



Munich Personal RePEc Archive

A CONDITIONAL CORRELATION ANALYSIS FOR THE COLOMBIAN STOCK MARKET

Sandoval Paucar, Giovanni

25 May 2021

Online at <https://mpra.ub.uni-muenchen.de/107963/>
MPRA Paper No. 107963, posted 26 May 2021 03:36 UTC

A CONDITIONAL CORRELATION ANALYSIS FOR THE COLOMBIAN STOCK MARKET¹

ABSTRACT

The article investigates the uncertainty and interdependence between the Colombian stock market and the main international markets. A Dynamic Conditional Correlation Model (DCC) is estimated to study the interdependence between selected stock markets and a GARCH model to analyze conditional volatility. To this end, a daily data sample is used, covering the period between January, 2001 and September, 2018. The results show that the subprime crisis period generates a significant positive effect on the conditional volatility. In addition, there is a significant co-movement in time between the Colombian stock market and national and international markets. Finally, I find evidence of financial contagion in periods of the subprime crisis and European debt.

Keywords: Dynamic conditional correlation, financial crises, multivariate GARCH, financial markets, interdependence.

JEL Classification: F36; F32; G15; C15.

1. Introduction

The increasing integration of stock markets has contributed to the unification of the economic and financial space, apparently stimulating the transmission of financial crises. These episodes of financial fragility have occurred with high frequency in recent years, causing strong collapses in the international financial system and impetuous falls in the economic activity of the economies involved (Eichengreen and Gupta, 2015). In turn, financial volatility accentuates the vulnerability of stock markets to financial contagion.

This research explores the interdependence between the Colombian stock index and major stock indices, taken from a sample of Latin American, Asian, European and North American countries. The analysis includes the period from January 2003 to August 2018. To do this, firstly, analyze the degree of basic interdependence between the prices of the selected

1 This article is based in the pre-print: “Modelación de la correlación condicional para el mercado bursátil colombiano: una aplicación de DCC – MGARCH”, “Análisis de correlación condicional. Evidencia para el mercado colombiano” and “Contagio Financiero: Una Breve Revisión De Literatura”, hosted on MPRA Paper and Documentos de Trabajo - CIDSE (Universidad del Valle).

assets using the rolling correlation coefficients. Second, measure the effect of crisis periods on the conditional volatility of the Colombian market. Finally, determine the existence of contagion or interdependence between the Colombian stock market and the rest of the markets during the recent financial crises.

The rest of the paper is organized as follows. The second section provides a brief account of the literature on financial contagion. The methodology based on dynamic correlation analysis is described in the third part. The fourth section presents the sources of information and time series. The fifth section summarizes the empirical results, focuses on the evidence of contagion, and the last part, presents the conclusions and implications of the research.

2. Literature review

The academic literature has devoted a great effort to the study of the transmission of financial shocks between markets. Empirical research on contagion is one of the most interesting questions in contemporary financial economics. Understanding the mechanisms of shock propagation at the international level is critical for practitioners and regulators (Rigobon, 2019). However, there is no consensus on the concept of financial contagion. The reasons are diverse, the definitions of contagion depend on the conceptual distinctions of the researchers over time, the model, their beliefs, the characteristics of the data, among others (Rigobon, 2019).

The most representative and accepted definition by most researchers on financial contagion is the definition of *shift-contagion* by Forbes and Rigobon (2002). These authors define contagion as a significant increase in market linkages after a specific shock in a particular country or region. In turn, they define interdependence as the situation of two markets that present a high degree of co-movement, that is, when a shock occurs, the markets continue to be highly linkages without a significant change in the relationship between them.

The research uses the definition proposed by Forbes (2002) to analyze financial contagion. On the other hand, the MGARCH methodology is used to analyze co-movement between markets. This methodology allows the impact of financial crises on market returns and volatilities, and especially on the dynamic correlations between markets, to be measured.

2.1 Theoretical literature

Rigobon (2019) suggests that, in recent years, research on the international propagation of shocks has evolved in three different currents of thought: fundamental, financial and coordination vision.

2.1.1 Fundamental View

In the fundamental view, shocks are transmitted through the real channels of the economy. In this category, the linkages economies exist through trade relations, exogenous shocks from a common factor and the coordination of macroeconomic policies (Rigobon, 2019). The main channels studied are trade relations (Corsetti, Pesenti, Roubini and Tille, 2000), macroeconomic policies (Drazen, 1998) and exogenous shocks (Corsetti, Pericoli and Straccia, 2005).

These theories were used to explain the mechanisms of propagation of the Great Depression and the transmission of financial crises in Europe during the 70's and 80's. In these crisis episodes, the commercial channel had very significant relevance in the transmission of shocks (Rigobon, 2019). Recently, Pavlova and Rigobon (2007) and Martin (2013) have studied the relationships between trade in goods and the price models of financial assets.

2.1.2 Financial View

In this view, shocks are transmitted through financial channels, derived from restrictions and inefficiencies in financial institutions and international financial markets. In this category, the cross-country linkages exist through the theory of common lender (Kaminsky & Reinhart, 1998), margin calls (Yuan, 2005), liquidity aspects (Calvo & Reinhart, 2000) or wealth effect (Kyle & Xiong, 2001). This vision was used to study the transmission of the shocks of the Asian Crisis in 1997, the Russian Crisis and the bankruptcy of LTCM in 1998.

