Intensity of Financial Crises in Latin America: A Parametric and Non-Parametric Approach

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- Lehman Brothers bankruptcy and global financial crisis.
- ALM and liquidity position.
- Portfolio management and optimization.
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Motivation

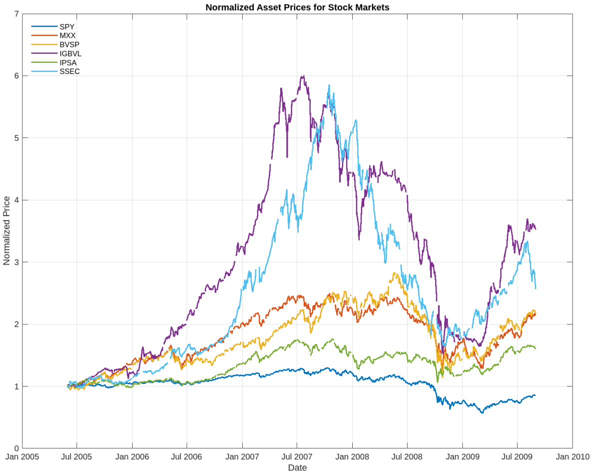


Figure: Normalized prices for stock index, 2005-2010

Motivation

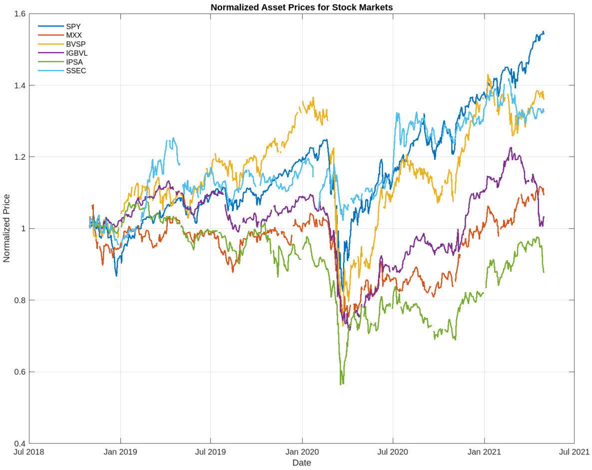


Figure: Normalized prices for stock index, 2018-2021

Motivation

Interdependence

If the comovement does not increase significantly, then any continued high level of market correlation suggests strong linkages between the two economies that exist in all states of the world.

Contagion

If two markets show a high degree of comovement during periods of stability, but cross-market comovement increases significantly after the shock.

Literature review

- Not contagion, only interdependence - Forber and Rigobon (2002).
- Structural changes in markets - Chiang et al. (2007).
- Linked by macroeconomic fundamentals - Celik (2012).
- Threshold in markets - Rodríguez and Perrotini (2019).
- Geographic factors - Cubillos-Rocha et al. (2019).
- Emerging markets against developed markets - Benkraiem et al. (2022).

DCC-GARCH

The multivariate GARCH model assume that returns from k assets are conditionally multivariate normal with zero expected value and covariance matrix H_t. Thus:

$$r_t|\mathcal{F}_{t-1} \sim \mathcal{N}\left(0, H_t\right) \tag{1}$$

and

$$H_t \equiv D_t R_t D_t \tag{2}$$

where D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from each univariate GARCH model with $\sqrt{h_{i,t}}$ on the i^{th} diagonal, and R_t is the time-varying correlation matrix.

DCC-GARCH

The log-likelihood of this estimator can be written as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(k\log\left(2\pi\right) + \log\left(\left|H_t\right|\right) + r_t^{'}H_t^{-1}r_t\right) \tag{3}$$

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(k\log\left(2\pi\right) + \log\left(\left|D_t R_t D_t\right|\right) + r_t^{'}D_t^{-1}R_t^{-1}D_t^{-1}r_t\right) \tag{4}$$

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left(k\log\left(2\pi\right) + 2\log\left(D_t\right) + \log\left(R_t\right) + \epsilon_t^{'}R_t^{-1}\epsilon_t\right) \tag{5}$$

where $\epsilon_t \sim \mathcal{N}\left(0, R_t\right)$ are the residuals standardized by their conditional standard deviation.

