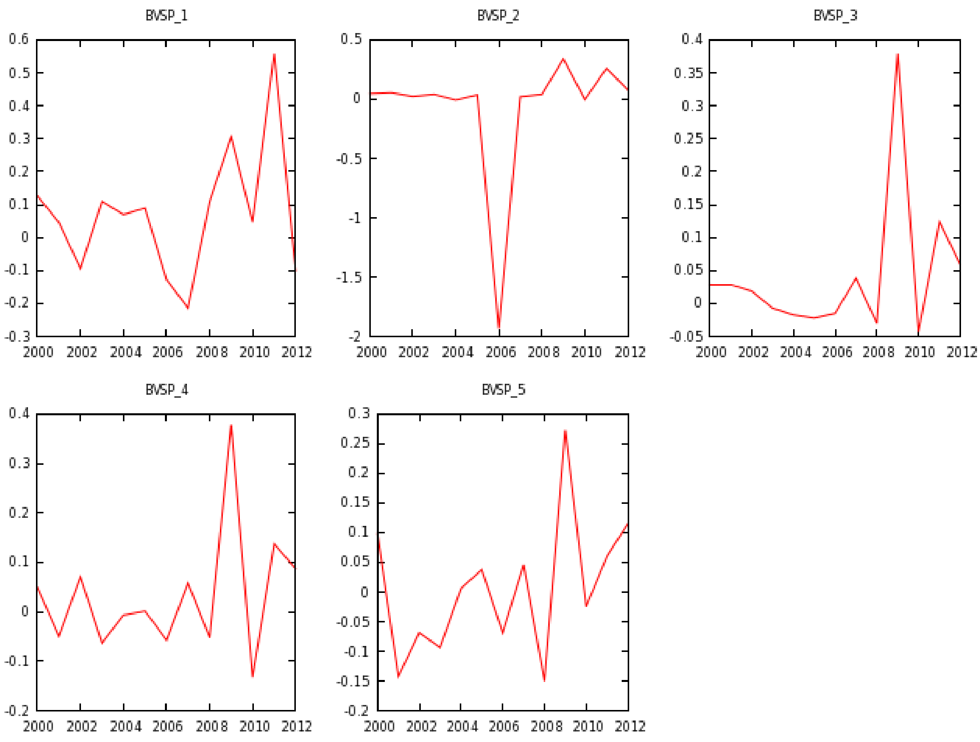
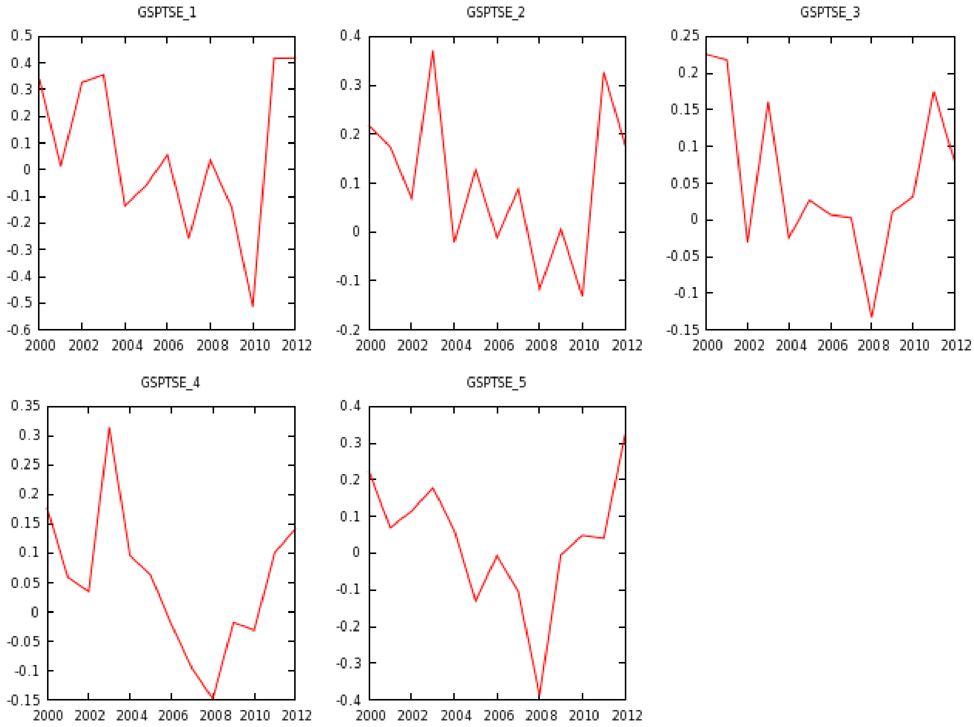


Figure 10 - Betas of the Toronto Index for all quantiles from 2000 to 2012.



Source: elaborated by the authors.

Figure 11 - Betas of the Hang Seng for all quantiles from 2000 to 2012.