The new theories in this category are related to network across financial institutions (Elliott, Golub & Jackson, 2014). Although, the transmission of financial shocks measured through network interconnections is a thriving branch of research, with many open questions (Rigobon, 2019). Recent authors have advanced in this category such as Panda and Nanda (2018), demonstrating strong linkages across the stock markets of Argentina, Brazil, Chile and Peru. Xu, Ma, Chen, and Zhang (2019) find that there is an asymmetric spillover effect across the oil market and the stock markets. Lastly, BenSaïda, Litimi and Abdallah (2018) show spillover effects across global financial markets.

2.1.3 Coordination View

In this last category, the transmission of financial shocks is based on coordination failure, related to problems of behavior and coordination between participants in financial

markets and economic policy makers. In this category, much of the propagation derived from investor decisions and it is generally learning or herd behavior problem. The main channels studied are multiple equilibrium (Masson, 1999), herding (Calvo & Mendoza, 2000), learning (Kodres and Pritsker, 2002) and political contagion (Drazen, 1998).

Thomas, Kashiramka and Yadav (2018) find that European stock markets show a higher degree of co-movement than Asia-Pacific markets. Pereira and Lagoa (2019) show the existence of contagion across the Irish and Portuguese markets during the crisis period of 2007-2013, especially in the European sovereign debt crisis. In turn, Jones and Collins (2019) show that the correlation changed to positive during the Great Recession and continued to be positive until the first half of 2017. Escobari and Jafarinejad (2019) demonstrate that investor uncertainty is higher during economic recessions, and is linked to lower investor confidence.

3. Methodology

The methodology contains three components. First, I use unobservable common factors to represent relevant financial indices for the Colombian market. Second, it analyzed the impact of the subprime crisis and the European debt crisis on the conditional volatility of the Colombian market. Finally, I study the correlations or interdependencies between the Colombian market and other markets.

3.1 Multidimensional indices

The construction of the multidimensional indices represents the non-observable common factors and is based on the Principal Component Analysis (PCA). The relationship between the observed series w_t and the unobservable factors z_t is explained by the model:

$$w_t = \alpha_t + Bz_t + e_t \quad (1)$$

where α_t is the intercept vector, B is the loading matrix and e_t is a random vector of the errors. It is assumed that the random vector e_t is not correlated with the latent variable z_t .

The elaboration of the indices contemplates the following steps. First, the stock markets are separated by common factors: G-7 Markets (I_{G7}), Europe and Oceania markets (I_{EO}), Asia markets (I_A) and Latin American markets (I_{AL}), as shown in table 1.

Table I. **Multidimensional Indices**

Multidimensional indices	Indices
G-7 Stock Markets (I_{G7})	SPX, CCMP, NKY, DAX, CAC, UKX, FTSEMIB, SPTSX
Stock Markets of Central Europe and Oceania (I_{EO})	SX5E, IBEX, AEX, OMX, SMI, AS51
Asia Stock Markets (I_A)	RTSI, NKY, HSI, SHSZ300, KOSPI, NIFTY, TWSE, JCI, FBMKLCI, STI
Latin American Markets (I_{AL})	MEXBOL, IBOV, IPSA, Merval, SPBLPGPT

Note: The table shows the composition of the multidimensional index in its 4 elements.

3.2 Conditional Volatility

In this paper, conditional volatility is represented through a GARCH model. Specifically, the adjusted model for the conditional volatility of the Colombian stock market is a GARCH model [1,1] such that:

$$r_t = c_{0t} + u_t, u_t / \Psi_{t-1} N(0, h_t) \quad (2)$$

$$h_t = \omega_{0i} + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \omega_{1i} D_{1t} + \omega_{2i} D_{2t} + \omega_{3i} D_{3t} \quad (3)$$

Ψ_{t-1} is the set of information available in $t-1$. r_t is the return of the Colombian market. h_t is the conditional variance of the Colombian market that follows a GARCH scheme (1,1). Variables D_{1t} , D_{2t} and D_{3t} , are dummy variables. Specifically, they are defining the periods of financial crises according to Baur (2012) and Lane (2012): D_{1t} represents the subprime crisis, taking the value 1 for the crisis period and 0 otherwise, D_{2t} represents the crisis of European debt, taking the value 1 for the crisis period and 0 otherwise and D_{3t} represents the set of both crises, taking the value 1 for the crisis period and 0 otherwise.

3.3 Dynamic conditional correlation (DCC)

A multivariate GARCH model is used that allows both the conditional mean and the conditional covariance to be dynamic. In this sense, the dynamic conditional correlation model is characterized by a type structure VAR (1), in which the conditional volatilities multi-equation follows the GARCH (1,1) scheme of dynamic correlation proposed by Engle (2002), which allows to introduce the effect of crisis periods on returns, variances and correlation conditions. This model can be written as follows:

$$r_{col} = \gamma + \phi r_{t-1} + \phi_{ij} r_{jt-1} + u_{1t}, j=1, \dots, k \quad (4)$$

$$\varepsilon_t = (u_{1t})' / \psi_{t-1} N(0, \Omega_t) \quad (5)$$

$$h_{col} = \omega_i + \alpha_i u_{t-1}^2 + \beta_{1i} h_{t-1} \quad (6)$$

$$h_{colj,t} = \eta_{ij} \sqrt{h_{it} h_{jt}}, \forall j = 1, \dots, k \quad (7)$$

$$\eta_{colj,t} = \rho_{ij} + \rho_1 D_{1t} + \rho_2 D_{2t} + \rho_3 D_{3t}, \forall j = 1, \dots, k \quad (8)$$