DCC-GARCH

The elements of D_t comes from a univariate GARCH model, thus:

$$h_{i,t} = \omega_i + \sum_{p=1}^{P_i} \alpha_{i,p} r_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{i,q} h_{i,t-q} \tag{6}$$

Properties

- $\omega_i > 0$.
- $\alpha_{i,p} \in [1, ..., P_i]$ and $\beta_{i,q} \in [1, ..., Q_i]$ are such that $h_{i,t}$ will be positive with probability one.
- Non-negativity of variances.
- Stationary: $\sum_{p=1}^{P_i} \alpha_{i,p} + \sum_{q=1}^{Q_i} \beta_{i,q} < 1$.

DCC-GARCH

Then the dynamic correlation structure is:

$$Q_t = \left(1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n\right) \bar{Q} + \sum_{m=1}^{M} \left(\epsilon_{t-m} \epsilon_{t-m}^{'}\right) + \sum_{n=1}^{N} \beta_n Q_{t-n} \quad (7)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (8)$$

where $\bar{Q}$ is the unconditional covariance of standardized residuals resulting from the first stage estimation. Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t.

Copula

Let $x_1, x_2, \ldots, x_n$ random variables with marginal distributions $u_1 = F_1(x_n), u_2 = F_2(u_2), \ldots, u_n = F_n(u_n)$, then the copula function is defined as:

$$F\left(x_1, x_2, \cdots, x_n\right) = C\left(u_1, \cdots, u_n\right) \forall C : \mathbb{I}^n \rightarrow \mathbb{I} = [0, 1] \tag{9}$$

Types of Copulas

- Archimedean copulas (Gumbel, Clayton and Frank).
- Elliptical copulas (Normal and T-student).

Clayton Copula

- If we are particularly concerned with extreme values, which is the characteristic of any shock, we can use the concept of tail dependence.
- Among different pair-copula families, Clayton's is preferred for financial data since it allows for more asymmetric tail dependence in the negative tail. Then the bivariate copula can be expressed as:

$$C\left(u_1, u_2\right) = \left(u_1^{-\theta} + u_2^{-\theta} - 1\right)^{-1/\theta} \ \forall\theta \neq 0 \tag{10}$$

- θ is the parameter of the copula. When $\theta \to \infty$ exists the Clayton copula implies comonotonicity and $\theta \to 0$ implies independence between u_1 and u_2.

Clayton Copula

We use τ Kendall's from Clayton's copula to measure the intensity of financial contagion between two markets. Thus:

$$\tau_c\left(x_1, x_2\right) = 1 - 4\int_{\mathbb{I}^2} \frac{\partial C(u_1.u_2)}{\partial u_1}\frac{\partial C(u_1.u_2)}{\partial u_2}dx_1dx_2 \tag{11}$$

- Intensity Test:

$$\begin{cases} \Delta\tau_{A-B} = (\tau_1^A - \tau_2^A) \leq (\tau_1^B - \tau_2^B) \\ \Delta\tau_{A-B} = (\tau_1^A - \tau_2^A) > (\tau_1^B - \tau_2^B) \end{cases} \tag{12}$$

Data

1. To explore the contagion effect between the United States and China to Latin America emerging markets. Stock market indexes were selected as data samples.
   - Developed markets: S&P500 and SSEC.
   - Emerging markets: Bovespa, IPSA, IPyC and IGBVL.
2. The daily closing prices of these markets were collected from Bloomberg.
3. All closing-price series were nonstationary, so the closing-price series were transformed into return series of these selected stock markets.

Multivariate GARCH

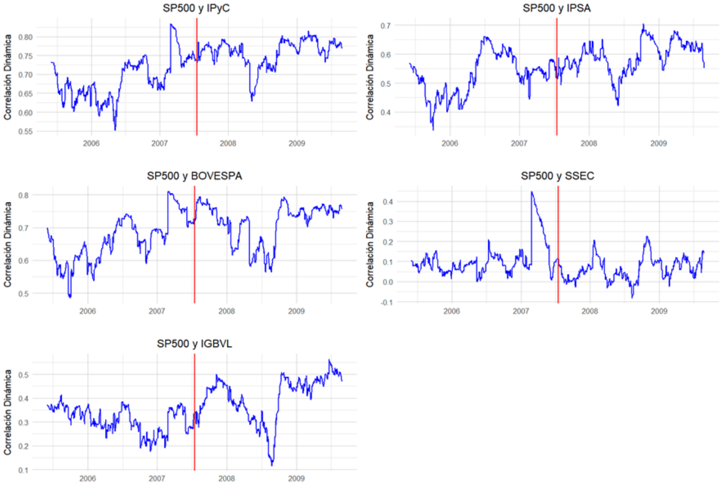
Table: Dynamic Conditional Correlation GARCH

