A DCC-GARCH analysis of regulatory impacts and financial contagion in Latin American markets derived from two relevant crisis at the dawn of the 21st Century in the US: the telecommunications bust in 2001 and the great recession in $2007-2009$

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Abstract

The aim of this research consists on compare and examine the time-varying correlation between the returns of the most important capitalization-weighted index in the telecommunications sector, the NASDAQ telecommunications index and the stock indices' returns of the three main Latin American economies (Argentina, Brazil and Mexico). The study involves the use of the Dynamic Conditional Correlation (henceforth, DCC) GARCH model in order to examine the financial contagion phenomenon during two differentiated turmoil economic periods in $21st$ century: the bust in telecommunications sector in 2001 and the US great recession of 2007 - 2009. Each case derived from a particular source: the first one from a US Federal Communications Commission's (henceforth, FCC) vague regulatory initiative aimed at improving the competition in local phone services; the second one from financial disruptions, oil shocks and the bursting housing-bubble in 2007. Thus, our purpose is to illustrate the relationship between NASDAQ telecommunications index and Latin America's stock market indices following two important economic shocks with differentiated origins. Additionally, it allows to distinguish the correlation sign and the reaction on Latin American's markets to external economic situations. Futhermore, it can shed light to Latin American telecommunications regulators about how external policy decision-making affect their national stock markets, and consequently other aspects of their national economies. Even though we are not directly considering a telecommunications growth indicator, it is generally considered that the development of stock market indices is positively and robustly correlated with economic growth. On the other hand, the DCC-GARCH model consists on an efficient version of ARCH models in order to modelize volatilities in financial time series. The estimation process is easier since it involves fewer parameters. In addition, and more importantly, DCC-GARCH model is capable of capturing volatility clustering in financial time series. Estimation results reveal that NASDAQ telecommunications index's returns tended to move in the same direction as stock market indices' returns in both periods, however, the $2007-2009$ period is much more volatile.

Keywords: DCC - GARCH, NASDAQ Telecommunications Index, Regulatory Impacts.
JEL Classification: $C51$

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1 Introduction

The current economic globalization process has generated a strong linkage between financial markets worldwide. In this respect, sudden shocks in volatility in an international stock market could be reflected across other financial markets given the integration of the global financial system. The analysis of periods of economic and financial crisis and the existence of a contagion phenomenon derived from a policy decision-making is of the utmost importance for policy-makers. This paper focuses on the examination of the financial contagion phenomenon between the returns of the NASDAQ telecommunications index and stock market indices' returns of Argentina, Brazil and Mexico following two of the main economic crisis of the last three lustrums: the bust in telecommunications sector at the first years of the 21*st* century and the US great recession of December 2007 - June 2009. The boom and bust in telecommunications sector overlapped with the dot-com bubble which formed around internet companies between 1995 and 2001. According to Couper, et al. (2003) the telecom bust was caused by the rising levels of concern among telecommunication companies about the FCC's 1996 Telecommunications Act which was designed to endorse competition in local phone services. The issue was interpreted as a lack of clarity change in the regulatory environment, difficult to interpret and with a fuzzy implementation. The result was a myriad of court demands against the FCC that inhibited the 1996 Act's efficacy. Moreover, the initial overestimation of the positive effects of the Act leads to large forecast errors in the demand for long-haul fiber. Furthermore, the rapid technological progress strengthened the idea of the development of new applications which would lead to a greater demand of bandwidth. However, at the end the theoretical virtuous circle was never accomplished. Thus, a regulatory initiative that was meant to be a way to increase competititon at the local exchange carrier level ended up becoming a catastrophe: the stock market meltdown due to 2001‘s telecom stock bust.

In addition, it is not superfluous to stress that the development of the stock markets play a significant role in economic growth. For instance, Adjasi and Biekpe (2006) found a statistically significant positive relationship between stock markets and economic growth of upper middle income African countries. In the endogenous growth theory framework (Levine, 1997) it is stated that the stock market development fosters long-run economic growth because it optimizes the allocation of resources; also, it incentivices the capital accumulation and the technological innovation. In another contribution, Levine (1991) establishes that stock markets positively affect firm efficiency by dismissing the premature withdrawal of capital from firms. This is how an increasing average amount of capital maintained in a firm stimulates the growth rate of human capital and therefore economic growth.

In regards to the US great recession that began in 2007, it was a general slowdown that started as a turbulence in the sub-prime mortgage segment of the US housing market. Additionally, the deregulation in the US financial markets considerable affected the expansion of the crisis. In this sense, the US recession was a totally different economic phenomenon with respect to the bust in telecommunications. Thus, the comparison of two effects derived from different economic movements and their spillover effect can contribute to shed light to Latin America's telecommunications regulators about how external policy decision-making in the telecommunications sector and financial shocks affect the national stock markets and, in consequence, companies in general and telecommunications firms in particular. Then, we highlight the scope and divergences that the time-varying correlation between the returns of NASDAQ telecom index and stock markets indices' returns have for each case. That is, we capture the sign of their relationship in different states of the business cycle. Moreover, telecommunications sector is an important case to be analyzed since it is recognized that it is essential in terms of maintaining the well functioning of the market economy and to promote the volume of domestic and foreign trade.

In order to capture this relationship we use Engle's (2002) dynamic conditional correlation (DCC) GARCH model. Furthermore, one advantage of this approach is that it allows to capture and compare the relationship between indices in different states of the business cycle by using fewer parameters.

We proceed as follows. In section 2 we discuss the structure of the NASDAQ Telecom index. In section 3 we explain the methodological approach based in Engle's (2002) DCC GARCH model. In section 4 we describe our data, while in section 5 we present our substantive results. We conclude in section 6.

2 Nasdaq Telecom Index

The NASDAQ telecommunications index (Symbol: IXTC) includes securities of NASDAQ index listed companies classifed according to the Industry Classification Benchmark (ICB) as telecommunications or telecommunications equipment. The NASDAQ telecommunications index is defined as a market capitalization-weighted index. The value of the index equals the aggregate value of the index share weights of each of the index securities multiplied by each such security's last sale price, and divided by the divisor of the index. It should be noted that in order to be eligible for inclusion in the index a security must be listed on the NASDAQ Stock Market and be classified according to the ICB as Telecommunications (code: 6000) or Telecommunications Equipment (code: 9578). Table 1 shows the industry structure and definitions of ICB's classification. Due to increasing accesibility to technology and globalization, it is considered that NASDAQ telecommunications index has been one of the most developing sector indices in last years.

Table 1. Industry Classification Benchmark

Industry	Supersector	Sector	Subsector	Definition
6000 Telecommunications	6500 Telecommunications	6530 Fixed Line Telecommunications	6535 Fixed Line Telecommunications	Providers of fixed-line telephone services, including regional and long-distance. Includes companies that primarily provides telephone services through theinternet. Excludes companies whose primary business is Internet access, whichare classified under Internet.
		6570 Mobile Telecommunications	6575 Mobile Telecommunications	Providers of mobile telephone services, including cellular, satellite and paging services. Includes wireless tower companies that own, operate and lease mobile site towers to multiple wireless service providers.
9000 Technology	9500 Technology	9570 Technology Hardware & Equipment	9578 Telecommunications Equipment	Makers and distributors of high-technology communications products, including satellites, mobile telephones, fiber optics, switching devices, local and wide-area networks, teleconferencing equipment and connectivity devices for computers, including hubs and routers.

