Interdependency and Asymmetric Relationship of Credit Default Swap: Latin America Evidence

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Abstract

This paper investigates the co-movement of CDS in different countries by employing a second order vector autoregressive model fitting with a DCC GARCH process proposed. Our binary results show that the correlation between each group of two countries is strongly significant and the variance of residuals from VAR model is highly persistent over time. Our results also provide evidence that change of CDS spreads in Brazil, Mexico and Panama have the most important effect on the change of CDS spreads in other countries. Finally we employ a model proposed by Daigler et al (2014) to exploit and confirm the persistency and asymmetric relationship of the volatility of CDS. We confirm that the volatility is very persistent and four countries-Brazil, Mexico, Venezuela and Panama have asymmetric volatility which also indicates a possible mean reversion trend.

JEL classification: G13

Keywords: Credit Default Swap (CDS), DCC GARCH, Vector Autoregressive (VAR)

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1. Introduction

Credit derivatives are financial contracts whose payoffs depend on whether some credit entity defaults on its debt. Traded are many different varieties of credit default swap (CDS), credit derivatives on baskets, and collateralized default obligation. This market has been growing dramatically for the past two decades. In 2007, it is estimated that outstanding notional in credit derivatives to be over 62 trillion dollars where at the same time equity market is only about 10 trillion dollars. In the mean time the literature about CDS is sparse before 2003 because of the data limitation. Started from Hull et al (2004), they investigate how credit default spreads is related to bond yields and they reached conclusions on the benchmark risk-free rate and credit rating on the announcement date. Blanco et al (2005) investigate the dynamic relationship between bond and CDS. Norden and Weber (2009) also study the co-movement among stock market, bond and CDS. More attentions have been paid to this growing research area in finance.

This paper investigate the co-movement of CDS in different countries by employing a second order vector autoregressive model fitting with a DCC GARCH process proposed by Engle (2002). Our binary results show that correlation between each two countries are strongly significant and the variance of residuals from VAR model is very persistent over time. The multivariate DCC GARCH model also show the consistent results. Our results provide the evidence that change of CDS from Brazil, Mexico and Panama have the most important effect on change of CDS in other countries. The positive change of CDS in Brazil and Mexico will lead to positive change of CDS in other countries. The positive change of CDS in Panama will lead to negative change of CDS in other countries. We also employ a model proposed by Daigler et al (2014) to exploit and confirm the persistency and asymmetry relationship of volatility of CDS. We confirm that the volatility is very persistent and four countries-Brazil, Mexico, Venezuela and Panama have asymmetric volatility which also indicates a possible mean reversion trend.

This paper contributes at least three strands to the literature about interdependency and co-movement of CDS. First of all, we employ a VAR model fitting with DCC GARCH which is one step further about methodology used for co-movement analysis. Previous analysis used simple VAR or error correction model to implement the co-movement of varieties series. DCC GARCH would show a dynamic moving correlation among different variables. Secondly, this is the first paper study the co-movement of CDS among different countries. Previous literature focus on interdependency or co-movement analysis between CDS and other economic variables. Finally this paper enlarge the current literature about asymmetric relationship of volatility; we find that the volatility for change of CDS also exist an asymmetric relationship and the volatility is very persistent.

The rest of the paper is organized as follow. Section 2 we provided a brief literature overview about CDS and co-movement. Section 3 described the data and summary statistics. Section 4 provides the VAR DCC GARCH model estimated results. Section 5 provides the alternative and robustness tests. Finally section 6 concludes.

2. Literature Review about CDS and Comovement

Blanco et al (2005) test the theoretical equivalence of credit default swap (CDS) prices and credit spreads originally derived by Duffie (1999), finding support for the parity relation as an equilibrium condition. They also find two forms of deviation from parity. First, for three firms, CDS prices are substantially higher what they are supposed to be over long periods of time, they are arguing the mispricing are mainly because of imperfect contract specification and the measurement errors when computing the credit default spread. Second, they find short-lived deviations from parity for all other companies due to a lead for CDS prices over credit spreads in the price discovery process. Narayanan and Uzmanoglu (2013) empirically show that credit spreads –the credit risk component of bond yields –are positively related with CDS exposure, proxied by the amount of CDS contracts outstanding per dollar of total debt. This result shows the evidence that the costs of CDS exceed the benefits. And the effect are significant only when the creditors are over issued. In addition, they found that the benefits of CDS are higher when debtor bargaining power is higher and the costs are higher when the liquidation costs rise. Norden and Weber (2009) investigate the relationship among credit default swap (CDS), bond yield and stock markets during time periods of 2000–2002. They reach a conclusion that stock returns are leading CDS and bond spread changes. In the meantime only the CDS spread changes Granger causality cause bond spread changes. Moreover, the CDS market is more sensitive to the stock market than the bond market and the strength of the co-movement increases as less credit quality and larger bond issue magnitude. They finally conclude that the CDS market contributes more to price discovery than the bond market and this relationship is stronger for US firms than for European firms. Hassan et al (2013) investigates the link between the price discovery dynamics in sovereign credit default swaps (CDS) and bond markets and degree of financial integration of emerging markets. Using CDS and sovereign bond spreads, the price discovery mechanism was tested using vector error correction model. They find that sovereign CDS and bond markets are co-integrated. In five out of seven sovereigns (71%), the bond market leads in price discovery by adjusting before CDS to new information regarding credit risk. In 29% of times, CDS markets are sources of price discovery. They also find a positive correlation of 0.66 between degree of financial integration and bond market information share.