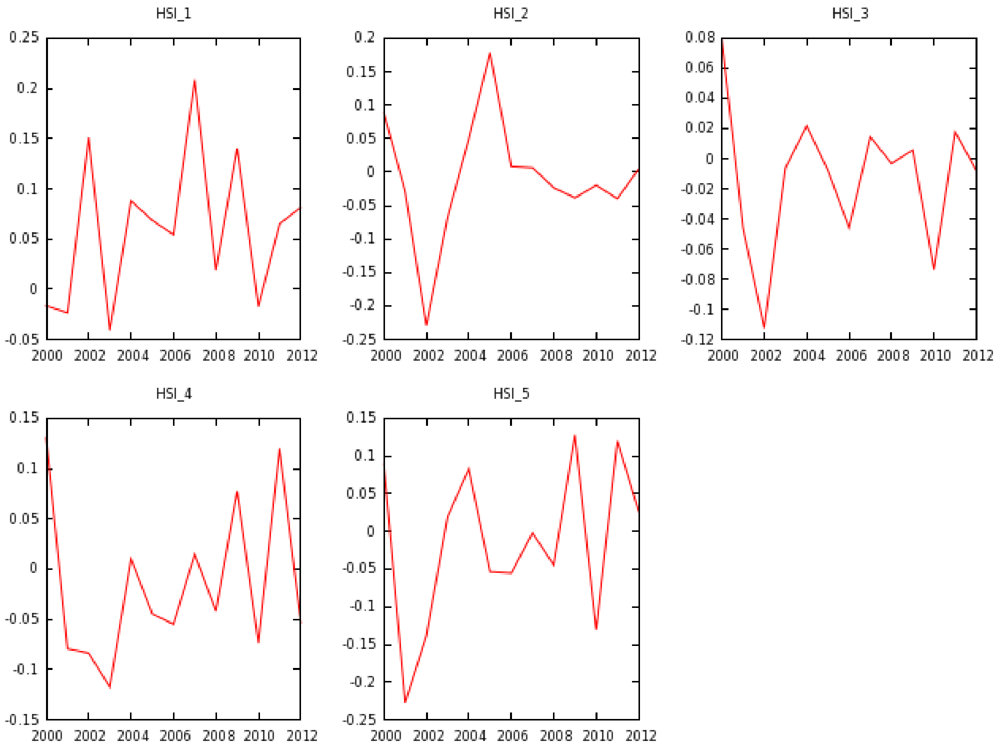


Figure 12- Betas of the IBEX for all quantiles from 2000 to 2012.

