VOLATILITY CO-MOVEMENT AMONG LATIN AMERICAN STOCK EXCHANGES: BAD TIMES VS. GOOD TIMES

Jesús Téllez Gaytán*
Escuela de Graduados en Negocios
Tecnológico de Monterrey, Campus Estado de México

Carlos A. Martínez
Departamento de Matemáticas
Tecnológico de Monterrey, Campus Estado de México

(Received 15 July 2005, accepted 24 November 2005)

Abstract

This document compares volatility behavior among Latin American stock exchanges in two periods: crises times versus tranquil times. The purpose is to verify the level and direction of volatility movements among Latin American stock exchanges. The empirical results show that daily stock index returns are fat-tailed distributed, then the GARCH model was estimated under the assumption of standardized errors distributed as a student-t. The VAR system shows that IP&C, IPSA, IBOVESPA and Merval, are the more correlated stock exchanges. The volatility co-movement among these markets was stronger during crises times than tranquil ones, so volatility worked on both directions during bad times. It is conclude that volatility co-movement defined also as volatility contagion, can be classified as a contagion of the type of increasing correlation of shocks. .

Resumen

En este documento se compara el comportamiento de la volatilidad entre Bolsas de Valores de América Latina durante dos periodos: tiempos de crisis contra tiempos tranquilos. El propósito es verificar el nivel y dirección de los movimientos de la volatilidad. Los resultados arrojan que los rendimientos de los índices accionarios se distribuyen con colas anchas, por lo que el modelo GARCH se estimó bajo el supuesto de distribución t-student en los errores estandarizados. El sistema VAR indica que el IP&C, IPSA, IBOVESPA y Merval, son los mercados fuertemente correlacionados. El co-movimiento de la volatilidad entre estos mercados fue mayor durante tiempos de crisis respecto a tiempos tranquilos, por lo que la volatilidad fue bi-direccional en tiempos malos. Se concluye que el co-movimiento de la volatilidad definida también como contagio de la volatilidad, se puede clasificar como un tipo de incremento en la correlación de shocks.

JEL classification: C22, G15
Keywords: Heteroskedasticity, Contagion, VAR.

* Departamento de Finanzas, Tecnológico de Monterrey, Campus Estado de México, Carretera Lago de Guadalupe Km. 3.5, Col. Atizapán de Zaragoza, Edo. de México. C. P. 52929 Teléfono: +52(55)58645555, E-mail: jctellez@itesm.mx

1. Introduction

Theoretical models about financial contagion try to explain the contagion phenomenon of financial crises from one country to another and classify contagion as:

- monzon effect,
- spreading and
- pure contagion.

The best intuitive way to measure contagion is by the increasing of correlation among markets from one country to others. So contagion can be understood as the increasing in the coefficient correlation among markets and in that country in which crisis came up.

The World Bank defines contagion in three ways:

1. Broad: Contagion is the cross-country of shocks or the general cross country effects.

2. Restrictive: Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. Also referred as excess on co-movement.

3. Very Restrictive: Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times."

In this paper we apply statistical and econometric tools in such a way to identify the type of financial contagion defined by the World Bank that best describes the transmission of shocks among Latin American stock exchanges, in which shocks are measured by the conditional heteroskedasticity variance. The paper is organized as follows: Section 2 describes the econometric techniques such as the GARCH model, the VAR system, the Impulse-Response Functions and the Granger Pairwise Causality Tests. Then in section 3 we describe the methodology and data used in the empirical research. Section 4 gives the empirical results and finally in section 5 are given the conclusions.

2. Econometric Technique

2.1 The GARCH Model

Conditional volatility models are very popular in time series analysis and include a variety of models that may represent different characteristics of financial time series. These models are relatively new and were firstly developed by Engle whose original model was the ARCH model -a model that explains conditional volatility as a linear function of the q lagged residuals. This model has been widely used to:

- Model no constant volatility over time;
- Show that volatility is an up-and-down behavior;
- Identify existence of important memory in the process;
- Predict future volatility.