Comovement also has been well documented by many researchers. Engle (2002) has documented time varying correlations are often estimated with multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models which now are commonly used to study interdependency among different economic variables. In this paper he developed a new class of multivariate models called dynamic conditional correlation models. These have the flexibility of univariate GARCH models coupled with parsimonious parametric models for the correlations. They are not linear but can often be estimated very simply with univariate or two-step methods based on the likelihood function. It is shown that they perform well in a variety of situations and provide sensible empirical results Greenwood (2005) focuses on Japanese market, and shows that the Nikkei 225 index is equally weighted rather than a value-weighted index. Antón and Polk (2009) have investigated comovement in a bottom-up framework, and find that stocks that are held by the same active fund managers and covered by the same analysts comove more than other stocks, controlling for other similarities between stocks. Greenwood and Thesmar (2009) develops and applies a measure of "co-fragility" in US equity markets which focus on the correlations between two different assets owners and two assets are considered as "co-fragile" if these two investors have correlations of cash inflows and outflows.

3. Data Descriptions

We obtain the daily and monthly CDS index from Thomson Reuters. Five countries' CDS index have been selected which are Brazil, Mexico, Panama, Venezuela and Ecuador respectively based on the longest data span we could have. The CDS indices are started from Aug 1st, 1996 and are ended at Nov 21st. 2013. We also download each country's stock market index and the S&P 500 implied volatility index from Bloomberg terminal with the same data span. We use MSCI emerging market index for Brazil and Mexico, for Panama we use Bolas de Valores de Panama general index, for Venezuela we use Caracas stock exchange market index and for Ecuador we use Ecuador stock market index. Then we simply merge all series by deleting a specific day observation if any country has a missing variable at this date. We also calculate the change of the each series by taking the log difference between current value and lag value of each variable. Table 1 provides the basic summary statistics for all variables we choose for empirical analysis.

[Insert Table 1 Here]

From table one we could see that mean returns of CDS are all less than 0.1 percent per day. The returns are considerably fluctuated and ranging from negative 74 percent (Ecuador) to positive 37 percent (Brazil). In the meantime the stock market returns for each country are also varying dramatically from negative 48 percent (Brazil) to roughly positive 40 percent (Ecuador) in a given day. Besides Mexico, not a single country's daily mean stock market return excess 0.1 percent. Compared with return of CDS, the stock market return in each country overall has higher kurtosis which indicates more extreme value happened in stock market. Moreover most countries have negative skewness which also indicated more negative movement of stock market.

By showing the possible CDS market integration of different country over time, we calculate a binary rolling correlation between each two countries with a rolling window of 252 days. In each day, the correlation is calculated by past one year percentage change of CDS.

[Insert Figure 1 Here]

Overall the rolling correlation is also highly varied over time no matter which two countries are combined. As the biggest country in the sample we select, correlation between Brazilian CDS and other countries drops are the 2008 financial crisis expect the correlation between Brazil and Mexico. Interestingly the correlation of Brazilian CDS and Mexican CDS is strong over time since it never drops below 0.5 compared with other countries. Actually the correlation between Brazil and Mexico is continuously increasing after 2001. For Mexico, its change of CDS has very low correlation (close to zero) during the time period of 1999-2001 when the peso crisis was happening at that time. Basically for all correlations they are decreasing during the time period of 1999-2002 and after 2008 financial crisis which is a very interesting phenomenon since during the crisis the credit risk should be higher in each country that would further strengthen the correlation of each country's change of CDS.

[Insert Table 2 Here]

We then calculate the correlation matrix of change in CDS for all five countries. The results are provided in table 2. Numbers in the parenthesis are p-value. From table 2 we find that Brazil has highest correlation with Mexico and Panama where the correlations are both greater than 0.7. Similarly Mexico also has high correlation with Brazil and Panama and the correlation between Mexico and Panama is roughly 0.72. Ecuador has lowest correlation with the other four countries where no single correlation is greater than 0.4 and Venezuela has moderate correlation with the four countries where the correlation is ranging within 0.38 and 0.80.

4. Methodology and Empirical Results

To address interdependency among different countries' CDS, we investigate the data by using a VAR model fitting with a multivariate DCC (dynamic conditional correlation) GARCH which is proposed by Engel (2002). The DCC GARCH model could be written as:

$$Y_t = \beta \sum_{p=1}^{i} X_{t-p} + \epsilon_t$$

$$\epsilon_t = H_t^{1/2} \upsilon_t$$

$$H_t = D_t^{1/2} R_t D_t^{1/2}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$$

$$Q_t = (1 - \lambda_1 - \lambda_2) R + \lambda_1 \tilde{\epsilon}_{t-1} \tilde{\epsilon}'_{t-1} + \lambda_2 Q_{t-1} \qquad (1)$$

Here the Y_t is dependent variable which is change of CDS of each country and X_{t-p} are the lag terms of dependent variables. So equation one specify the vector autoregressive model format and the rest of equations simply specify the GARCH format for residuals from estimated VAR model. H_t here is the Cholesky factor of the time-varying conditional covariance matrix and D_t is a diagonal matrix of conditional variances. R_t is a matrix of conditional quasicorrelations which could be expressed as:

$$R_t = \begin{pmatrix} 1 & \cdots & \rho_{1m,t} \\ \vdots & \ddots & \vdots \\ \rho_{1m,t} & \cdots & 1 \end{pmatrix}$$

So we could have a time-varying covariance matrix for the residuals from VAR model and we will estimate the correlation matrix and λ_1 and λ_2 to find whether the residuals from VAR are following a GARCH (1, 1) process.

[Insert Table 3 Here]

We first run a binary first order autoregressive model with DCC GARCH and each combination of any two countries are estimated through the model we just proposed. From the table 3, we find that no matter which two countries combination are used, all residuals are very persistent which indicate a strong evidence of GARCH (1, 1) process. The λ_1 and λ_2 are all highly significant at 1 percent level.

On the other hand all correlations between each two countries are highly significant at 1 percent level as well. The estimated correlation are very close to correlation matrix in table 2. Again Brazil is the most important country in sample we select and no correlation is below 0.5. Ecuador is probably the least important country in our sample since the correlation with other four countries are relatively weak. Surprisingly Panama is also very important country in our sample since the correlations with other four countries are relatively high.