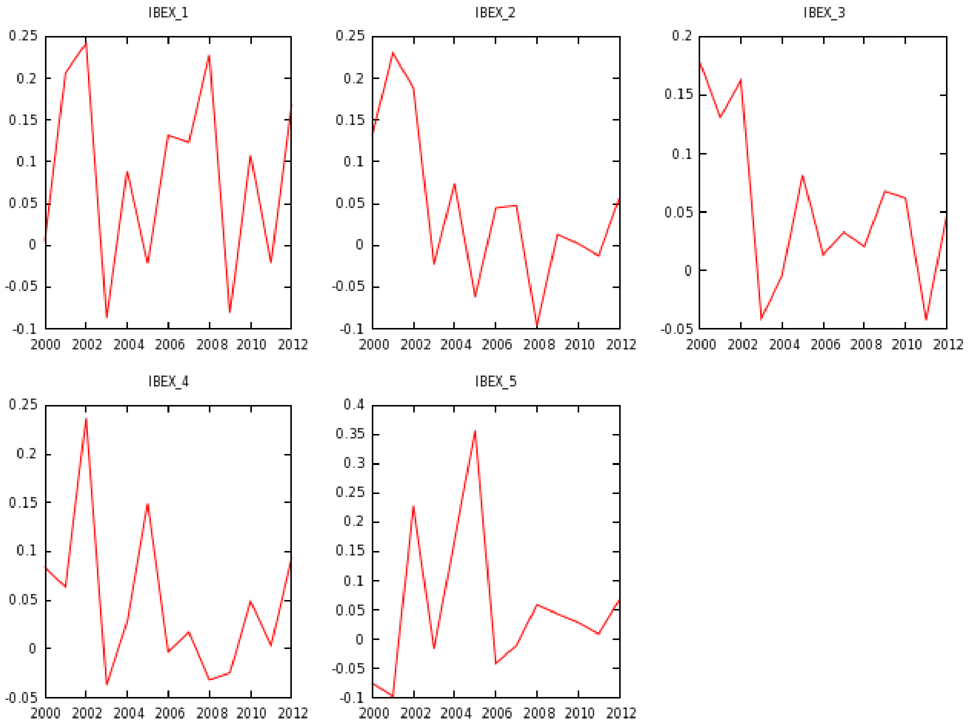
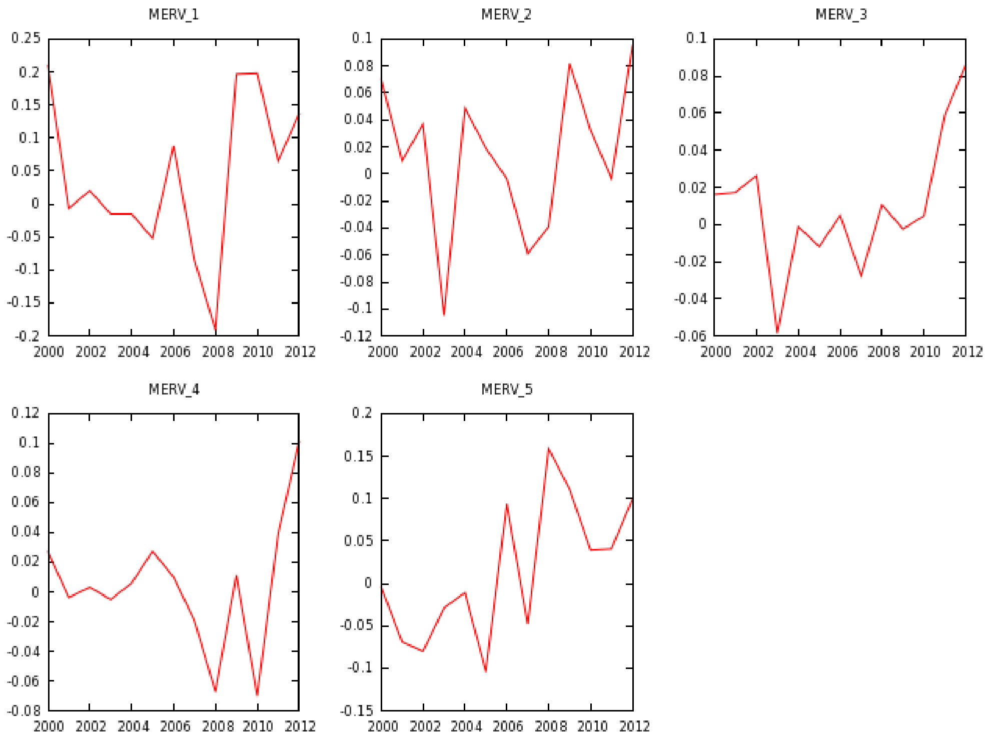
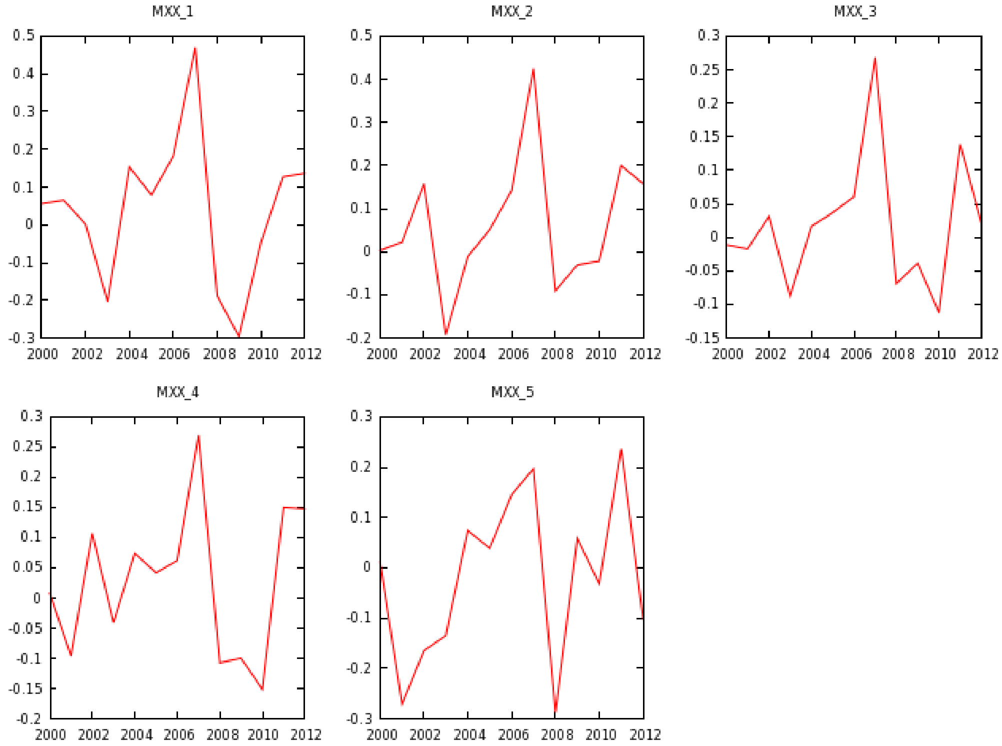


Figure 13 - Betas of the MERVAL for all quantiles from 2000 to 2012.