	Global Financial Crisis						
	μ	AR(1)	MA(1)	ω	α	β	$\alpha + \beta < 1$
SP500	0.0004***	0.6931***	-0.7851***	0.0000	0.0953	0.9036***	0.9986
	(0.0002)	(0.0711)	(0.0604)	(0.0000)	(0.1741)	(0.1475)	
IPyC	0.0011***	-0.4092	0.4880	0.0000	0.1018***	0.8808***	0.9826
	(0.0004)	(0.3093)	(0.2972)	(0.0000)	(0.0168)	(0.0178)	
Bovespa	0.0014***	-0.9013***	0.8954***	0.0000***	0.0768***	0.9068***	0.9836
	(0.0005)	(0.0841)	(0.0849)	(0.0000)	(0.0161)	(0.0205)	
IPSA	0.0009***	-0.1935	0.3569***	0.0000	0.1694***	0.8117***	0.9811
	(0.0002)	(0.1911)	(0.1791)	(0.0000)	(0.0278)	(0.0268)	
SSEC	0.0019***	0.0073	-0.0246	0.0000	0.0803***	0.9186	0.9989
	(0.0005)	(0.2071)	(0.2038)	(0.0000)	(0.0445)	(0.0446)	
IGBVL	0.0019***	0.1563	0.0491	0.0000	0.3079***	0.6910***	0.9989
	(0.0004)	(0.1999)	(0.1965)	(0.0000)	(0.0620)	(0.0485)	
Akaike Information Criteria	-36.680						
Bayes Information Criteria	-36.373						
N	1070						
Series	6						
Distribution: multivariate t-student							

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

DCC-GARCH

Figure: Conditional correlation during global financial crisis



DCC-GARCH

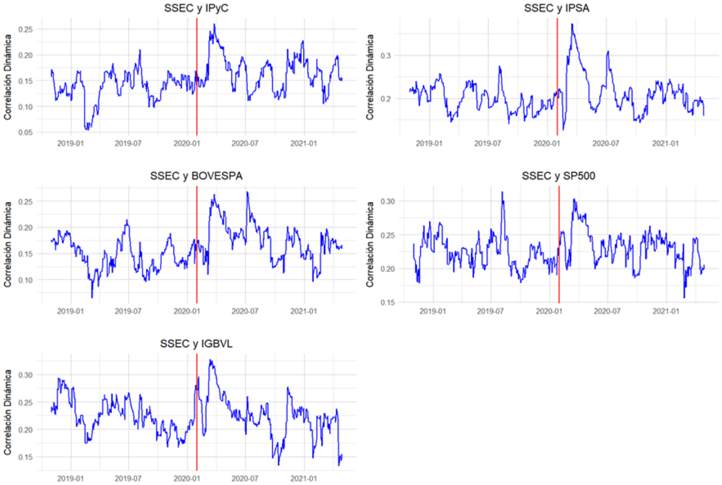
Table: Dynamic Conditional Correlation GARCH

	Global Financial Crisis						
	μ	AR(1)	MA(1)	ω	α	β	$\alpha + \beta < 1$
SP500	0.0011***	0.8082***	-0.8983***	0.0000	0.1692***	0.8078***	0.9770
	(0.0001)	(0.1045)	(0.0822)	(0.0000)	(0.0406)	(0.0414)	
IPyC	0.0002	-0.2622	0.3640*	0.0000	0.1145	0.8450***	0.9595
	(0.0005)	(0.2217)	(0.2031)	(0.0000)	(0.1425)	(0.1864)	
Bovespa	0.0009**	0.5535***	-0.6374	0.0000***	0.1381***	0.8099***	0.9480
	(0.0005)	(0.0841)	(0.0849)	(0.0000)	(0.0161)	(0.0205)	
IPSA	-0.0003	0.0653	0.0682	0.0000	0.1628***	0.8361***	0.9989
	(0.0004)	(0.1488)	(0.1437)	(0.0000)	(0.0539)	(0.0586)	
SSEC	0.0005	0.5034**	-0.4768**	0.0000	0.0755***	0.8844***	0.9599
	(0.0004)	(0.1989)	(0.1913)	(0.0000)	(0.0161)	(0.0179)	
IGBVL	0.0003	-0.7452***	0.6945***	0.0000	0.1546***	0.8207***	0.9989
	(0.0003)	(0.0718)	(0.0735)	(0.0000)	(0.0453)	(0.0450)	
Akaike Information Criteria	-38.377						
Bayes Information Criteria	-37.909						
N	627						
Series	6						
Distribution: multivariate t-student							