where the sub-index $j = (r_i^n, r_i^i, r_i^{AL}, r_i^{is})$. r_{col} is the return of the Colombian stock market. r_i^n are the returns of the national financial markets: Interest rate of the Colombian 10 years Government Bond (B_{col}), exchange rate Peso-US Dollar (TC_{col}) and Colombian Interbank Rate (TI_{col}). r_i^i are the G-7 stock indices: S&P500 (USA), Nikkei 225 (J Japan), DAX (Germany), CAC (France), FTSE 100 (UK), FTSE MIB (Italy) and S&P/TSX Composite (Canada). r_i^{AL} represents the Latin American indices: Mexbol (Mexico), Ibovespa (Brazil), IPSA (Chile), Merval (Argentina), SPBLPGPT (Peru). r_i^{is} symbolizes the indices: G-7 (I_{G7}), Europe and Oceania (I_{EO}), Asia (I_A) and Latin America (I_{AL}). u_{it} is the residual of the i th market. Ω_t is the covariance matrix of the errors in period t .

The parameters of the MGARCH DCC model are estimated by maximum likelihood. The unconcentrated logarithmic likelihood function based on the multivariate normal distribution for observation t is

$$l_t = -0.5 m \log(2\pi) - 0.5 \log\{\det(R_t)\} - \log\{\det(D_t^{\frac{1}{2}})\} - 0.5 \varepsilon_t R_t^{-1} \varepsilon_t \quad (9)$$

where $\varepsilon_t = D_t^{-\frac{1}{2}} \varepsilon_t$ is a vector of the standardized residuals $m \times 1$, $\varepsilon_t = y_t - Cx_t$. The log-likelihood function $\sum_{t=1}^T l_t$.

4. Data

This paper explores the financial contagion between the Colombian stock index and the main international stock indices. The analysis is performed from January 2003 to August 2018. The data source for the series of the financial markets is Bloomberg. Each of the variables is expressed in terms of the differences in the log prices of the assets. All series show the typical characteristics of stationarity (Augmented Dickey-Fuller test, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin).

The multidimensional index includes a sample of data from 29 stock markets for its preparation.

5. Results

5.1 Conditional volatility

This section shows the results of the estimation of the GARCH model (1,1) for the Colombian stock market, as shown in Table 2. This specification is a simple modeling of uncertainty using GARCH model models. In general terms, the coefficients of the variance equation are significant in the different estimated models, showing some degree of persistence of the ARCH effects (news shock). In turn, a significant effect of the subprime crisis is observed in the conditional volatility of the Colombian market. In contrast, when the model is extended to the joint effect of the subprime and European debt crises, the statistical significance is extends to the period of the European debt crisis, which shows that the conditional volatility of the Colombian market was significantly influenced by two periods, it is necessary to emphasize that the subprime crisis had a relatively greater influence.

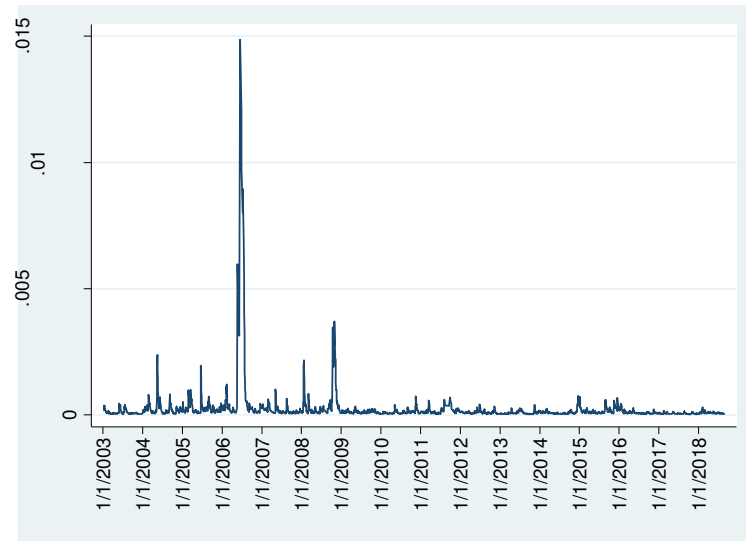
Table 2. Estimation results from GARCH (1,1) model

Estimates of Conditional Variance - No Crisis Periods					
Mean Equations			Variance Equations		
	const.		const.	arch(1)	garch(1)
r_{colcap}	0.0006 (0.0001) ***		6.21e-06 (6.25e-07) ***	0.224 (0.006) ***	0.762 (0.008) ***
Estimates of the Conditional Variance - Periods of Subprime and European sovereign debt Crisis					
Mean Equations			Variance Equations		
	D_1	D_2	const.	arch(1)	garch(1)
r_{colcap}	0.0012 (0.0003) ***	0.0003 (0.0004)	6.56e-06 (6.52e-07) ***	0.232 (0.006) ***	0.753 (0.008) ***
Estimates of the Conditional Variance – Joint period of financial crises					
Mean Equations			Variance Equations		
		D_3	const.	arch(1)	garch(1)
r_{colcap}		0.00082 (0.00026) ***	6.61e-06 (6.51e-07) ***	0.233 (0.006) ***	0.753 (0.008) ***

Note: The table presents the estimates of the GARCH (1,1) models in its three variants: No Crisis periods, subprime crisis and the European sovereign debt crisis, Joint period of financial crises. Asterisks denote significance at the level of * 90%, ** 95%, and *** 99%.