[Insert Table 4 Here]

In the next step we include all five countries' CDS into the VAR model. In order to select the precise lag terms for the VAR, we provide the criterion values for model fitness. From table 4, we find all criterion values have no big difference no matter how many lags are selected. Basically VAR (2) and VAR (3) model have the lowest AIC and SBC. For parsimony purpose, we select two lags in our VAR model.

[Insert Table 5 Panel A Here]

Table 5 provides the detail result for estimated correlation matrix and estimated coefficients for λ_1 and λ_2. Basically the results are very consistent with binary DCC GARCH model. Brazil is still the most important country since the correlations with other country are all higher than 0.5 except the correlation with Ecuador has dropped to 0.43. Interestingly the correlations between Ecuador and other countries have all decreased dramatically by roughly 10-15 percent compared with binary results. Similarly λ_1 and λ_2 are very significant at 1 percent level which indicates the strong persistency of the residuals even in the multivariate format.

[Insert Table 5 Panel B Here]

Table 6 provides the estimated parameters in the VAR model and again the numbers in the parenthesis are p-value. Surprisingly Panama seems to be the most important countries in our sample. All lag one period and lag two periods change of CDS of Panama are significant at 1 percent level and all estimated coefficients are negative. A decreasing CDS in Panama will lead to increasing CDS in other countries of our sample. Moreover, Mexico is also another important country in our sample.

The lag one period and lag two periods change of CDS of Mexico are significant for all other countries at 5% level or higher except for itself. The change of CDS in Mexico is not decided by its own lag terms. The coefficient are all positive which means an increasing CDS in Mexico would lead to an increasing of CDS in other countries. Finally lag one period change of CDS of Brazil also would positively affect change of CDS in other countries except Venezuela. The lag two periods change of CDS of Brazil are not significant in any country.

5. Alternative and Robustness Tests

To further exploit the asymmetry relationship in volatility and confirm the persistency of variance of the residuals, we employ a simply OLS model from Daigler et al (2014) which could be expressed as following:

$$\Delta\sigma_{i,t} = \beta_1\Delta r_{i,t} + \beta_2\Delta r_{i,t-1} + \beta_3\Delta r_{i,t-2} + \beta_4\Delta r_{i,t-3} + \gamma_1\Delta\sigma_{i,t-1} + \gamma_2\Delta\sigma_{i,t-2} + \gamma_3\Delta\sigma_{i,t-3} + \varepsilon_t \qquad (2)$$

$$\Delta\sigma_{i,t} = \beta_1\left|\Delta R_{i,t}\right| + \beta_2\Delta r_{i,t-1} + \beta_3\Delta r_{i,t-2} + \beta_4\Delta r_{i,t-3} + \gamma_1\Delta\sigma_{i,t-1} + \gamma_2\Delta\sigma_{i,t-2} + \gamma_3\Delta\sigma_{i,t-3} + \theta_1\Delta VIX_t + \varepsilon_t \qquad (3)$$

$$\Delta\sigma_{i,t} = \beta_1\left|\Delta r_{i,t}\right| + \beta_2\Delta r_{i,t-1} + \beta_3\Delta r_{i,t-2} + \beta_4\Delta r_{i,t-3} + \gamma_1\Delta\sigma_{i,t-1} + \gamma_2\Delta\sigma_{i,t-2} + \gamma_3\Delta\sigma_{i,t-3} + \theta_1\Delta Stock_t + \theta_2\Delta VIX_{i,t} + \varepsilon_t \qquad (4)$$

Here σ_t stands for the volatility of CDS, and r_t is the change of CDS in each country and we also include stock market returns in each country and S&P 500 implied volatility index. We calculate a rolling standard deviation for the change of CDS in each country based on a 25 days rolling windows as a representative of volatility. We also include the lag terms for volatility and change of CDS in each model. We run these three equation for each country and those three equation would investigate and confirm the persistency of the variance for change of CDS.

[Insert Table 6 Here]

Table 6 provides detail estimated parameters for each model and numbers in the parenthesis are p-value. These models confirm the persistency of variance for the change of CDS in all countries since we could see that there are clearly AR process for any model used in each country. For Brazil, Ecuador and Mexico, lag one period and lag three periods volatility are positively and negatively significant respectively at 1 percent level and contemporaneous change of CDS also positively significant at 1 percent level. There is a possible mean reversion effect for change of CDS in these countries since the less current lag terms and more current lag terms are negatively correlated. The change of CDS would reverse the trend within the three days periods. For Venezuela the lag one period volatility is positively significant at 1 percent level and lag two periods volatility is negatively significant at 10 percent level. The volatility is not that persistent after three lags which is different from the other three countries mentioned above. Volatility of Panama is very persistent since all three lags are significant and the lag two periods and lag three periods volatility are negative which also indicates a possible mean reversion trend. We conclude at this point that the volatility of change in CDS is very persistent in all countries and contemporaneous change in CDS is positively affect the change of volatility. Moreover the stock market return and VIX have no impact on the change of volatility in any model.

[Insert Table 7 Here]

To investigate possible asymmetry relationship in the volatility. We divide our sample into two groups with positive change of CDS and negative change of CDS then we run the regression of equation 4 for each country. We find clear evidence of asymmetry relationship in volatility for Brazil and Venezuela. When using the data with positive change of CDS, then contemporaneous absolute change of CDS is not significant. On the other hand, when negative change in CDS is used for regression. The contemporaneous returns are significant at 1 percent level which indicates a decreasing CDS index would lead to a more fluctuated CDS movement. For Panama and Mexico, the contemporaneous change in CDS are both significant no matter positive or negative data is used, but coefficient is larger when the negative change of CDS is used which also provides the evidence of a weak asymmetry relationship in volatility. Finally we do not find any asymmetric volatility for Ecuador.