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

DCC-GARCH

Figure: Conditional Correlation during Covid19



Kolmogorov-Smirnov Test

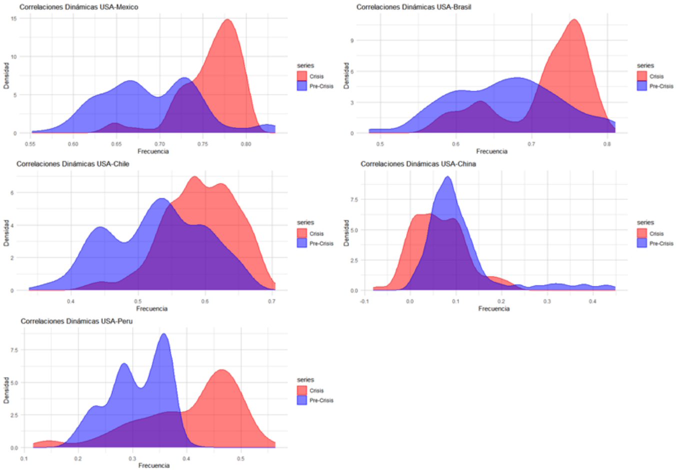
Table: Kolmogorov-Smirnov Test

Financial Crisis	KS test	p value	Covid19	KS test	p value
SP500-IPyC			**SSEC-IPyC**		
Upper	0.6112	0.0000	Upper	0.4042	0.0000
Lower	0.0392	0.4385	Lower	0.0000	0.9999
Two-sided	0.6112	0.0000	Two-sided	0.4042	0.0000
SP500-IPSA			**SSEC-IPSA**		
Upper	0.4168	0.0000	Upper	0.1560	0.0004
Lower	0.0000	0.9999	Lower	0.0445	0.5370
Two-sided	0.4168	0.0000	Two-sided	0.1560	0.0009
SP500-Bovespa			**SSEC-Bovespa**		
Upper	0.4579	0.0000	Upper	0.3715	0.0000
Lower	0.0411	0.4047	Lower	0.0000	0.9999
Two-sided	0.4579	0.0000	Two-sided	0.3715	0.0000
SP500-SSEC			**SSEC-SP500**		
Upper	0.0000	0.9999	Upper	0.2156	0.0000
Lower	0.3236	0.0000	Lower	0.0095	0.9718
Two-sided	0.3332	0.0000	Two-sided	0.2156	0.0000
SP500-IGBVL			**SSEC-IGBVL**		
Upper	0.6336	0.0000	Two-sided	0.0811	0.1269
Lower	0.0336	0.5457	Lower	0.1146	0.0162
Two-sided	0.6336	0.0000	Upper	0.1143	0.0325