Figure 1 shows the temporal evolution of the conditional variance of the Colombian market. In general, a stationary behavior is observed, however, there are periods in which the conditional variance is very high, mainly during the subprime crisis, which indicates an increase in the uncertainty of the Colombian stock market around said dates.

Figure 1. Colcap conditional volatility



Note: The figure shows the conditional volatility for the Colcap index. In the subprime crisis period, conditional volatility increases significantly.

5.2 Dynamic Conditional Correlation (DCC)

Table 3 (Panels A, B and C) presents the estimation of the DCC-GARCH multivariate model. In Panel A, the results for national markets are presented. The constant term in the mean equation was statistically significant. The terms representing national markets in the mean equation was not statistically significant, only the bond market coefficient. Meanwhile, the lagged effect of the stock market was statistically significant and positive. This shows a moderate interdependence between national markets and the stock market. In the variance equation, the coefficients are significant, demonstrating the adequacy of the GARCH (1,1) specification. Furthermore, the sum of the coefficients is 0.981, demonstrating the persistence of volatility.

On the other hand, the coefficients of the DCC equations are statistically significant, indicating significant time-varying co-movement. In turn, the conditional correlations between national markets show a high persistence, the sum of the two coefficients is 0.978 during the sample period.

Panel B presents the estimation results with international markets. As in the national market model, the constant term in the mean equation was statistically significant. The effect of US market equity returns is significant, confirming the influential role of this stock market in emerging economies (Corsetti et al., 2005; Boyer, Kumagai & Yuan, 2006). In contrast, the equity returns of Germany, Japan, France, the United Kingdom, Italy and Canada had no significant effect on the returns of Colombian stocks. In the variance equation, the results

coincide with the national market model. Regarding the DCC equation, its coefficients are significant, indicating significant time-varying co-movement and high persistence.

Panel C shows the results for the international indices. As in previous models, the constant term in the mean equation was statistically significant. The influence of the indices of the G-7 countries (I_{G7}) and Europe and Oceania (I_{EO}) are significant, showing that the behavior of the Colombian market is affected by the stock markets of the G-7 countries, Europe and Australia. However, the stock markets in Asia and Latin America did not have a significant effect on the Colombian markets, this finding coincides with Panda and Nanda (2018). In the equation of variance, the results coincide with the previous models. As for the DCC equation, its coefficients are significant, indicating a significant time-varying co-movement and low persistence (0.38).

Panel D presents the results of the estimation with the Latin American markets. As in the other models, the constant term in the mean equation was statistically significant. The effects of stock returns from the Latin American markets are significant except for the Argentine and Peruvian markets, which confirms the influential role of these stock markets in the Colombian market (Panda & Nanda, 2018). In the equation of variance, the results coincide with the rest of the models. As for the DCC equation, its coefficients are significant, indicating a significant co-movement in time and high persistence.

Table 3. Estimation results from the DDC-GARCH models

Panel A. COLCAP - National Markets											
	Mean Equations					Variance Equations				Multivariate DDC Equation	
	const.	$r_{colcap(-1)}$	B_{col}	TC_{col}	TI_{col}	const.	arch(1)	garch(1)	Persistencia	A	B
r_{colcap}	0.0005 (0.000) ***	0.1199 (0.019) ***	0.0976 (0.013) ***	0.0001 (0.022)	0.0023 (0.006)	6.03e-06 (1.07e-06) ***	0.204 (0.017) ***	0.774 (0.018) ***	0.98	0.017 (0.003) ***	0.952 (0.008) ***
Quasi-Conditional Correlations											
	B_{col}	TC_{col}	TI_{col}								
r_{colcap}	-0.189 (0.026) ***	-0.246 (0.025) ***	-0.049 (0.029) **								
Panel B. COLCAP - G-7 Stock Indices											
Mean Equations											
	const.	ColCap	S&P500	Nikkei	DAX	CAC	FTSE100	FTSEMIB	S&P/TSX		
r_{colcap}	0.001 (0.000) ***	0.119 (0.019) ***	0.101 (0.024) ***	0.002 (0.011)	0.038 (0.028)	-0.057 (0.038)	-0.031 (0.029)	-0.003 (0.019)	0.026 (0.027)		
Variance Equations						Multivariate DDC Equation					
	const.	arch (1)	garch(1)	Persistence	A	B					
	6.50e-06	0.200	0.779	0.979	0.010	0.974					