5. Conclusion

In conclusion, this paper investigate the co-movement of CDS in different countries by employing a second order vector autoregressive model fitting with a DCC GARCH process proposed by Engle (2002). Our binary results show that correlation between each two countries are strongly significant and the variance of residuals from VAR model is very persistent over time. The multivariate DCC GARCH model also show the consistent results. Our results provide the evidence that change of CDS from Brazil, Mexico and Panama have the most important effect on change of CDS in other countries. The positive change of CDS in Brazil and Mexico will lead to positive change of CDS in other countries. The positive change of CDS in Panama will lead to negative change of CDS in other countries. We also employ a model proposed by Daigler et al (2014) to exploit and confirm the persistency and asymmetry relationship of volatility of CDS. We confirm that the volatility is very persistent and four countries-Brazil, Mexico, Venezuela and Panama have asymmetric volatility which also indicates a possible mean reversion trend.

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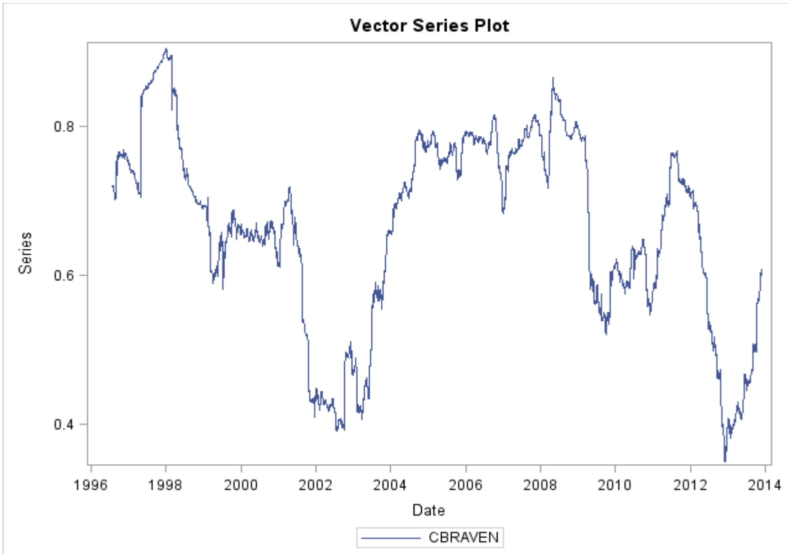
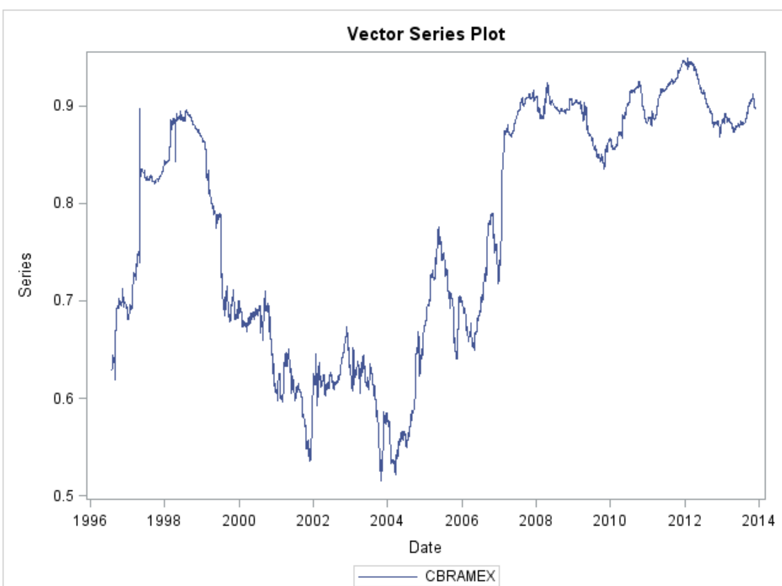
252 days rolling window correlation measure between each two countries.



Brazil and Venezuela



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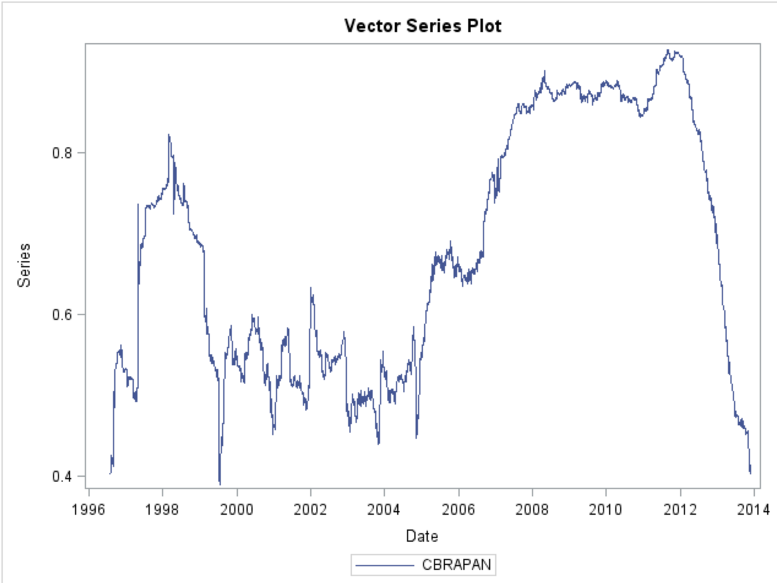