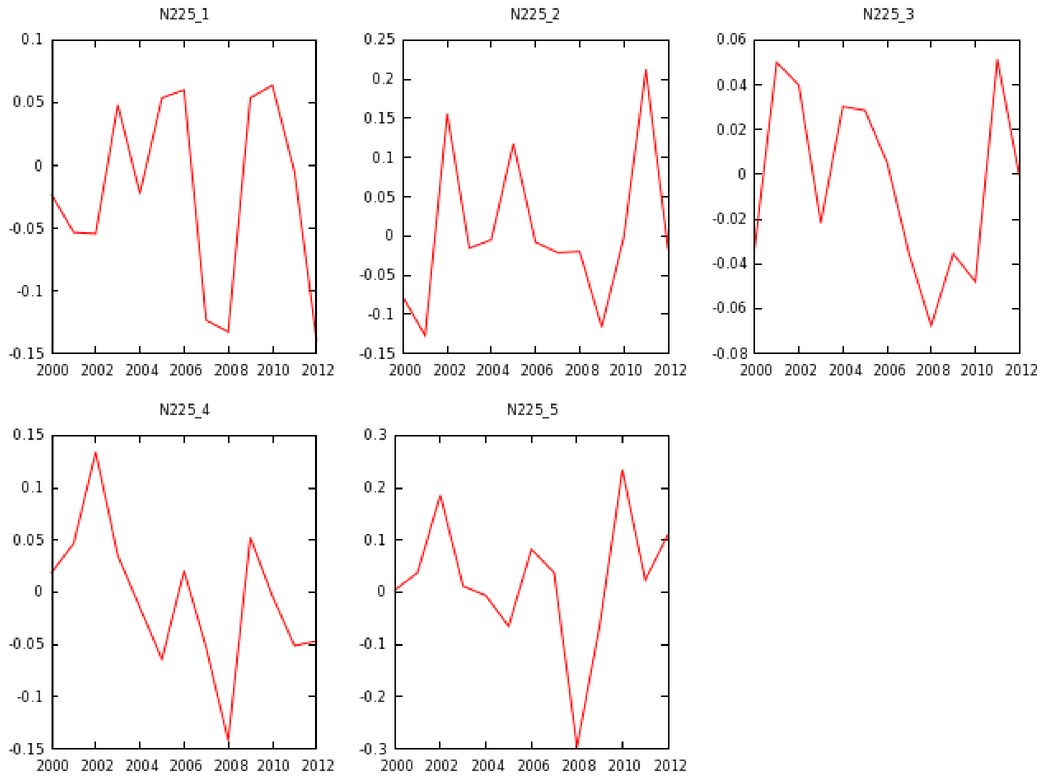
Source: elaborated by the authors.

Figure 14 - Betas of the MMX for all quantiles from 2000 to 2012.



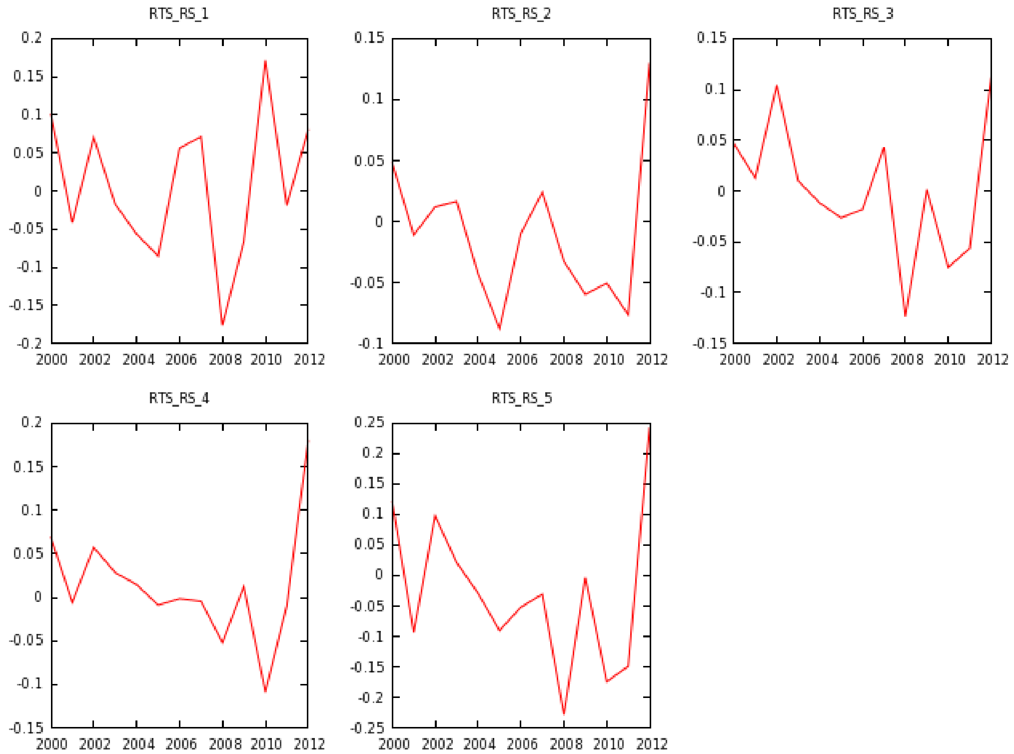
Source: elaborated by the authors.