Table 2. Components for NASDAQ Telecommunications Index

Symbol	Name	Symbol	Name
AAOI	Applied Optoelectronics, Inc.	LTRX	Lantronix, Inc.
ACIA	Acacia Communications, Inc.	MIFI	Novatel Wireless Inc.
ADTN	ADTRAN, Inc.	MITL	Mitel Networks Corporation
AEY	ADDvantage Technologies Group Inc.	MRVC	MRV Communications, Inc.
AFOP	Alliance Fiber Optic Products Inc.	NICE	NICE Systems Ltd.
ALSK	Alaska Communications Systems Group Inc.	NIHD	NII Holdings Inc.
AMOV	America Movil S.A.B. de C.V.	NMRX	Numerex Corp.
ARCW	ARC Group Worldwide, Inc.	NTGR	Netgear Inc.
ARRS	ARRIS International plc	OCC	Optical Cable Corp.
ATNI	Atlantic Tele-Network, Inc.	OCLR	Oclaro, Inc.
AUDC	AudioCodes Ltd.	ORBC	ORBCOMM, Inc.
AVNW	Aviat Networks, Inc.	OTEL	Otelco Inc.
BBRY	BlackBerry Limited	PCO	Pendrell Corporation
BOSC	B.O.S. Better Online Solutions Ltd.	PDVW	pdvWireless, Inc.
BRCD	Brocade Communications Systems, Inc.	PLCM	Polycom, Inc.
CALL	magicJack VocalTec Ltd.	PLPC	Preformed Line Products Company
CAMP	CalAmp Corp.	PMTS	CPI Card Group, Inc.
CLFD	Clearfield, Inc.	PRKR	Parkervision Inc.
CLRO	ClearOne, Inc.	PTNR	Partner Communications Company Ltd.
CMTL	Comtech Telecommunications Corp.	QLGC	QLogic Corp.
CNSL	Consolidated Communications Holdings Inc.	RDWR	Radware Ltd.
CNTF	China Techfaith Wireless Communication Technology Limited	RESN	Resonant Inc.
COMM	CommScope Holding Company, Inc.	RITT	RiT Technologies Ltd.
CPSH	CPS Technologies Corp.	RRM	RR Media Ltd.
CRDS	Crossroads Systems, Inc.	SAAS	inContact, Inc.
CRNT	Ceragon Networks Ltd.	SATS	EchoStar Corp.
CSCO	Cisco Systems, Inc.	SBAC	SBA Communications Corp.
DGII	Digi International Inc.	SCON	Superconductor Technologies Inc.
DRWI	DragonWave Inc.	SEAC	SeaChange International, Inc.
EGHT	8x8 Inc.	SHEN	Shenandoah Telecommunications Co.
ELNK	EarthLink Holdings Corp.	SHOR	ShoreTel, Inc.
ERIC	Telefonaktiebolaget LM Ericsson (publ)	SOFO	Sonic Foundry, Inc.
EXFO	EXFO Inc	SONS	Sonus Networks, Inc.
EXTR	Extreme Networks Inc.	SPOK	Spok Holdings, Inc.
FFIV	F5 Networks, Inc.	SUNW	Sunworks, Inc.
FNSR	Finisar Corp.	SWIR	Sierra Wireless Inc.
FRP	Fairpoint Communications, Inc.	TCCO	Technical Communications Corporation
FSNN	Fusion Telecommunications International, Inc.	TESS	TESSCO Technologies Inc.
FTR	Frontier Communications Corporation	TMUS	T-Mobile US, Inc.
GILT	Gilat Satellite Networks Ltd.	TWER	Towerstream Corporation
GNCMA	General Communication Inc.	UBNT	Ubiquiti Networks, Inc.
GRMN	Garmin Ltd.	UTSI	UTStarcom Holdings Corp.
HCOM	Hawaiian Telcom Holdco, Inc.	VIAV	Viavi Solutions Inc.
HLIT	Harmonic Inc.	VIP	VimpelCom Ltd.
IDSY	ID Systems Inc.	VOD	Vodafone Group Plc
IFON	Infosonics Corp.	VOXX	VOXX International Corporation
IGLD	Internet Gold Golden Lines Ltd.	VSAT	ViaSat Inc.
INVT	Inventergy Global, Inc.	WILN	Wi-Lan Inc.
IQNT	Inteliquent, Inc.	WIN	Windstream Holdings, Inc.
IRDM	Iridium Communications Inc.	WPCS	WPCS International Incorporated
ITRN	Ituran Location & Control Ltd.	WSTC	West Corporation
JCS	Communications Systems Inc.	WSTL	Westell Technologies, Inc.
KUTV	Ku6 Media Co., Ltd.	XCOM	Xtera Communications, Inc.
KVHI	KVH Industries Inc.	XELB	Xcel Brands, Inc.

Symbol	Name	Symbol	Name
LITE	Lumentum Holdings Inc.	XXIA	Ixia
LMOS	Lumos Networks Corp.	YY	YY Inc.
LORL	Loral Space & Communications, Inc.	ZHNE	Zhone Technologies Inc.
LRAD	LRAD Corporation		

3 DCC GARCH model

The DCC-GARCH model was originally developed by Engle (2001, 2002) and Engle and Sheppard (2001). The model is based on the Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982), the Generalized Autoregressive Conditional Heteroskedastic process (GARCH) (Bollerslev, 1986), and Bollerslev's (1990) constant conditional correlation (CCC) model. The DCC estimator is viewed as an efficient version of ARCH models for volatility modelling because the number of parameters to be estimated has no relation with the number of series to be correlated. Hence, the DCC-GARCH model does not have the complexity of conventional multivariate GARCH models and it allows for the examination of time-varying conditional correlations coefficients and variances of several variables. Since DCC-GARCH model continuously adjust the correlation for time-varying volatility, its measure for correlation does not have any bias from volatility.

In Engle (2001) the author assumes the following process for a random variable r_t. The assumption of normality gives rise to a likelihood function; however, even if we do not stablish this assumption the estimator still have a Quasi-Maximum Likelihood (QML) interpretation.

$$r_t \mid \mathcal{F}_{t-1} \sim N(0,\, D_t R_t D_t)$$

The DCC model can be estimated in two steps. In the first one the estimation of each asset's conditional variance is done through a univariate GARCH (p, q) process.

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-p} \qquad for\ i = 1, 2, 3, ...k \qquad (1)$$

The non-negativity and stationarity conditions satisfy the equation $\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1$. In the second step, the conditional covariance matrix (H_t) is estimated by using the standardized residuals of the previous step in the following form:

$$H_t \equiv D_t R_t D_t \qquad (2)$$

Where $D_t = diag(h_{11t}^{1/2}, ..., h_{NNt}^{1/2})$ is a $k \times k$ diagonal matrix of time-varying standard deviations from a univariate GARCH model; while R_t contains the time-varying conditional correlations, *i.e.* the $DCC(M, N)$ structure:

$$R_t = diag(q_{11t}^{-1/2}, ..., q_{NNt}^{-1/2})Q_t diag(q_{11t}^{-1/2}, ..., q_{NNt}^{-1/2}) \qquad (3)$$

The log-likelihood is written in the following form:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(k\, log\,(2\pi) + 2\, log \mid H_t \mid + r_t' H_t^{-1} r_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(k\, log\,(2\pi) + 2\, log \mid D_t R_t D_t \mid + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t\right)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(k\, log\,(2\pi) + 2\, log \mid D_t \mid + log\left(\mid R_t \mid + \varepsilon_t' R_t^{-1} \varepsilon_t\right)\right)$$