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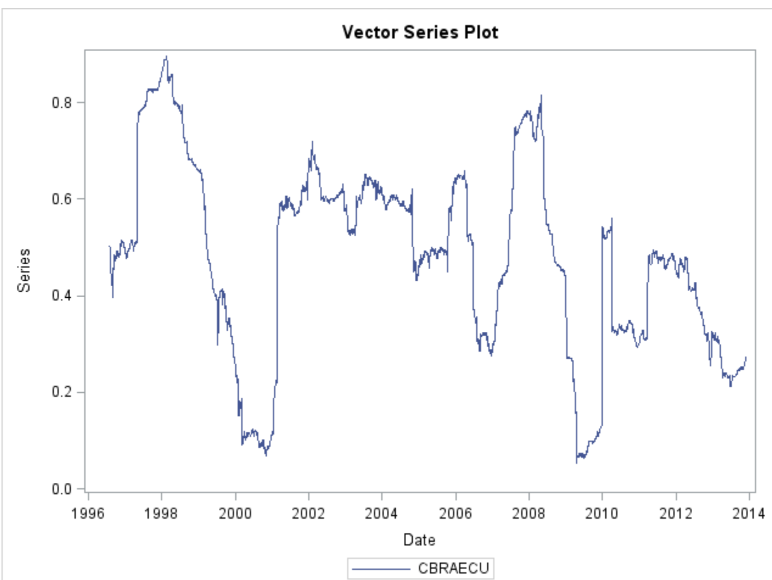

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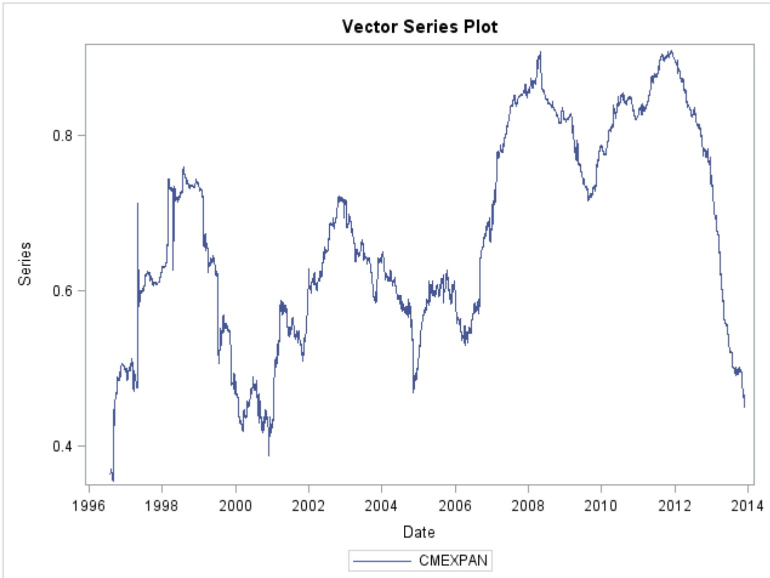

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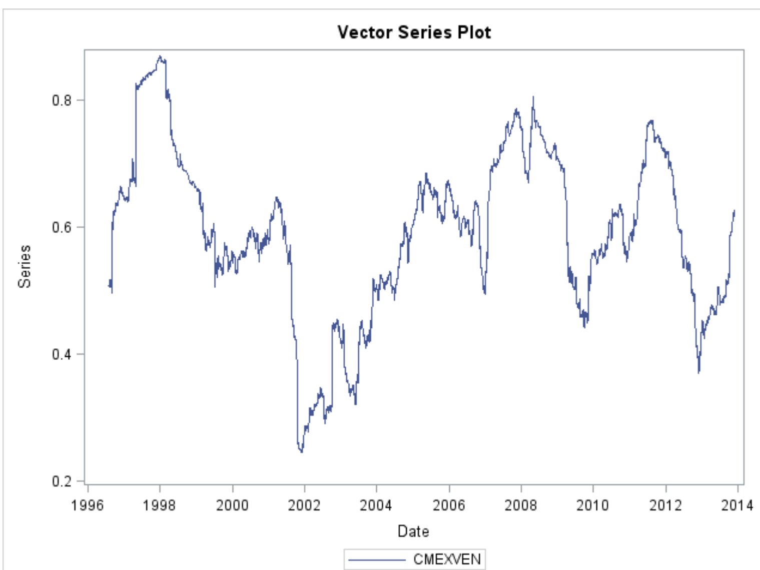

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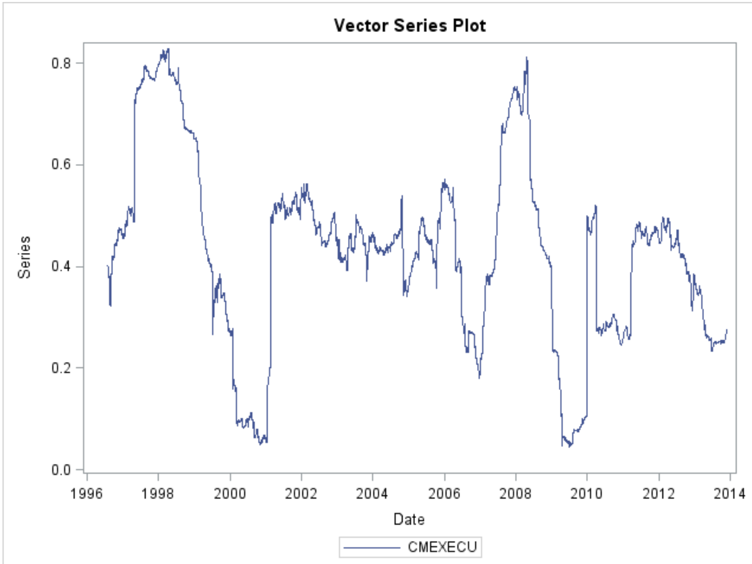
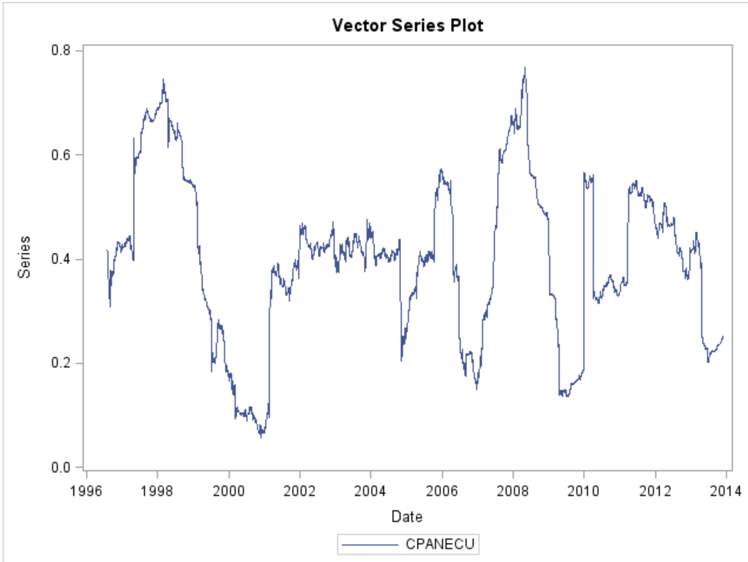