Figure 15 - Betas of the NIKKEI for all quantiles from 2000 to 2012.



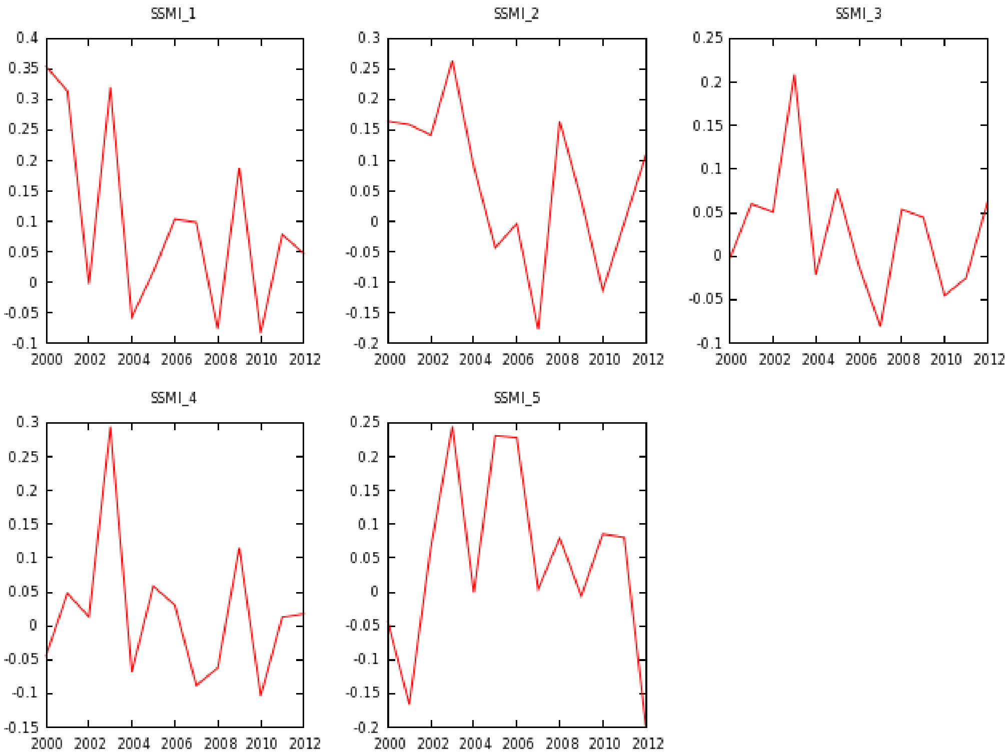
Source: elaborated by the authors.

Figure 16 - Betas of the RTS for all quantiles from 2000 to 2012



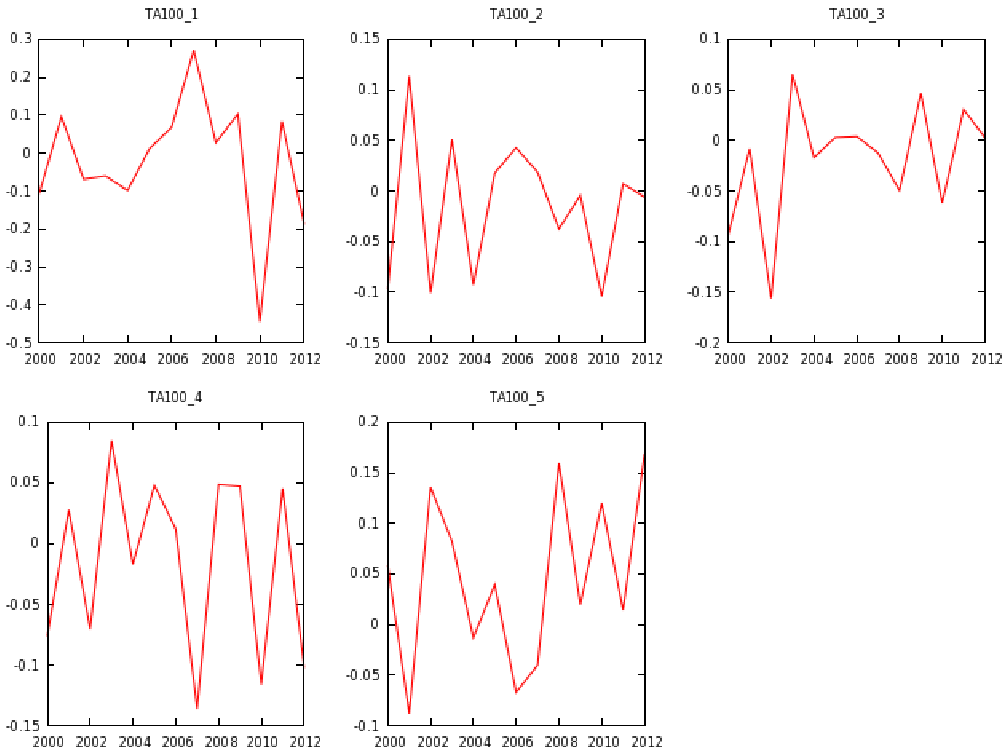
Source: elaborated by the authors.