Standardized residuals (i.e. divided by conditional standard deviation) are equal to $\varepsilon_t = D_t^{-1} r_t$. On the other hand, Q_t is an $N \times N$ symmetric positive definite matrix, which represents the dynamic correlation structure:

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\overline{Q} + \sum_{m-1}^{M} a_m\left(\varepsilon_{t-m}\varepsilon_{t-m}'\right) + \sum_{n=1}^{N} b_n Q_{t-n} \qquad (4)$$

$$R_t = {Q_t}^{*-1} Q_t {Q_t}^{*-1}$$

Where $\overline{Q}$ is the unconditional (time-invariant) covariance matrix of dimension $N \times N$ of the standardized residuals from the univariate GARCH model (1). While $Q^* = diag\left\{\sqrt{q_{ii}}\right\}$ is a diagonal matrix containing the square root of the diagonal elements of Q_t. The key element of interest is R_t, which is the positive definite matrix of time-varying conditional correlations, between NASDAQ telecommunications index and each stock market indices. Each element of would be $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$. In a different manner than Bollerslev's Conditional Constant Correlation (CCC) model the DCC estimator allows a time-varying dynamic to the volatilities, covariances and correlations.

4 Data

In this paper we investigate the daily rates of return of NASDAQ telecom index and main Latin America's stock market indices: Argentina's Merval (Symbol: MERV), Brazil's Bovespa (Symbol: BVSP) and Mexico's IPC (Symbol: MXX). As it was aforementioned, we analyze two of the main economic and financial crisis periods of the first decade of $21st$ century: the bust in telecommunications sector from march 2001 to november 2001, and the US great recession from december 2007 to june 2009. In this respect, we use the NBER [2] defined recession dates. Other authors as Naoui et. al (2010) analyze the subprime mortgage crisis and define a period that starts in August 2007 and ends in February 2010. Following NBER's recession definition, the recession date starts at the peak of the

[2]http://www.nber.org/cycles.html

business cycle and ends at the trough. The rate of return is defined by the following equation which corresponds to a continuous compounding rate:

$$X_t = logP_t - logP_{t-1}$$

The data set is downloaded from http://www.finance.yahoo.com using the *R* package *tseries.* However, our data set suffers from missing values for all variables. In this respect, it is recognized that missing values are unavoidable and they have the potential to undermine the validity of research results. In order to deal efficiently with problems that arise with missing values we apply an imputation non-parametric method that is in *R* package *missForest.* The method is trained on the observed values of a data matrix in order to predict the missing values [3]. Morever, the package yields a imputation error estimate.

Figure 1 shows the close prices for all indices from peak (march 2001) to trough (november 2001). These dates correspond to the business cycle reference dates defined by NBER. It is clear that the close prices consistently start to decline by june 2001, with the exception of Mexico's IPC, which shows a slightly recovery during june and july of that year. Figure 2 depicts the close prices for all indices from december 2007 to june 2009, corresponding to the US great recession of those years. It is clear that the prices reached it lowest level in the last quarter of 2008.

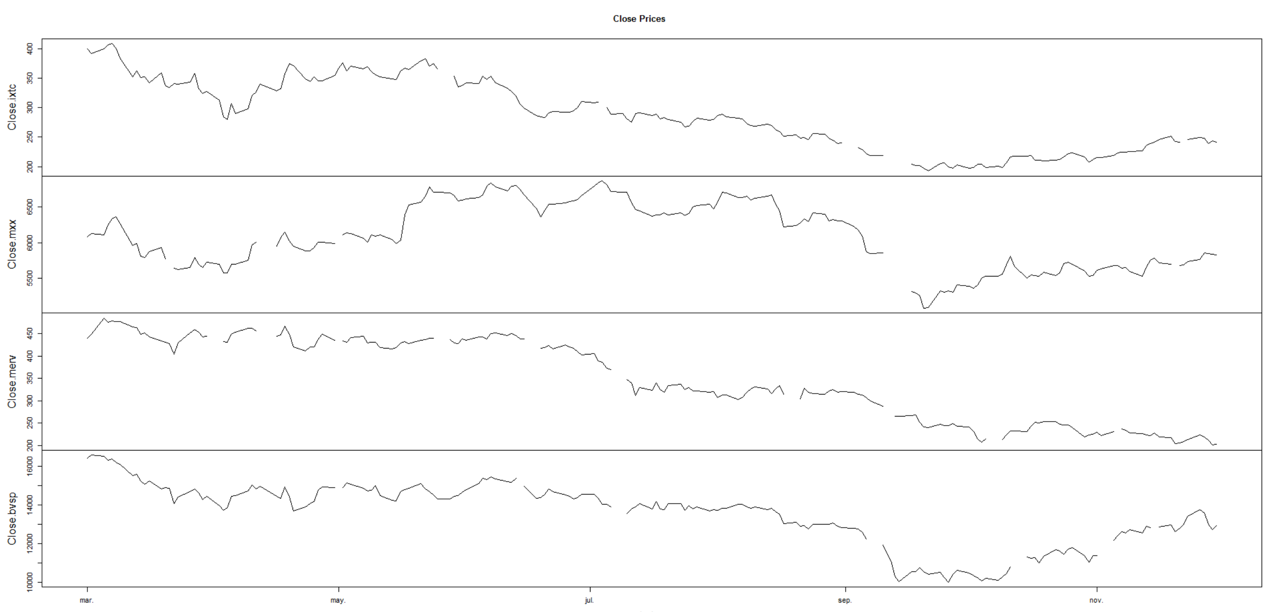

Figure 1. NASDAQ Telecommunications Index and Latin American Stock Market Indices (IPC, MERVAL and Bovespa) close prices, from March 2001 to November 2001.

[3]https://github.com/stekhoven/missForest

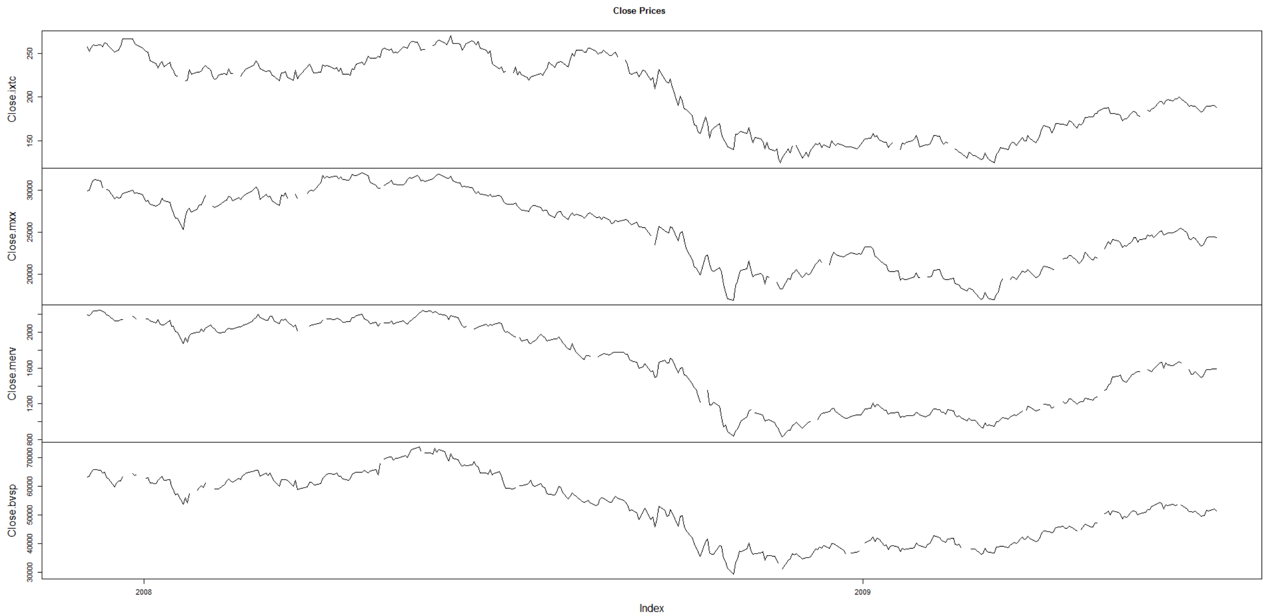

Figure 2. NASDAQ Telecommunications Index and Latin American Stock Market Indices (IPC, MERVAL and Bovespa) close prices, from december 2007 to june 2009.