Mexico and Ecuador

Panama and Venezuela



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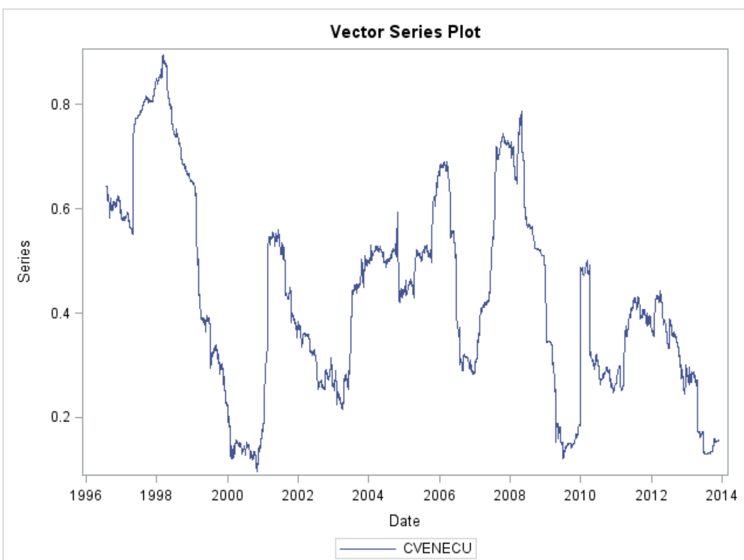

Venezuela and Ecuador

Figure 1. 252 days window rolling correlation measures between each country from August 1st, 1996 to November 21st, 2013.

Table 1: Summary Statistics

Variable	Minimum	Maximum	Median	Mean	Std Dev	Skewness	Kurtosis	N
ΔCDS_{Brazil}	-0.2170	0.3762	0.0000	-0.0002	0.0306	0.9624	10.4101	4516
$\Delta CDS_{Venezuela}$	-0.1996	0.3629	0.0000	0.0001	0.0274	1.4206	20.1031	4516
ΔCDS_{Mexico}	-0.2468	0.3661	0.0000	-0.0003	0.0341	0.4799	7.1999	4516
ΔCDS_{Panama}	-0.2018	0.3509	0.0000	-0.0002	0.0300	0.5588	8.6630	4516
$\Delta CDS_{Ecuador}$	-0.7433	0.3313	0.0000	-0.0002	0.0302	-3.5183	111.1740	4516
Δr_{BRA}	-0.4826	0.2089	0.0006	0.0005	0.0240	-4.0797	87.2940	2994
Δr_{VEN}	-0.5143	0.3277	0.0003	0.0019	0.0230	-2.2155	116.8596	2994
Δr_{MEX}	-0.2915	0.2272	0.0009	0.0007	0.0187	-1.1267	40.4913	2994
Δr_{PAN}	-0.1126	0.1529	0.0000	0.0007	0.0084	4.2196	109.0236	2994
Δr_{ECU}	-0.2593	0.3963	0.0000	0.0001	0.0183	2.4005	153.0976	2994
ΔVIX	-0.4368	0.6659	-0.0048	-0.0002	0.0713	0.9357	8.6241	2994

Table 2: Correlation Coefficients Matrix for Change of CDS

	ΔCDS_{Brazil}	$\Delta CDS_{Venezuela}$	ΔCDS_{Mexico}	ΔCDS_{Panama}	$\Delta CDS_{Ecuador}$
ΔCDS_{Brazil}	1.0000	0.6649	0.8072	0.7184	0.4500
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\Delta CDS_{Venezuela}$	0.6649	1.0000	0.5915	0.5270	0.4421
	(<.0001)		(<.0001)	(<.0001)	(<.0001)
ΔCDS_{Mexico}	0.8072	0.5915	1.0000	0.7183	0.3862
	(<.0001)	(<.0001)		(<.0001)	(<.0001)
ΔCDS_{Panama}	0.7184	0.5270	0.7183	1.0000	0.3563
	(<.0001)	(<.0001)	(<.0001)		<.0001
$\Delta CDS_{Ecuador}$	0.4500	0.4421	0.3862	0.3563	1.0000
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	

Table 3: Binary VAR with DCC GARCH

	BRA&VEN	BRA&MEX	BRA&PAN	BRA&ECU	MEX&PAN
Correlation	0.6659	0.7988	0.6953	0.5226	0.6941
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
λ_1	0.0431	0.0333	0.0540	0.0786	0.0518
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
λ_2	0.9382	0.9557	0.9294	0.9039	0.9243
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
	MEX&VEN	MEX&ECU	PAN&ECU	PAN&VEN	ECU&VEN
Correlation	0.5966	0.4233	0.3811	0.5330	0.5303
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
λ_1	0.0402	0.1090	0.0780	0.0413	0.0591
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
λ_2	0.9293	0.8521	0.9004	0.9323	0.9281
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)

Binary correlation between each country and coefficient for DCC GARCH estimation.
Numbers in the parenthesis are *p*-value.