Figure 17 - Betas of the SSMI for all quantiles from 2000 to 2012.



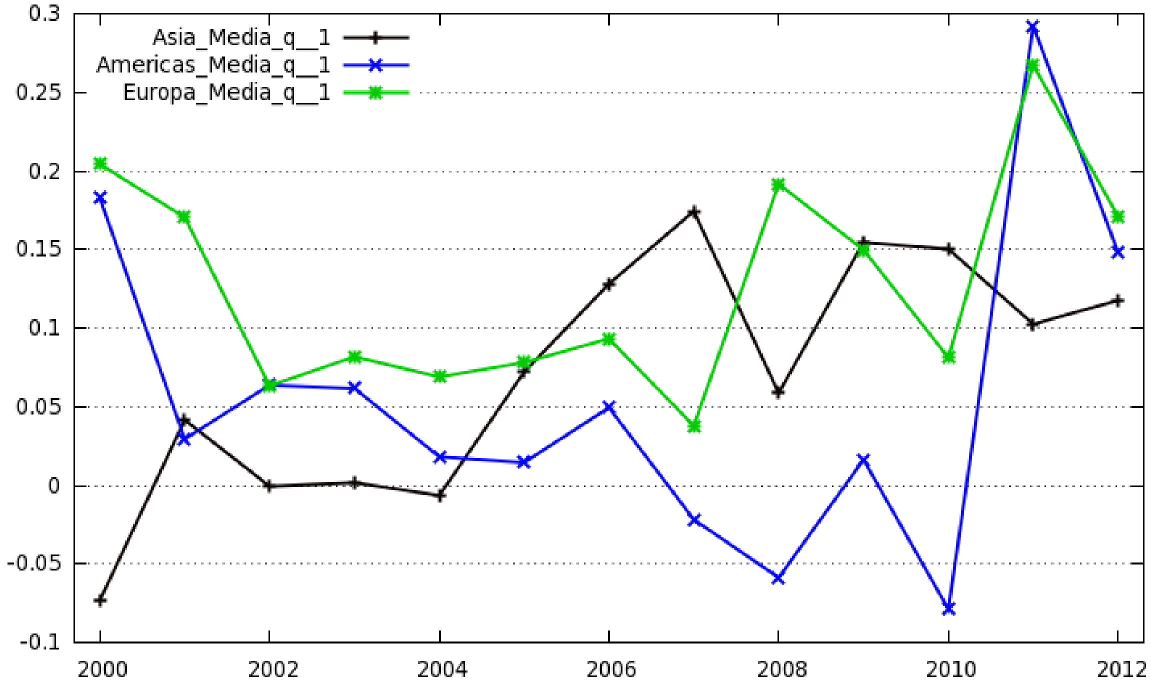
Source: elaborated by the authors.

Figure 18 - Betas of the TA100 for all quantiles from 2000 to 2012.