On the other hand, Figure 3 shows the daily rates of returns for the indices, from march 2001 to november 2001. We can observe from the first graph that NASDAQ telecom index shows a greater volatility at the beginning of the period than in the rest. The same in the case of Mexico's IPC. Argentina's Merval also shows a considerable volatility in the firsts months but it is greater for september of 2001.Bovespa's behavior also shows greater volatility in the last three months of 2001. Figure 4 depicts the daily rates of returns for the second busines cycle reference dates under analysis (december 2007 to june 2009). It is clear that the period with greater volatility for all indices corresponds to the fourth quarter of 2008, while IPC and Merval shows important fluctuations in the second quarter of 2009.

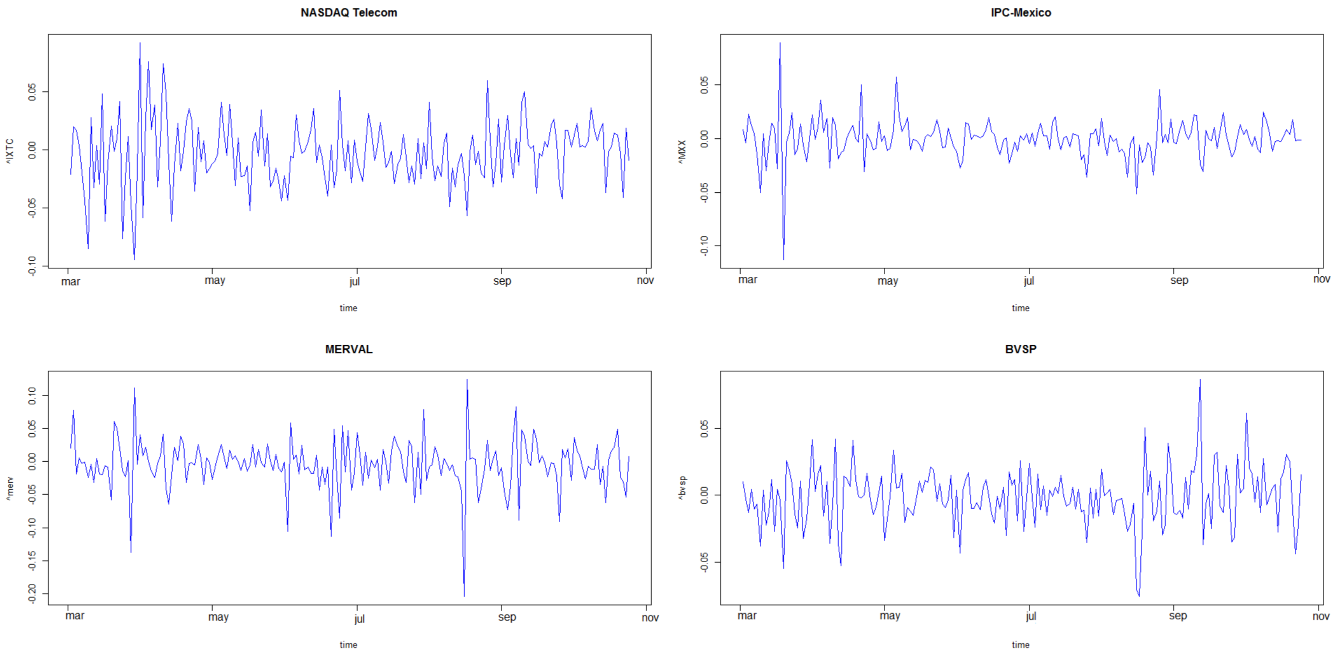

Figure 3. NASDAQ Telecommunications Index and Latin American Stock Market Indices (IPC, MERVAL and Bovespa) daily rates of returns, from March 2001 to November 2001.

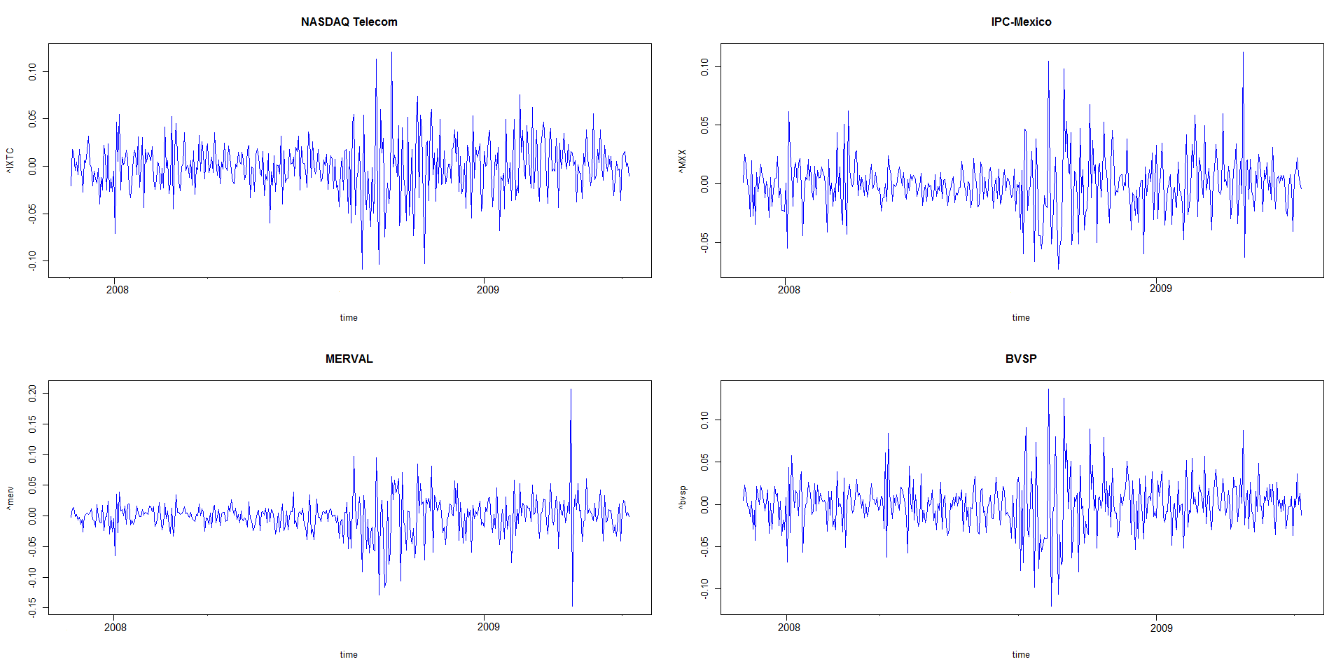

Figure 4. NASDAQ Telecommunications Index and Latin American Stock Market Indices (IPC, MERVAL and Bovespa) daily rates of returns, from december 2007 to june 2009.