Table 4: Information Criteria

Lag	AIC	SBC	HQC	AICC
$p=1$	-37.7163	-37.7518	-37.7393	-37.7518
$p=2$	-37.7544	-37.6833	-37.7294	-37.7543
$p=3$	-37.7502	-37.6436	-37.7126	-37.75
$p=4$	-37.6084	-37.7506	-37.7005	-37.7504
$p=5$	-37.7498	-37.572	-37.6872	-37.7495

Table 5: Multivariate VAR Fitting DCC GARCH

Panel A: DCC GARCH Correlation

	ΔCDS_{Brazil}	$\Delta CDS_{Venezuela}$	ΔCDS_{Mexico}	ΔCDS_{Panama}	$\Delta CDS_{Ecuador}$
ΔCDS_{Brazil}	1.0000	0.6667	0.7912	0.7046	0.4286
		(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\Delta CDS_{Venezuela}$	0.6667	1.0000	0.5926	0.5140	0.4093
	(<.0001)		(<.0001)	(<.0001)	(<.0001)
ΔCDS_{Mexico}	0.7912	0.5926	1.0000	0.7114	0.3796
	(<.0001)	(<.0001)		(<.0001)	(<.0001)
ΔCDS_{Panama}	0.7046	0.5140	0.7114	1.0000	0.3427
	(<.0001)	(<.0001)	(<.0001)		(<.0001)
$\Delta CDS_{Ecuador}$	0.4286	0.4093	0.3796	0.3427	1.0000
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	
	$\lambda 1$	0.0276	$\lambda 2$	0.9615	
		(<.0001)		(<.0001)	

PANEL B: DCC GARCH Coefficient Estimation

	ΔBRA_{t-1}	ΔVEN_{t-1}	ΔMEX_{t-1}	ΔPAN_{t-1}	ΔECU_{t-1}	ΔBRA_{t-2}	ΔVEN_{t-2}	ΔMEX_{t-2}	ΔPAN_{t-2}	ΔECU_{t-2}
ΔBRA	0.0974	-0.0006	0.0372	-0.0837	-0.0158	0.0164	-0.0025	0.0522	-0.0632	-0.0121
	[<.0001]	[0.974]	[0.037]	[<.0001]	[0.189]	[0.469]	[0.882]	[0.004]	[<.0001]	[0.323]
ΔVEN	-0.0061	0.0885	0.0354	-0.0244	0.0012	0.0039	0.0033	0.0601	-0.0691	-0.0087
	[0.760]	[<.0001]	[0.027]	[0.115]	[0.914]	[0.843]	[0.858]	[<.0001]	[<.0001]	[0.441]
ΔMEX	0.1117	-0.0149	0.0327	-0.0923	-0.0136	0.0486	0.0010	0.0320	-0.0988	-0.0076
	[<.0001]	[0.453]	[0.140]	[<.0001]	[0.365]	[0.052]	[0.960]	[0.151]	[<.0001]	[0.612]
ΔPAN	0.0859	0.0134	0.0607	-0.0499	-0.0147	0.0066	-0.0081	0.0732	-0.0710	-0.0134
	[<.0001]	[0.440]	[0.001]	[0.011]	[0.218]	[0.755]	[0.642]	[<.0001]	[<.0001]	[0.264]
ΔECU	0.0760	-0.0905	0.1267	-0.0837	-0.0279	-0.0393	-0.0311	0.1512	-0.1220	0.0389
	[0.001]	[<.0001]	[<.0001]	[<.0001]	[0.198]	[0.084]	[0.126]	[<.0001]	[<.0001]	[0.076]

Table 6: OLS Regression With VIX and Stock Market Return in Each Country

COUNTRY	Δr_t	Δr_{t-1}	Δr_{t-2}	Δr_{t-3}	$\Delta \sigma_{t-1}$	$\Delta \sigma_{t-2}$	$\Delta \sigma_{t-3}$	$\Delta Stock$	ΔVIX_i	$\Delta \lvert r_t \rvert$	R^2	*Adj.* R^2
	-0.0016	-0.0002	0.0018	0.0018	1.1390	-0.0492	-0.0918				0.9970	0.9970
	[0.1491]	[0.8532]	[0.2825]	[0.2274]	[<.0001]	[0.2012]	[0.0004]					
Brazil		-0.0005	0.0015	0.0015	1.1311	-0.0459	-0.0914	0.0019		0.0061	0.9971	0.9970
		[0.6491]	[0.3680]	[0.3463]	[<.0001]	[0.2338]	[0.0004]	[0.2424]		[3.78]		
		0.0001	0.0014	0.0014	1.1308	-0.0453	-0.0918	0.0013	-0.0004	0.0062	0.9971	0.9970
		[0.6293]	[0.3855]	[0.3541]	[<.0001]	[0.2390]	[0.0004]	[0.4193]	[0.4191]	[0.0001]		
	0.0003	-0.0004	0.0009	0.0011	1.2062	-0.1965	-0.0127				0.9955	0.9954
	[0.8349]	[0.7220]	[0.6098]	[0.4982]	[<.0001]	[0.0752]	[0.6053]					
Venezuala		-0.0004	0.0006	0.0010	1.2014	-0.1951	-0.0134	0.0024		0.0059	0.9955	0.9955
		[0.7113]	[0.7073]	[0.5383]	[<.0001]	[0.0791]	[0.5815]	[0.0956]		[0.0031]		
		-0.0004	0.0006	0.0010	1.2016	-0.1953	-0.0133	0.0023	-0.0002	0.0060	0.9955	0.9955
		[0.7032]	[0.7168]	[0.5558]	[<.0001]	[0.0789]	[0.5841]	[0.1110]	[0.6671]	[0.0032]		
	-0.0001	-0.0018	0.0003	0.0037	1.1108	-0.0143	-0.0981				0.9974	0.9974
	[0.8894]	[0.1847]	[0.8458]	[0.0027]	[<.0001]	[0.6673]	[<.0001]					
Mexico		-0.0019	0.0000	0.0036	1.1033	-0.0132	-0.0961	0.0024		0.0059	0.9974	0.9974
		[0.1640]	0.9933	[0.0044]	[<.0001]	[0.6957]	[<.0001]	[0.2690]		[<.0001]		
		-0.0019	0.0000	0.0036	1.1033	-0.0131	-0.0962	0.0017	-0.0003	0.0060	0.9974	0.9974
		[0.1604]	[0.9886]	[0.0047]	[<.0001]	[0.6973]	[<.0001]	[0.4491]	[0.5133]	[<.0001]		