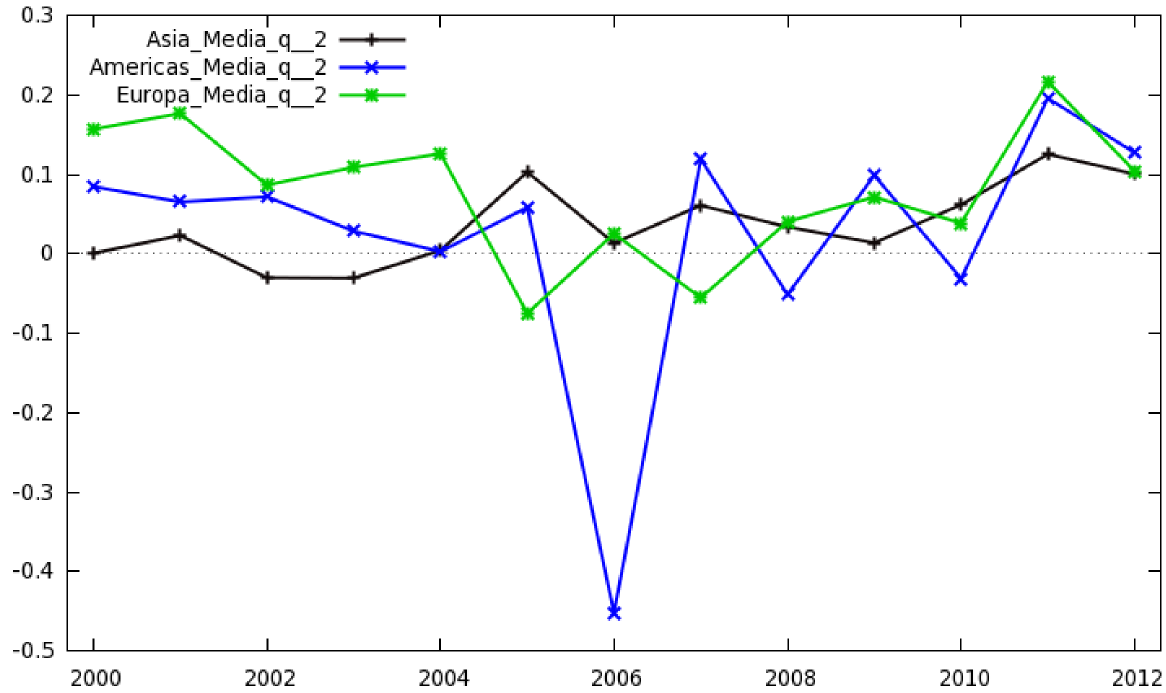
Source: elaborated by the authors.

Figure 19 – Average betas grouped by geographic region for the 1st quantile from 2000 to 2012.



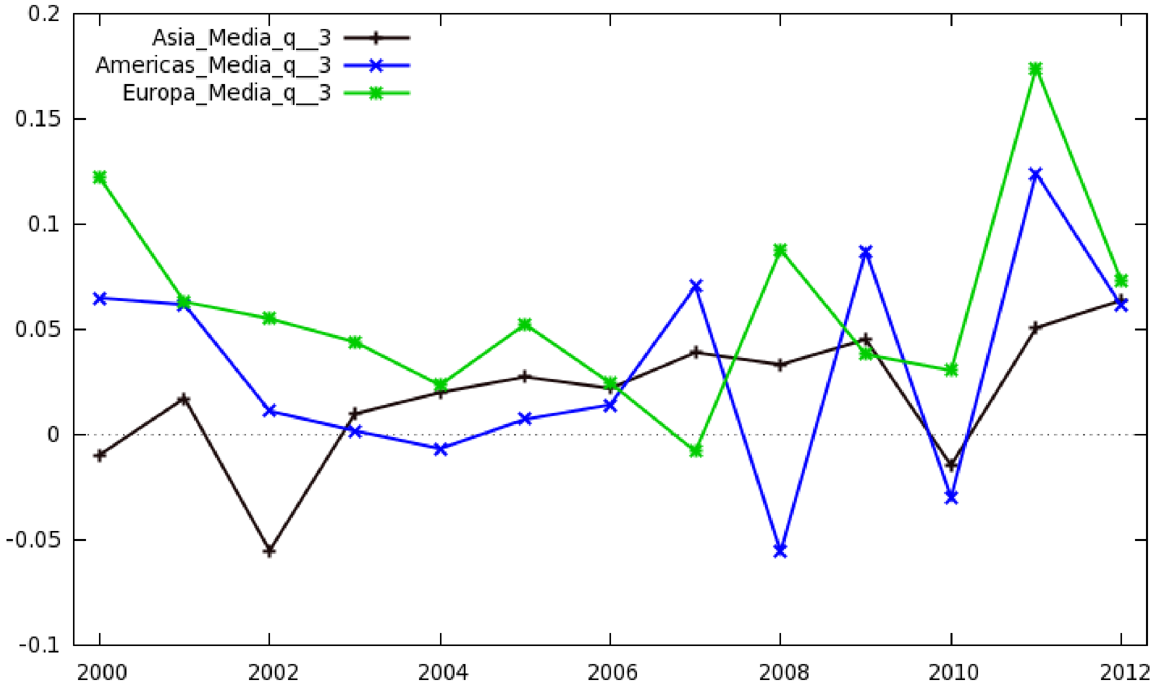
Source: elaborated by the authors.

Figure 20 – Average betas grouped by geographic region for the 2nd quantile from 2000 to 2012.