5 Results

5.1 Bust in Telecommunications Sector, 2001.

In this subsection we present the results regarding evolution of the dynamic conditional correlation between NASDAQ telecommunications index's returns and the returns of each stock market index, during the bust in telecommunications sector in 2001. Table 3 shows the descriptive statistics for each index's returns. When the sums of α and β in GARCH equations approach to unity, it implies a high persistence in conditional variances, *i.e.* that the movements of the conditional variance have a considerable duration in time when they are not close to their long-run mean. Table 4 displays the estimation results for the DCC (1,1) - GARCH (1,1) model, where we have the following sums for the GARCH coefficients: $\alpha_{ixtc} + \beta_{ixtc} = 0.958$; $\alpha_{mxx} + \beta_{mxx} = 0.953$; $\alpha_{merv} + \beta_{merv} = 0.484$; $\alpha_{bvsp} + \beta_{bvsp} = 0.940$. We can conclude that there exists a high persistence of volatility for all indices, except in the case of Argentina's Merval. Further, the sum of the joint correlation parameters $(a_{dcc1} + b_{dcc1})$ is 0.933**.** It implies the existence of a *linkage effect*, *i.e.* a considerable correlation among the analyzed variables.

The evolution of the conditional correlations of the three Latin American countries is positive in the reference date, however in the case of Argentina's Merval it is considerable weak given that it does not exceed 15% (view Figure 6). Additionally, on december 2001 Argentina declared a default of its debt inside a severe economic and political crisis, which affected its economy considerable. On the other hand, as shown in Figures 5 and 7, Mexico's IPC and Brazil's Bovespa show a strong dynamic conditional correlation with NASDAQ telecommunications index for the same period. The former reached the 40%, while the latter exceeded that percentage. Our results strengthen the idea of a close association between the bust in US telecommunications sector and Brazil and Mexico's stock markets. If we focus on data from the real economy we can observe similar effects. For instance, Martins and Galina (2009) concluded that after world crisis in the sector in 2001 the investments in activities of innovation in telecommunications equipment companies in Brazil were vulnerable to the economic environment of the industry. Other social consequences were a decrease in the number of workers and in their average salaries.

Table 3. Descriptive statistics

	ixtc	**mxx**	**merv**	**bvsp**
$\overline{x}$	-0.002619	-0.000214	-0.003997	-0.001230
σ	0.028	0.018	0.038	0.021
$skew$	0.016	-0.573	-0.832	0.016
$kurt$	4.087	12.911	8.142	4.866

Table 4. DCC-GARCH model estimation results, 2001				
	Estimate	**Std. Error**	**t-value**	**Pr(>$\mid t \mid$)**
μ_{ixtc}	-0.002364	0.002109	-1.121110	0.262241
a_{ixtc}	-0.335853	0.170666	-1.967894	0.049080*
b_{ixtc}	0.468388	0.150275	3.116871	0.001828*
ω_{ixtc}	0.000027	0.000019	1.389098	0.164803
α_{ixtc}	0.068946	0.033403	2.064044	0.039014*
β_{ixtc}	0.889296	0.041970	21.188844	0.000000*
$shape_{ixtc}$	37.146771	78.009747	0.476181	0.633945
μ_{mxx}	0.000261	0.000981	0.266493	0.789859
a_{mxx}	-0.059504	0.200516	-0.296757	0.766652
b_{mxx}	0.188940	0.189867	0.995117	0.319679
ω_{mxx}	0.000013	0.000002	8.202258	0.000000*
α_{mxx}	0.038360	0.009292	4.128064	0.000037 *
β_{mxx}	0.915290	0.019093	47.937578	0.000000*
$shape_{mxx}$	3.153163	0.387833	8.130219	0.000000*
μ_{merv}	-0.002610	0.001174	-2.223571	0.026177*
a_{merv}	0.702938	0.196074	3.585063	0.000337*
b_{merv}	-0.812765	0.153291	-5.302111	0.000000*
ω_{merv}	0.001074	0.000668	1.607265	0.107996
α_{merv}	0.484689	0.269318	1.799693	0.071909
β_{merv}	0.000000	0.307952	0.000000	1.000000
$shape_{merv}$	3.028249	0.596731	5.074731	0.000000*
μ_{bvsp}	-0.001410	0.001226	-1.149709	0.250264
a_{bvsp}	-0.994258	0.015675	-63.429540	0.000000*
b_{bvsp}	0.969215	0.019278	50.274931	0.000000*
ω_{bvsp}	0.000017	0.000026	0.659627	0.509493
α_{bvsp}	0.099821	0.073737	1.353738	0.175820
β_{bvsp}	0.873146	0.069808	12.507753	0.000000
$shape_{bvsp}$	5.816900	2.719823	2.138705	0.032460
a_{dcc1}	0.000000	0.000194	0.000001	0.999999
b_{dcc1}	0.933639	0.782384	1.193325	0.232742
$shape_{joint}$	5.472899	0.713146	7.674306	0.000000*
Akaike: -19.254				

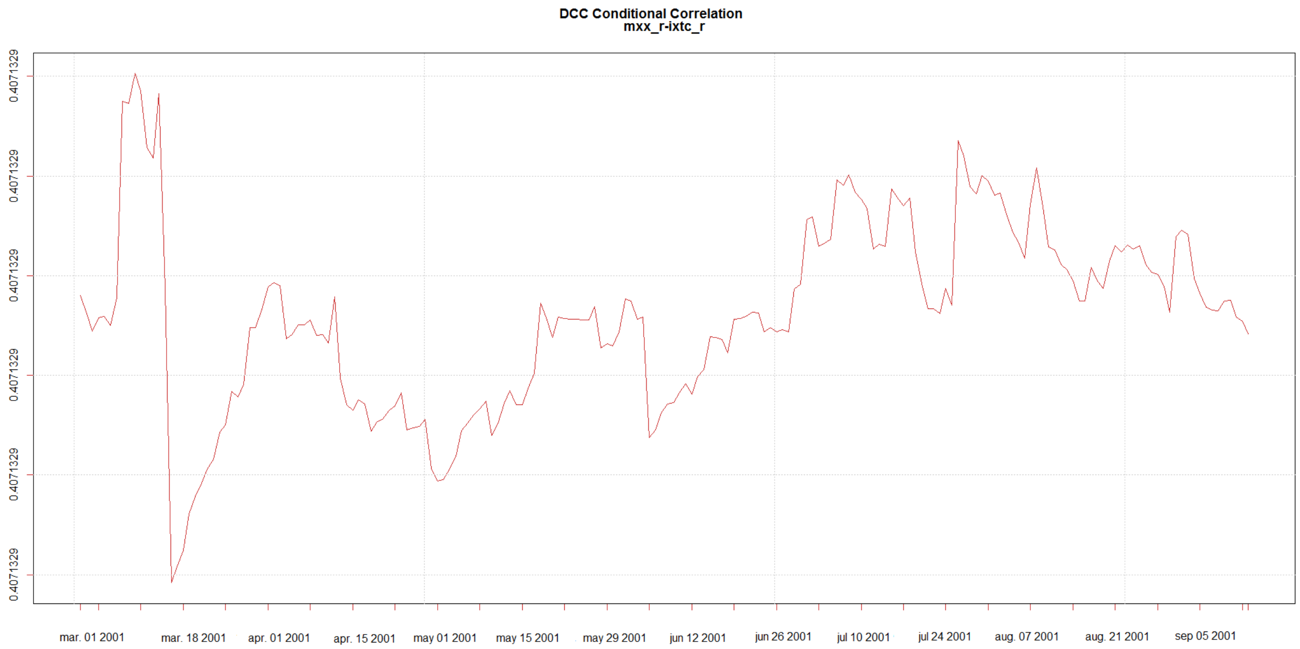

Figure 5. Dynamic Conditional Correlation between NASDAQ telecommunications index and IPC, 2001.