Nota: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

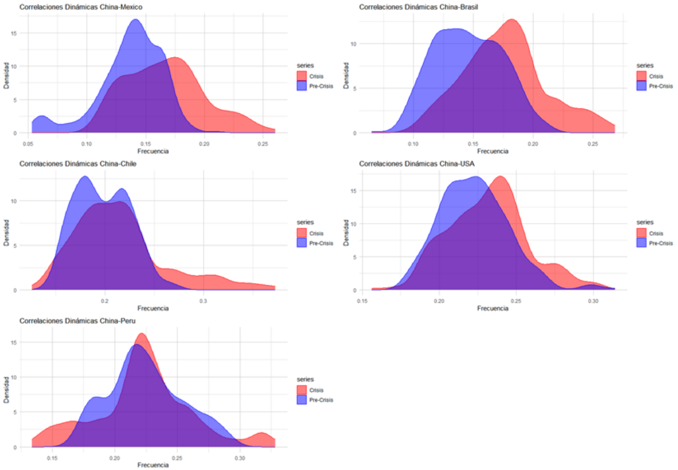
Distribution of DCC

Figure: Distribution ex-ante and ex-post global financial crisis



Distribution of DCC

Figure: Distribution ex-ante and ex-post pandemic crisis



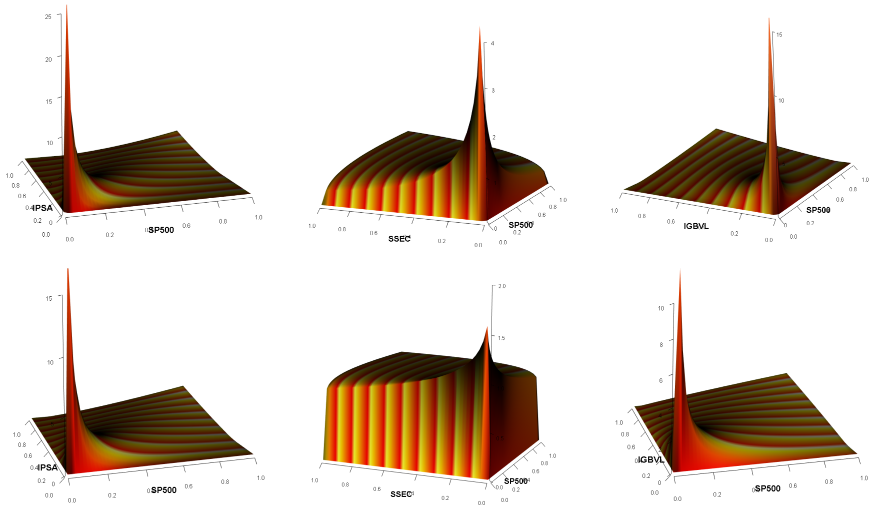
Measuring intensity of financial contagion

Table: Resultados de la estimación y selección de umbrales

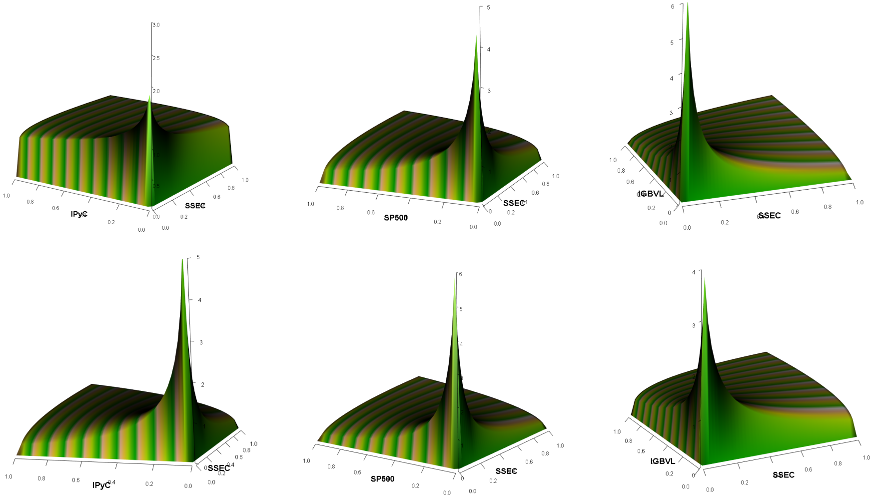
	Kendall's (τ)						
	ex-ante	*ex-post*	$\Delta\tau^A$		*ex-ante*	*ex-post*	$\Delta\tau^b$
SP500-BVSP	0.5631	0.5530	-0.0101	SSEC-BVSP	0.0516	0.1348	0.0832
SP500-IPyC	0.5361	0.5791	0.0430	SSEC-IPyC	0.0455	0.1730	0.1275
SP500-SSEC	0.1466	0.0326	-0.1140	SSEC-SP500	0.1441	0.1911	0.0470
SP500-IPSA	0.5089	0.4161	-0.0928	SSEC-IPSA	0.1076	0.1281	0.0205
SP500-IGBVL	0.3928	0.3202	-0.0726	SSEC-IGBVL	0.1992	0.1289	-0.0703

Stock Market	Global Financial Crisis	Covid19
BVSP		✓
IPyC		✓
IPSA		✓
IGBVL	✓	

Bivariate Copula - Global Financial Crisis



Bivariate Copula - Covid19



Conclusion

- Financial institutions had outstanding portfolios in toxic assets.
- The impact of each crisis on markets depended on the timely implementation of monetary and fiscal policies, which mitigated financial frictions and shielded the real economy.
- Effective trading strategies are key in a crisis, as poor risk management in structured asset portfolios can heighten contagion and credit risks.
- New empirical approach based on TGARCH models, Markov Chain and Machine Learning.