Table 6: OLS Regression With VIX and Stock Market Return in Each Country

Panama	-0.0002	0.0018	0.0017	0.0031	1.1074	-0.0629	-0.0461				0.9972	0.9972
	[0.8838]	[0.0915]	[0.1508]	[0.0059]	[<.0001]	[0.0362]	[0.0127]					
		0.0018	0.0015	0.0031	1.1010	-0.0585	-0.0493	0.0033		0.0070	0.9973	0.9973
		[0.1057]	[0.2089]	[0.0050]	[<.0001]	[0.0502]	[0.0075]	[0.5085]		[<.0001]		
		0.0018	0.0014	0.0030	1.1016	-0.0584	-0.0502	0.0026	-0.0009	0.0073	0.9973	0.9973
		[0.1077]	[0.2529]	[0.0061]	[<.0001]	[0.0501]	[0.0064]	[0.6115]	[0.0778]	[<.0001]		
Ecuador	0.0002	-0.0026	0.0032	0.0026	1.0196	-0.0192	-0.0115				0.9779	0.9779
	[0.9446]	[0.1782]	[0.1848]	[0.1647]	[<.0001]	[0.2884]	[0.0832]					
		-0.0034	0.0028	0.0025	1.0160	-0.0176	-0.0141	-0.0027		0.0104	0.9780	0.9780
		[0.1106]	[0.2366]	[0.1804]	[<.0001]	[0.3386]	[0.0678]	[0.1156]		[0.0770]		
		-0.0035	0.0027	0.0024	1.0163	-0.0178	-0.0143	-0.0027	-0.0009	0.0105	0.9780	0.9780
		[0.1027]	[0.2505]	[0.2023]	[<.0001]	[0.3350]	[0.0641]	[0.1191]	[0.2814]	[0.0754]		

Estimated coefficients of OLS regression with change of stock market return and VIX. All standard errors are White heteroscedasticity robusted and numbers in the bracket are *p*-value.

Table 7: OLS Regression with Positive or Negative Change of CDS

COUNTRY		Δr_{t-1}	Δr_{t-2}	Δr_{t-3}	$\Delta\sigma_{t-1}$	$\Delta\sigma_{t-2}$	$\Delta\sigma_{t-3}$	$\Delta Stock$	ΔVIX_i	$\Delta\lvert r_t\rvert$
Brazil	+	-0.0024	0.0046	0.0069	1.0582	-0.0533	-0.0063	-0.0004	-0.0013	0.0024
		[0.2400]	[0.1985]	[0.0532]	[<.0001]	[0.1273]	[0.1203]	[0.7229]	[0.2638]	[0.3888]
	-	-0.0058	0.0018	0.0007	0.9980	-0.0010	-0.0311	-0.0046	-0.0018	0.0282
		[0.1981]	[0.5662]	[0.7337]	[<.0001]	[0.9697]	[0.1684]	[0.1338]	[0.3267]	[0.0704]
Venezuala	+	0.0004	0.0018	0.0012	1.2080	-0.1704	-0.0409	0.0030	0.0006	0.0028
		[0.7852]	[0.3350]	[0.4843]	[<.0001]	[0.1758]	[0.2902]	[0.1576]	[0.2524]	[0.3309]
	-	-0.0016	-0.0007	0.0006	1.2002	-0.2220	0.0100	0.0018	-0.0016	0.0083
		[0.3999]	[0.8160]	[0.8265]	[<.0001]	[0.2400]	[0.8185]	[0.2817]	[0.1072]	[0.0024]
Mexico	+	-0.0018	0.0002	0.0057	1.0977	0.0192	-0.1210	0.0024	-0.0006	0.0053
		[0.2573]	[0.9171]	[0.0008]	[<.0001]	[0.6788]	[0.0015]	[0.4243]	[0.3891]	[0.0090]
	-	-0.0020	-0.0002	0.0014	1.1131	-0.0428	-0.0786	0.0014	-0.0002	0.0077
		[0.3324]	[0.9400]	[0.4589]	[<.0001]	[0.3983]	[0.0072]	[0.6717]	[0.8001]	[0.0005]
Panama	+	0.0010	0.0030	0.0024	1.1091	-0.0332	-0.0819	0.0087	-0.0005	0.0065
		[0.4648]	[0.0666]	[0.1498]	[<.0001]	[0.4287]	[0.0036]	[0.3028]	[0.4720]	[0.0020]
	-	0.0026	-0.0010	0.0036	1.1009	-0.0964	-0.0129	-0.0038	-0.0017	0.0078
		[0.1247]	[0.5321]	[0.0118]	[<.0001]	[0.0217]	[0.5711]	[0.3296]	[0.0290]	[0.0067]
Ecuador	+	-0.0035	0.0076	0.0076	1.0663	-0.0590	-0.0085	-0.0002	-0.0012	0.0073
		[0.2003]	[0.0792]	[0.0255]	[<.0001]	[0.0536]	[0.1904]	[0.8947]	[0.2555]	[0.2184]
	-	-0.0038	-0.0022	-0.0018	1.0013	-0.0050	-0.0269	-0.0082	-0.0020	0.0122
		[0.2280]	[0.2257]	[0.3787]	[<.0001]	[0.8241]	[0.1292]	[0.0535]	[0.2298]	[0.1556]