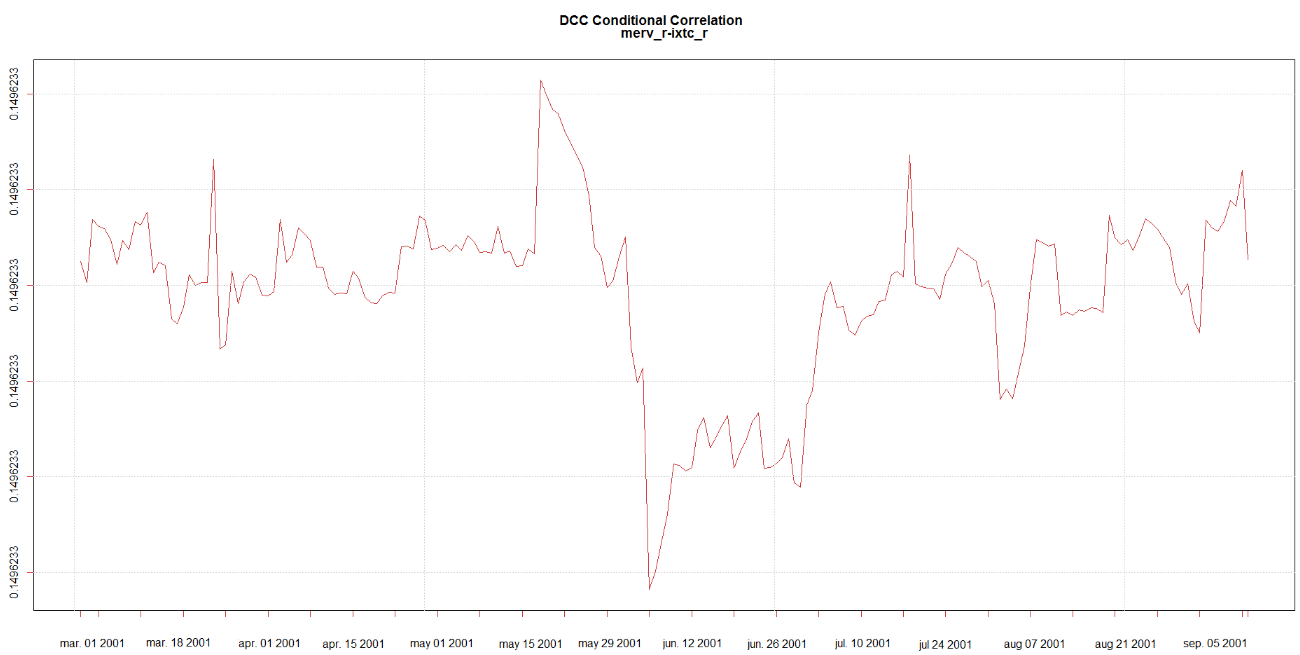

Figure 6. Dynamic Conditional Correlation between NASDAQ telecommunications index and MERVAL, 2001.

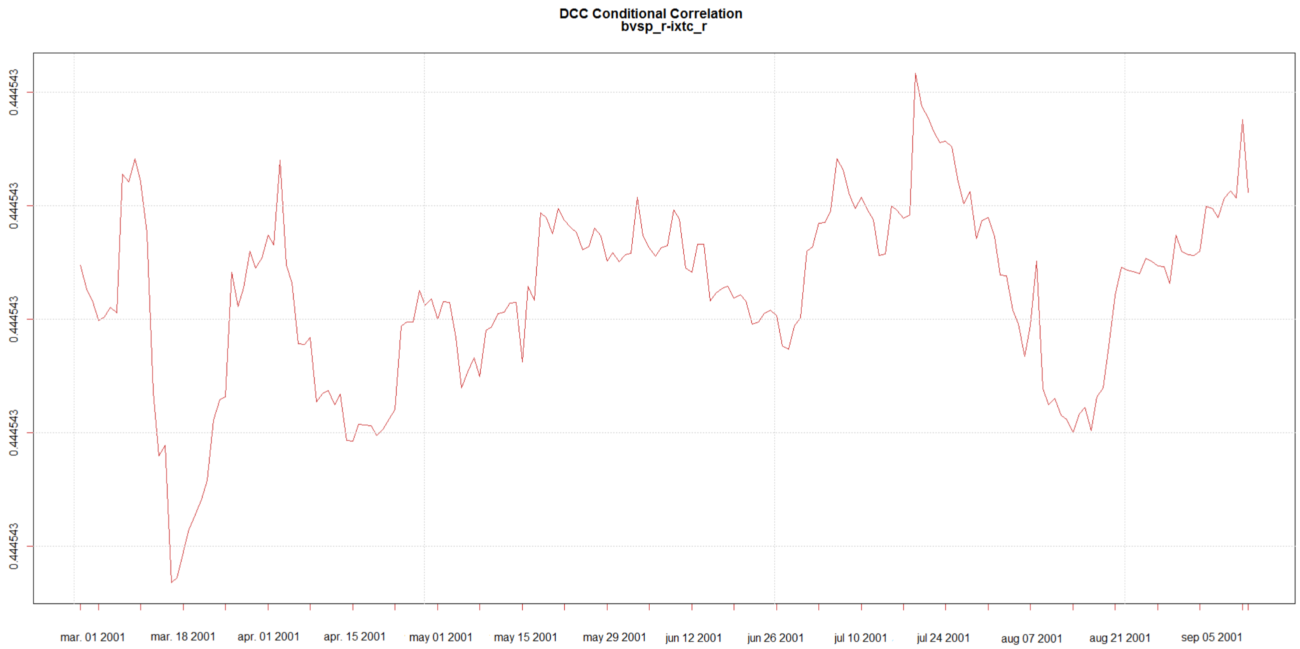

Figure 7. Dynamic Conditional Correlation between NASDAQ telecommunications index and Bovespa,2001.

A fundamental point to take into account is the evolution of the annual growth rate of gross domestic product (GDP). Figure 8 depicts a sharp drop in the growth rates of the three countries in 2001. It was more abrupt for Argentina, underpinned by its own economic and political crisis. While for the case of Brazil it was still positive; in the case of Mexico it dropped to negative values.

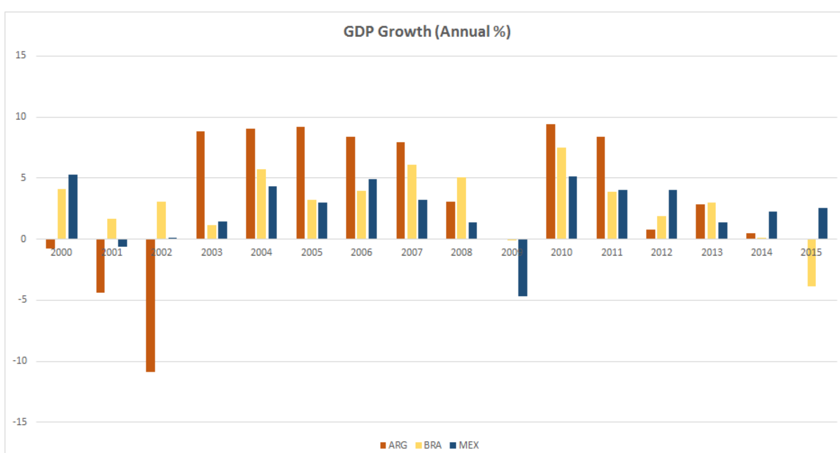

Figure 8. GDP Annual Growh Rate. Argentina, Brazil and Mexico. $2000 - 2015$.