1.35e-06 ***	(0.019) ***	(0.022) ***			(0.001) ***	(0.002) ***				
Quasi-Conditional Correlations										
	S&P500	Nikkei	DAX	CAC	FTSE100	FTSEMIB	S&P/TSX			
r_{colcap}	0.352 (0.025) ***	0.165 (0.028) ***	0.356 (0.025) ***	0.367 (0.025) ***	0.391 (0.025) ***	0.345 (0.024) ***	0.388 (0.025) ***			
Panel C. COLCAP – Multidimensional Indices										
	Mean Equations					Variance Equations				
	const.	ColCap(-1)	I_G7	I_EO	I_A	I_AL	const.	arch(1)	garch(1)	Persistence
r_{colcap}	0.001 (0.000) ***	0.119 (0.020) ***	0.038 (0.022) *	-0.040 (0.021) *	-0.007 (0.007)	0.029 (0.010) ***	8.12e-06 (1.65e-06) ***	0.198 (0.202) ***	0.764 (0.026) ***	0,962
	Quasi-Conditional Correlations					Multivariate DDC Equation				
	I_G7	I_EO	I_A	I_AL		A	B			
r_{colcap}	0.468 (0.036) ***	0.442 (0.036) ***	0.371 (0.042) ***	0.488 0.036 ***		0.004 (0.000) ***	0.991 (0.001) ***			
Panel D. COLCAP - Latin American Stock Indices										
	Mean Equations									
	const.	ColCap	Mexbol	Ibovespa	IPSA	Merval	SPBLPGPT			
r_{colcap}	0.001 (0.000) ***	0.129 (0.020) ***	0.069 (0.019) ***	0.035 (0.013) ***	-0.069 (0.019) ***	0.006 (0.009)	-0.014 (0.014)			
	Variance Equations			Multivariate DDC Equation						
	const.	arch (1)	garch(1)	Persistencia	A	B				
	7.24e-06 (1.51e-06) ***	0.203 (0.021) ***	0.775 (0.024) ***	0.978	0.007 (0.000) ***	0.989 (0.001) ***				
	Quasi-Conditional Correlations									
	Mexbol	Ibovespa	IPSA	Merval	SPBLPGPT					
r_{colcap}	0.473 (0.042) ***	0.472 (0.043) ***	0.469 (0.043) ***	0.383 (0.043) ***	0.382 (0.046) ***					

Note: The table presents the estimates of the DCC-GARCH models in their four variants. Panel A present the results for national markets. Panel B show the results for the G-7 stock indices. Panel C displays the estimates for the international indices. Panel D present values for the Latin American markets. Asterisks denote significance at the * 90%, ** 95%, and *** 99% level.

Figures 2, 3, 4 and 5 show the dynamic conditional correlations. A common characteristic of the correlation coefficients is the obtaining of their maximum values during the periods of the subprime crisis or the European sovereign debt crisis, suggesting the existence of contagion from these crises in the Colombian stock market. Figure 2 represents the dynamic conditional correlations between the Colcap index and the other Colombian financial markets, the results coincide with the unconditional correlation analysis, there is a negative relationship between them. For example, when the rate of Colombian bonds increases, the stock market

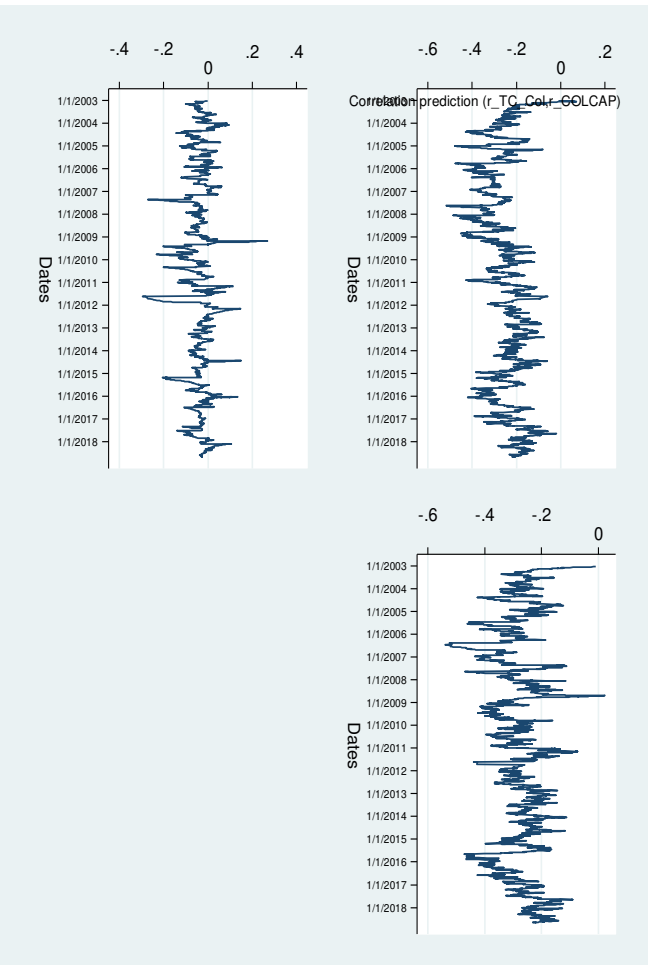
decreases to represent the decline in stock prices. When the exchange rate devalues, the Colcap index decreases, in part, due to the loss of confidence in the Colombian currency. On the other hand, the periods of greater correlation between the Colcap and the bond market occur between 2004 and 2009. In the case of Colcap and the exchange rate, the periods with the highest correlation are 2005-2007 and 2015-2017.

Figure 3 represents the dynamic conditional correlations between the Colcap index and the G-7 markets, the results show that the correlations of Colcap with these markets increase several times in the period from 2006 to 2012, suggesting that the interdependence between the markets increased or there was contagion during the two crisis periods: Subprime and European sovereign debt. Additionally, during the period of study the conditional correlation coefficient was always positive, indicating that the Colombian market is coupled with the main international stock indices, exposing it to their disturbances.

Figure 4 represents the dynamic conditional correlations between the Colcap index and the multidimensional indices. The findings show that the correlations between the Colcap and multidimensional indices increase in the 2006-2012 period, stronger with the Latin American index (I_{AL}) and to a lesser extent with the Asian index (I_A). A common feature in the correlation coefficients is an abrupt increase in 2006, reflecting the first symptoms of the subprime crisis. Especially, the Latin American index (I_{AL}) with which high levels of conditional correlation persist as of that period, strengthening the interdependence with these markets.