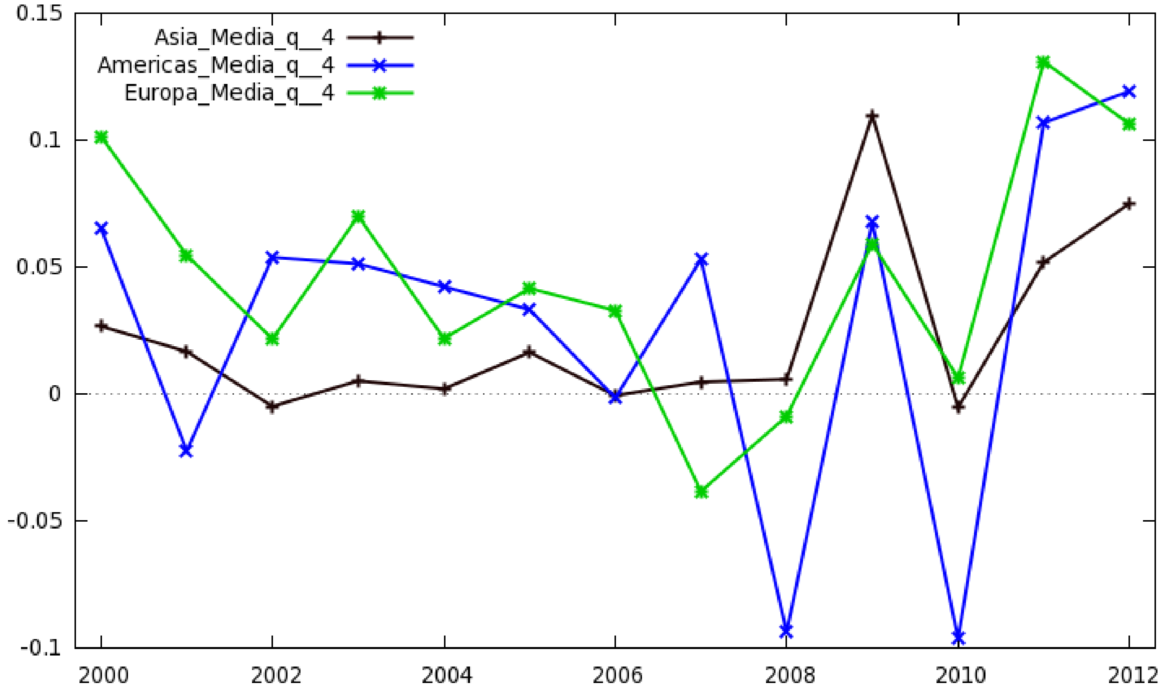
Source: elaborated by the authors.

Figure 21 - Average betas grouped by geographic region for the 3rd quantile from 2000 to 2012.



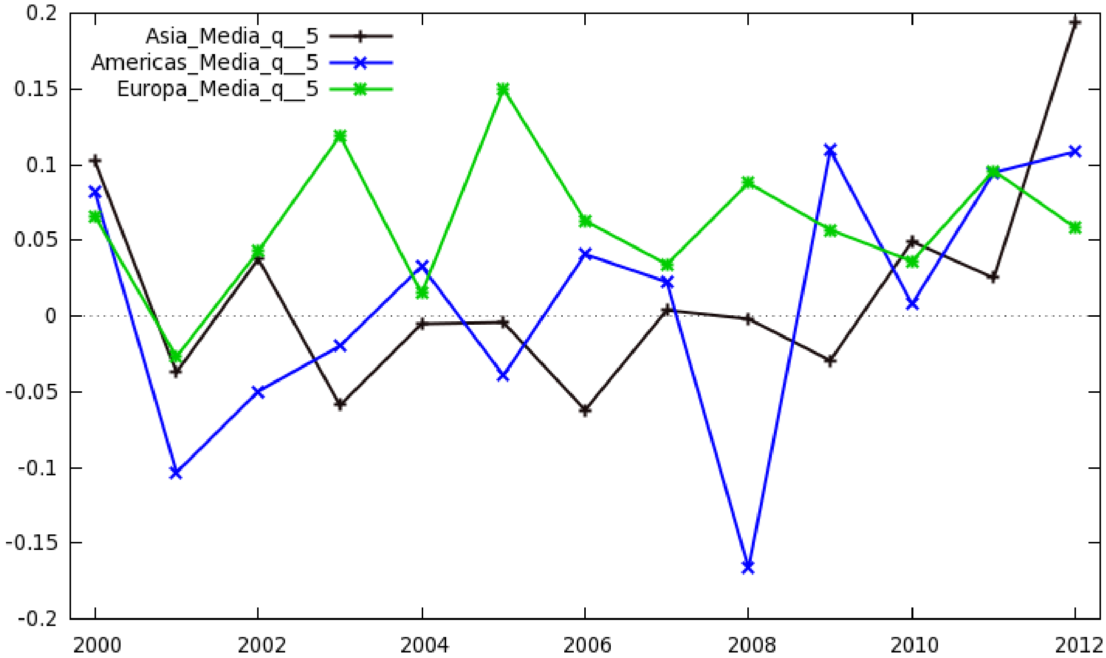
Source: elaborated by the authors.

Figure 22 - Average betas grouped by geographic region for the 4th quantile from 2000 to 2012.



Source: elaborated by the authors.

Figure 23 - Average betas grouped by geographic region for 5th quantile from 2000 to 2012.



Source: elaborated by the authors.