5.2 US Great Recession, 2007 - 2009.

In this subsection we perform the DCC-GARCH analysis of the indices based on the NBER's reference dates for the US great recession, in $2007 - 2009$. Table 5 presents the descriptive statistics for all five indices' returns.

Table 6 displays the estimation results for the DCC (1,1) - GARCH (1,1) model. The results for the sums of coefficients α and β of the univariate GARCH models are the following: $\alpha_{ixtc}+\beta_{ixtc}=0.982$; $\alpha_{mxx}+\beta_{mxx}=0.993$; $\alpha_{merv}+\beta_{merv}=0.998$; $\alpha_{bvsp}+\beta_{bvsp}=0.961$. It is clear that the persistence of volatility is high for all indices, in the analyzed period. Moreover, the sum of the parameters of joint correlation $(a_{dcc1}+b_{dcc1})$ is equal to 0.920. The conclusion is that during the US great recession the *linkage effect* among the analyzed indices' returns was considerable high.

On the other hand, Figures $9-11$ show the evolution of the time-varying correlation between NASDAQ telecom index's returns and the returns of each stock market index. The conditional correlation is positive in all cases, however it shows more volatility than the conditional correlation in the analysis of the bust of telecommunications sector. In Figure 9 we observe that the conditional correlation between NASDAQ telecommunications index and Mexico's IPC reached its lowest level ($<40\%$) in may 2008, while two months latter it reached its highest level ($>80\%$). The case of Argentina's Merval is quite similar since the conditional correlation almost reached the 30% in may 2008 and touched its highest level in july of the same year (view Figure 10). Finally, the case of Brazil's Bovespa is the most extreme of the three indices. Figure 11 depicts a high volatility in time-varying conditional correlation, since it dropped below 20% in march 2008, while it grew above the 80% in june 2008.

Table 5. Descriptive statistics

	ixtc	**mxx**	**merv**	**bvsp**
$\overline{x}$	-0.000774	-0.000511	-0.000796	-0.000507
σ	0.029	0.023	0.031	0.030
skew	-0.012	0.536	0.051	0.191
kurt	4.952	6.245	10.968	5.874

Table 6. DCC-GARCH model estimation results, 2007 − 2009.				
	Estimate	**Std. Error**	**t-value**	**Pr(>| t |)**
μ_{ixtc}	0.000320	0.000937	0.34186	0.732460
a_{ixtc}	0.348681	0.239049	1.45862	0.144671
b_{ixtc}	-0.475657	0.225615	-2.10826	0.035008*
ω_{ixtc}	0.000014	0.000027	0.51318	0.607826
α_{ixtc}	0.092395	0.059191	1.56098	0.118528
β_{ixtc}	0.890295	0.020510	43.40722	0.000000*
$shape_{ixtc}$	13.672545	12.124037	1.12772	0.259437
μ_{mxx}	-0.001039	0.000824	-1.26086	0.207358
a_{mxx}	-0.973407	0.003854	-252.55597	0.000000*
b_{mxx}	1.000000	0.000365	2739.66800	0.000000*
ω_{mxx}	0.000009	0.000010	0.98655	0.323863
α_{mxx}	0.126363	0.046351	2.72620	0.006407*
β_{mxx}	0.867540	0.024710	35.10830	0.000000*
$shape_{mxx}$	4.690887	1.004117	4.67165	0.000003*
μ_{merv}	0.000173	0.000906	0.19078	0.848701
a_{merv}	0.149467	0.733188	0.20386	0.838464
b_{merv}	-0.183246	0.738632	-0.24809	0.804066
ω_{merv}	0.000026	0.000014	1.89744	0.057770
α_{merv}	0.184536	0.069961	2.63769	0.008347*
β_{merv}	0.814463	0.062142	13.10644	0.000000*
$shape_{merv}$	3.864744	1.021025	3.78516	0.000154*
μ_{bvsp}	0.000095	0.000907	0.10429	0.916941
a_{bvsp}	0.669669	0.134871	4.96524	0.000001*
b_{bvsp}	-0.750493	0.118613	-6.32721	0.000000*
ω_{bvsp}	0.000033	0.000019	1.74643	0.080736
α_{bvsp}	0.110668	0.037238	2.97187	0.002960*
β_{bvsp}	0.851084	0.048768	17.45156	0.000000*
$shape_{bvsp}$	8.026730	3.199428	2.50880	0.012114*
a_{dcc1}	0.053694	0.018025	2.97881	0.002894*
b_{dcc1}	0.867045	0.066947	12.95121	0.000000*
$shape_{joint}$	5.951424	0.787862	7.55389	0.000000*
Akaike: -21.022				

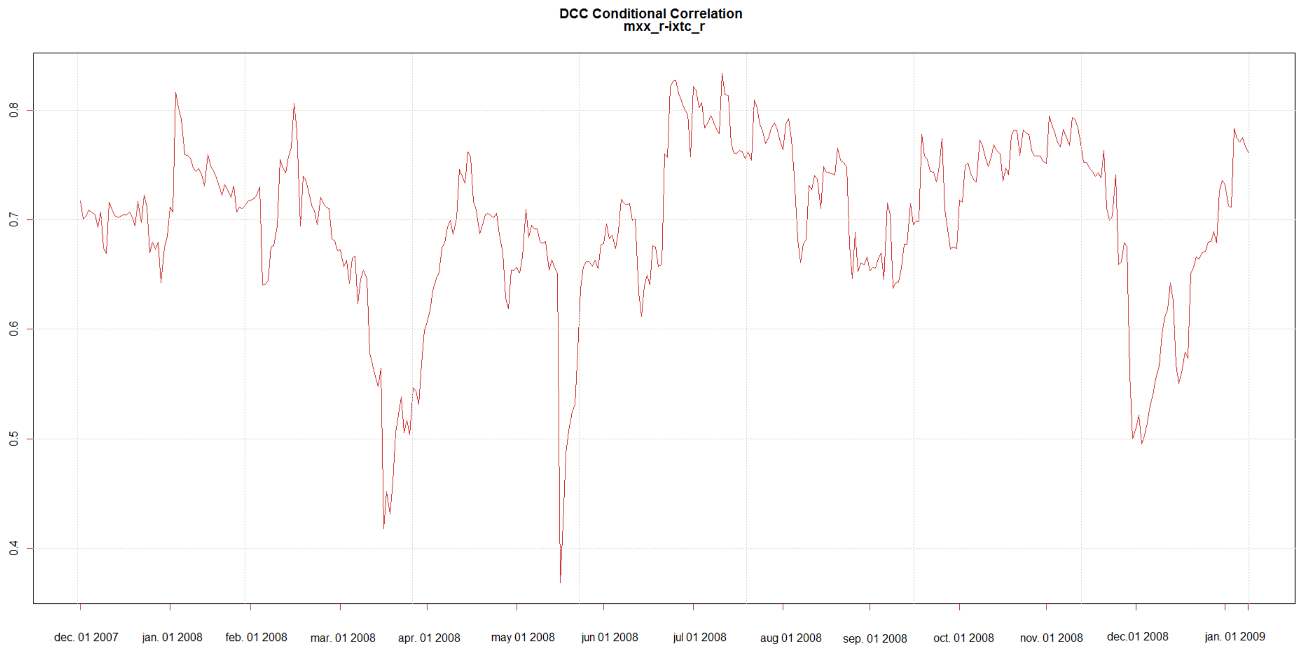

Figure 9. Dynamic Conditional Correlation between NASDAQ telecommunications index and IPC, 2007 – 2009.