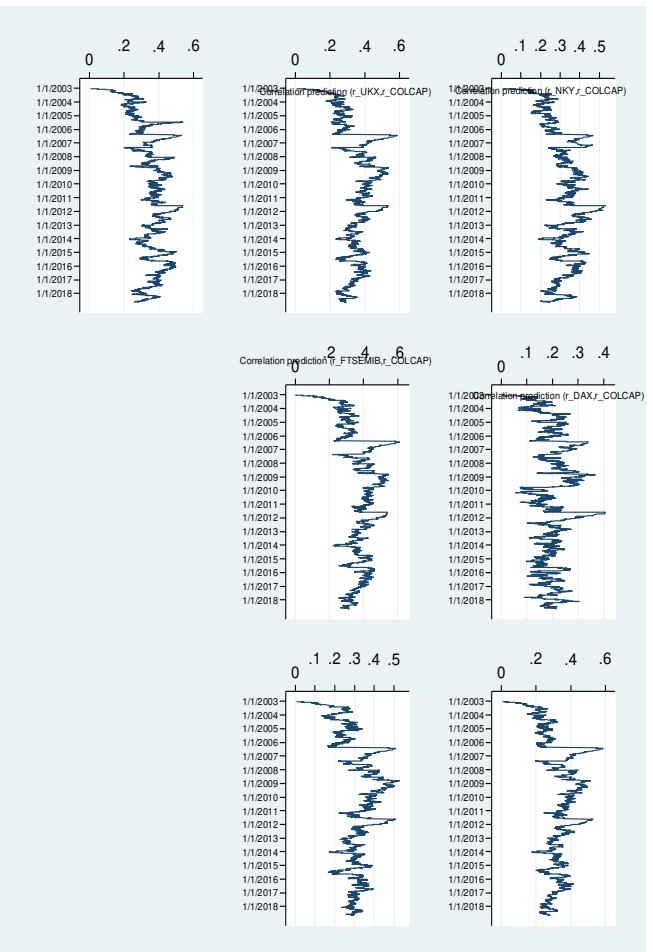
Figure 5 represents the dynamic conditional correlations between the Colcap index and Latin American indice. The results show that the correlations increase in the 2006-2018 period, except for the correlation with the Merval index that decreases strongly in the period 2012-2014. This result suggests a structural change in the conditional correlation with these markets and potential evidence of contagion from the Latin American indices on the Colombian Colcap index and the particularity of the Argentine index with which the conditional correlation reaches negative levels in 2005.

Figure 2. Dynamic Conditional Correlation. Colcap and national markets



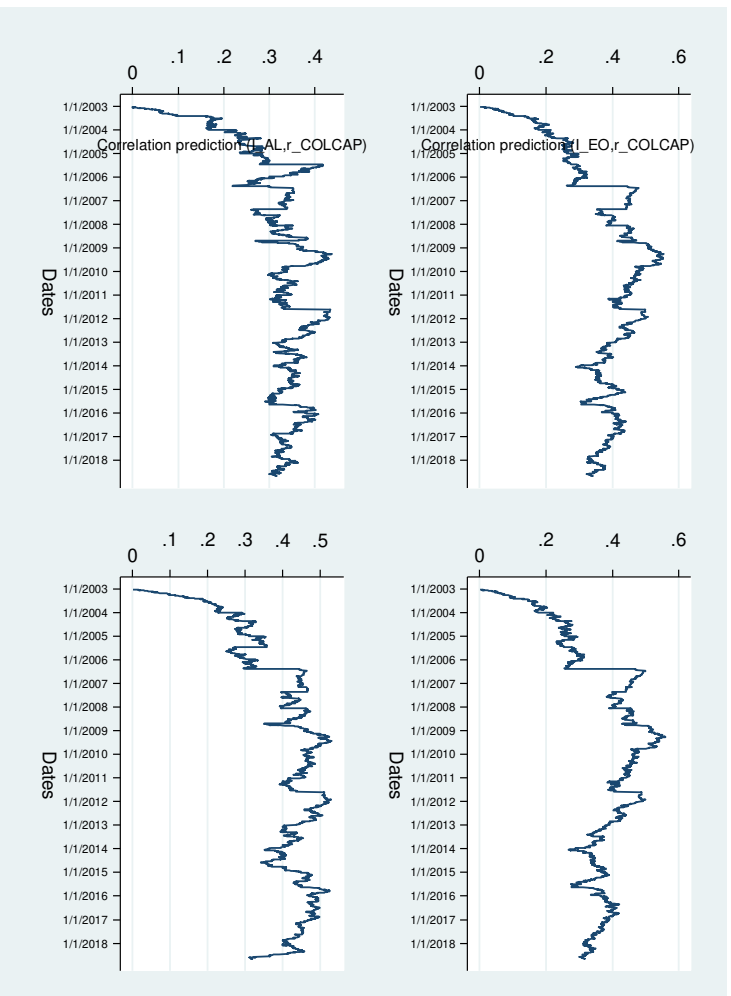
Note: The graph shows the dynamic conditional correlation between the Colcap index and national markets.

Figure 3. Dynamic Conditional Correlation. Colcap and G-7 markets



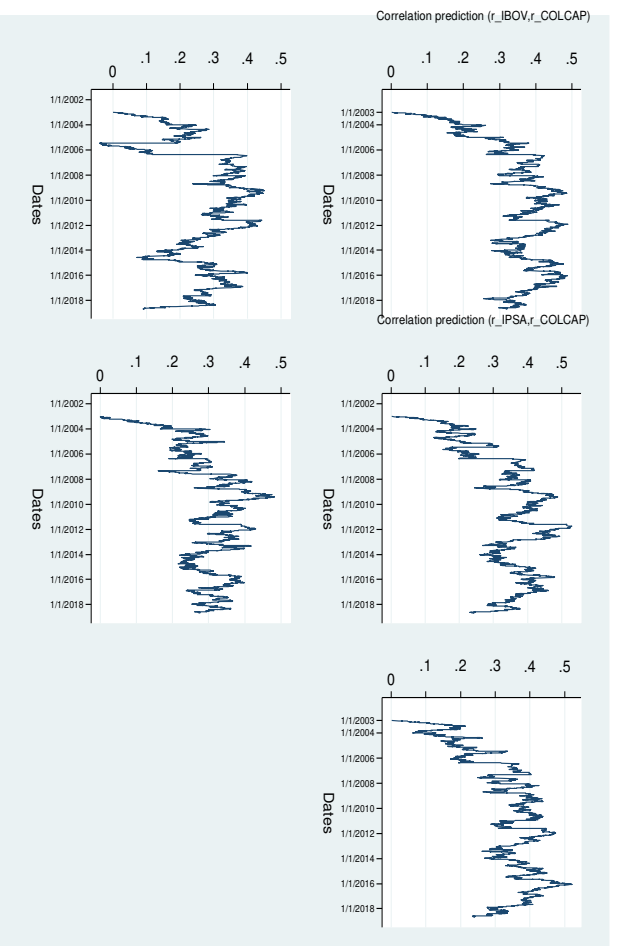
Note: The graph shows the dynamic conditional correlation between the Colcap index and G-7 markets.

Figure 4. Dynamic Conditional Correlation. Colcap and Multidimensional indices



Note: The graph shows the dynamic conditional correlation between the Colcap index and multidimensional indices.

Figure 5. Dynamic Conditional Correlation. Colcap and Latin American indice



Note: The graph shows the dynamic conditional correlation between the Colcap index and Latin american indice.

6. Conclusions

The strong links between international financial markets justify the aim of this paper, as has been indicated, it is none other than the study of short-term relationships between financial

markets, specifically the repercussions of international financial market disturbances on the Colombian stock market.

The findings reveal that the subprime and European sovereign debt crises infected Colombian stocks. In addition, they suggest evidence of a herd behavior in the Colombian stock index during the falls of global markets in financial crises.

Also, the dynamic conditional correlation between the Colombian stock market and national markets was generally negative during the study period, which suggests that the relations between Colombian markets conform to the general patterns of economic theory, for example, when the exchange rate decreases, the Colombian stock market increases, in part because of increased investor confidence in the Colombian economy.

Finally, the Colombian stock market presented a positive dynamic conditional correlation with international markets, which indicates that the behavior of the Colcap index tends in the same direction as international markets, making it difficult to diversify the risk of investors interested in Colombian stocks.

REFERENCES

- Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?. *Journal of Banking & Finance*, 35(1), 130-141. doi:10.1016/j.jbankfin.2010.07.021
- Baig, T., & Goldfajn, I. (1999). Financial Market Contagion in the Asian Crisis, *IMF Staff Papers*, 46(2), 167-195. doi:10.2307/3867666
- Baur, D. G. (2012). Financial contagion and the real economy. *Journal of Banking y Finance*, 36(10), 2680-2692. doi:10.1016/j.jbankfin.2011.05.019
- BenSaïda, A., Litimi, H., & Abdallah, O. (2018). Volatility spillover shifts in global financial markets. *Economic Modelling*, 73, 343-353. doi:10.1016/j.econmod.2018.04.011
- Calvo, G. A., & Mendoza, E. G. (2000). Rational contagion and the globalization of securities markets. *Journal of international economics*, 51(1), 79-113. doi:10.1016/S0022-1996(99)00038-0
- Caporin, M., Pelizzon, L., Ravazzolo, F. & Rigobon, R. (2018). Measuring sovereign contagion in Europe. *Journal of financial stability*, 34, 150-181. doi:10.1016/j.jfs.2017.12.004