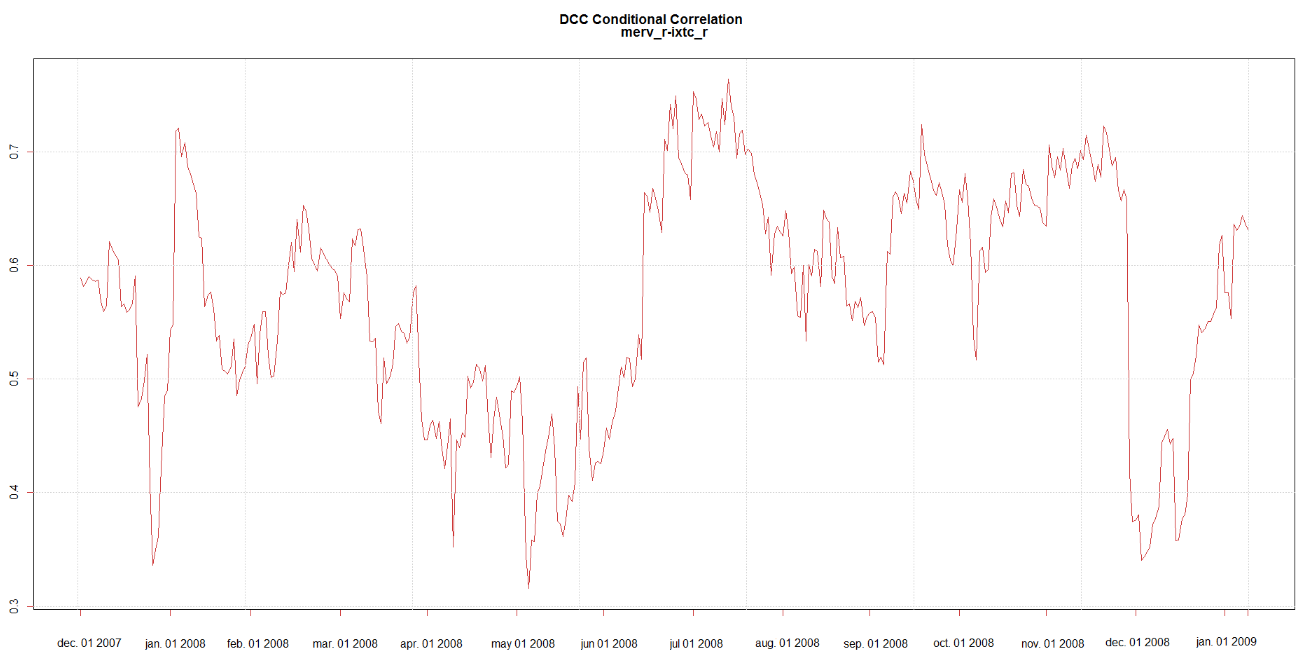

Figure 10. Dynamic Conditional Correlation between NASDAQ telecommunications index and Merval, 2007 – 2009.

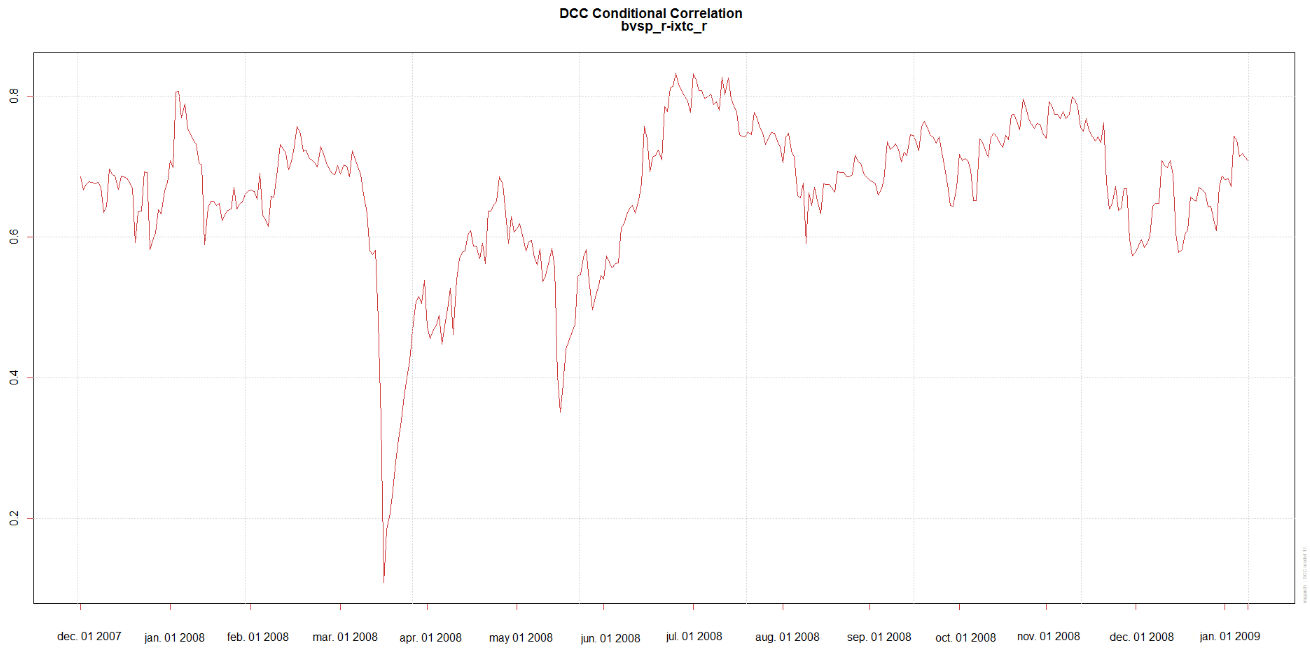

Figure 11. Dynamic Conditional Correlation between NASDAQ telecommunications index and Bovespa, 2007 – 2009.

6 Conclusions

This paper has investigated the relationship between the returns of the NASDAQ telecommunications index and stock market indices' returns of Argentina, Brazil and Mexico. Empirical results based on a DCC-GARCH model establish that there is a positive time-varying conditional correlation during both reference dates. However, the 2007 – 2009 period is much more volatile. Thus, we can conclude that all three national stock markets are strongly linked to the shocks over NASDAQ telecommunications index (maybe with the exception of Argentina's merval during 2001, but positive at the end), resultant from differentiated sources: *i*) an FCC's fuzzy regulatory initiative tended to improve competition in local phone services, and *ii*) the US great recession derived from financial disruptions and the bursting of asset bubbles in the housing market in 2007 – 2009. These findings are subject to different interpretations; however, for regulatory purposes it is relevant to emphasize the fact that an external policy decision-making generated an important contagion effect on Latin America's financial markets. Avenues for further research should consider an evaluation of Latin America's own policy decision's regulatory impacts on financial markets and, consequently, on the behavior of investments in their telecommunications sector.

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