- Corsetti, G., Pesenti, P., Roubini, N. & Tille, C. (2000). Competitive devaluations: toward a welfare-based approach. *Journal of International Economics*, 51(1), 217-241. doi:10.1016/S0022-1996(99)00043-4.
- Corsetti, G., Pericoli, M., & Sbracia, M. (2005). 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, 24(8), 1177-1199. doi:10.1016/j.jimonfin.2005.08.012.
- Drazen, A. (1998). Political Contagion in Currency Crisis. En P. Krugman. (Ed.) *Currency Crises* (pp. 47–67). Cambridge, UK: University of Chicago Press.
- Edwards, S. (1998). *Interest Rate Volatility, Capital Controls and Contagion*, Working Paper, 6756. National Bureau of Economic Research. doi:10.3386/w6756
- Ehrmann, M., Fratzscher, M., & Rigobon, R. (2011). Stocks, bonds, money markets and exchange rates: measuring international financial transmission. *Journal of Applied Econometrics*, 26(6), 948-974. doi:10.1002/jae.1173
- Eichengreen, B. & Gupta, P. (2015). Tapering talk: The impact of expectations of reduced Federal Reserve security purchases on emerging markets. *Emerging Markets Review*, 25, 1-15. doi:10.1016/j.ememar.2015.07.002
- Elliott, M., Golub, B., & Jackson, M. O. (2014). Financial networks and contagion. *American Economic Review*, 104(10), 3115-53. doi:10.1257/aer.104.10.3115
- Escobari, D. & Jafarinejad, M. (2019). Investors' Uncertainty and Stock Market Risk. *Journal of Behavioral Finance*, 20(2), 177-189. doi:10.1080/15427560.2018.1506787.
- Forbes, K., & Rigobon, R. (2001). Contagion in Latin America: Definitions, measurement, and policy implications. *Economía Journal*, 1(2), 1-46. Recuperado de www.jstor.org/stable/20065404
- Forbes K. J. & Rigobon R. (2002). No contagion, only interdependence: measuring stock market co-movements. *Journal of Finance*, 57(5): 2223–2261. doi:10.1111/0022-1082.00494.
- Hamao, Y., Masulis, R., & Ng, V. (1990). Correlations in Price Changes and Volatility across International Stock Markets. *The Review of Financial Studies*, 3(2), 281-307. Recuperado de <https://www.jstor.org/stable/2962024>
- Jones, P. M. & Collins, L. (2019). A change in the time-varying correlation between oil prices and the stock market. *Applied Economics Letters*, 26(7), 537-542. doi:10.1080/13504851.2018.1488037
- Kaminsky, G. L., & Reinhart, C. (1998). On Crises, Contagion, and Confusion. *Journal of International Economics*, 51(1), 145-168. doi:10.1016/S0022-1996(99)00040-9

- King, M., & Wadhvani, S. (1990). Transmission of Volatility between Stock Markets. *The Review of Financial Studies*, 3(1), 5-33. doi:10.1093/rfs/3.1.5
- Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, 21(1), 92-106. doi:10.1016/j.intfin.2010.08.005
- Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *The Journal of Finance*, 57(2), 769-799. doi:10.1111/1540-6261.00441
- Kyle, A. S., & Xiong, W. (2001). Contagion as a wealth effect. *The Journal of Finance*, 56(4), 1401-1440. doi:10.1111/0022-1082.00373
- Lane, P. R. (2012). The European sovereign debt crisis. *Journal of Economic Perspectives*, 26(3), 49-68. doi:10.1257/jep.26.3.49
- Martin, I. (2013). The lucas orchard. *Econometrica*, 81(1), 55-111. doi:10.3982/ECTA8446
- Masson P. (1999). Contagion: macroeconomic models with multiple equilibria. *Journal of International Money and Finance*, 18(4), 587-602. doi:10.1016/S0261-5606(99)00016-9
- Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, 19, 1-17. doi:10.1016/j.ememar.2014.04.002
- Nakamura, E., & Steinsson, J., (2018). High frequency identification of monetary non-neutrality: The Information. *The Quarterly Journal of Economics*, 133(3), 1283-1330. doi:10.1093/qje/qjy004
- Panda, A. K., & Nanda, S. (2018). Time-varying synchronization and dynamic conditional correlation among the stock market returns of leading South American economies. *International Journal of Managerial Finance*, 14(2), 245-262. doi:10.1108/IJMF-11-2016-0206
- Pavlova, A., & Rigobon, R. (2007). Asset prices and exchange rates. *The Review of Financial Studies*, 20(4), 1139-1180. doi:10.1093/revfin/hhm008
- Pereira, I. P. & Lagoa, S. (2019). Flight-to-quality and contagion in the European sovereign debt crisis: The cases of Portugal and Greece. *Journal of Financial Economic Policy*, 11(2), 264-274. doi:10.1108/JFEP-03-2018-0048
- Pontines, V., & Siregar, R. Y. (2009). Tranquil and crisis windows, heteroscedasticity, and contagion measurement: MS-VAR application of the DCC procedure. *Applied Financial Economics*, 19(9), 745-752. doi:10.1080/09603100802167239

- Rigobon R. (2019). Contagion, spillover and interdependence. *Economía Journal*, 19(2), 69-99. Recuperado de <https://muse.jhu.edu/article/722873/pdf>
- Rigobon, R., & Sack, B. (2008). Noisy macroeconomic announcements, monetary policy, and asset prices. En J. Y. Campbell (Ed), *Asset prices and monetary policy* (pp. 335-370). Cambridge, UK: University of Chicago Press.
- Rodríguez, J. C. (2007). Measuring Financial Contagion: A Copula Approach. *Journal of Empirical Finance*, 14(3), 401–423. doi: 10.1016/j.jempfin.2006.07.002
- Syllignakis, M. N., & Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance*, 20(4), 717-732. doi:10.1016/j.iref.2011.01.006
- Thomas, N. M., Kashiramka, S. & Yadav, S. S. (2018). The nature and determinants of comovement between developed, emerging and frontier equity markets: Europe versus Asia-Pacific. *Thunderbird International Business Review*, 61, 291-307. doi: 10.1002/tie.22015
- Yuan, K. (2005). Asymmetric price movements and borrowing constraints: A rational expectations equilibrium model of crises, contagion, and confusion. *The Journal of Finance*, 60(1), 379-411. doi: 10.1111/j.1540-6261.2005.00733.x
- Xu, W., Ma, F., Chen, W., Zhang, B. (2019). Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States. *Energy Economics*, 80, 310-320. doi: 10.1016/j.eneco.2019.01.014