The GARCH model was developed by Bollerslev -an extension of the ARCH model- in which it incorporates lags in the conditional variance. A GARCH model can be described as an infinite ARCH model and it is defined as:

$$\sigma_t^2 = \alpha_0 \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{q} \alpha_k \varepsilon_{t-k}^2; \quad \alpha_0 > 0; \alpha_k \geq 0; \beta_j \geq 0 \tag{2.1}$$

σ is the conditional variance;

$\alpha's$ and $\beta's$ are the parameters estimated by the model;

ε is the residual term

If p=0, the model reduces to an ARCH (q)

The common case of a GARCH model is the GARCH (1,1) specification:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2.2}$$

2.2 The VAR System and Impulse-Response Functions

The Vector Autoregression, is a system of stochastic linear equations in which each variable depends on its lags and the lags of the other variables. This technique is utilized to give an idea of the dynamic relationships among different time series and to show the possible behavior of the series when specific perturbations may be present in some of the variables. As an example, the VAR system has been used to analyze the effect of economic policy shocks on the economic variable of interest.

A VAR system of two time series (X_t and Y_t), is represented as:

$$\begin{aligned} X_t &= C_1 + a_{11}X_{t-1} + a_{12}Y_{t-1} + U_{1t} \\ Y_t &= C_2 + a_{21}X_{t-1} + a_{22}Y_{t-1} + U_{2t} \end{aligned} \tag{2.3}$$

The perturbations (U_{1t}, U_{2t}), incorporate the specific shocks of the X_t variable, (ε_{xt}), and those of the Y_t variable, (ε_{yt}). The assumption is that the perturbations of the variables are linearly related with the specific shocks of the variables X and Y occurred in time t:

$$\begin{aligned} U_{1t} &= k_{11}\varepsilon_{xt} + k_{12}\varepsilon_{yt} \\ U_{2t} &= k_{21}\varepsilon_{xt} + k_{22}\varepsilon_{yt} \end{aligned} \tag{2.4}$$

The above is represented by the U_t vector.

Then, (2.3) can be re-written as:

$$\begin{aligned} X_t &= C_1 + a_{11}X_{t-1} + a_{12}Y_{t-1} + k_{11}\varepsilon_{xt} + k_{12}\varepsilon_{yt} \\ Y_t &= C_2 + a_{21}X_{t-1} + a_{22}Y_{t-1} + k_{21}\varepsilon_{xt} + k_{22}\varepsilon_{yt} \end{aligned} \tag{2.5}$$

Since shocks are possibly to be correlated (*i.e.* changes in ε_{xt} may cause changes in ε_{yt} and viceversa), it cannot be shown that a change in the first element of U_t is due exclusively to a shock on X or Y.

The main importance of a VAR analysis is to find the way in which the variables of the system are interrelated and such analysis focuses on the estimation of the impulse-response functions. These functions show the way in which a shock on the variable Y, ε_{yt}, in period t affects the variable X on successive periods, mean while the effect of ε_{yt} on X in time t is null. This means that the covariance of the errors of X and Y in time t is null. Then the system we are interested in, is that in which shocks are not correlated:$cov[\varepsilon_{xt}, \varepsilon_{yt}] = 0$

2.3 Granger Causality Tests

An important consequence of cointegration and error correction models is that cointegration between two variables means causality (Granger causality) between them at least in one direction. But cointegration cannot be utilized to infer about causality directions among variables, so there is need to perform causality tests. Granger empirically defined causality based mainly in the information content: if X_t causes Y_t then Y_{t+1} is a better forecast if it is used information from X_t. Then the error variance of the forecast would be the least one. As an example, if two markets are integrated, then the price p_1 in the first market would Granger cause the price p_2 in the second market, and/or viceversa. Then Granger Causality Tests help to identify about existence and directions of price transmissions among markets.

3. Methodology and Data

The following methodology was used in such a way to identify the level and direction of volatility among Latin American stock exchanges:

1)Normality tests. Empirical research has shown that financial time series are not normally distributed, most of them have shown heavy tails and can be inferred that they follow a student-t distribution or a mix of normal densities. The importance of normality tests is to verify which probability distribution better fits the empirical one and estimate as better as possible the GARCH model.

2)The GARCH (1,1) is estimated so to get the conditional variance series - also volatility series- of each stock index return. The GARCH model captures volatility and tranquil periods on the series $\{y_t\}$, and by plotting the conditional variance series it can be identified breakpoints and dated periods of high volatility.

3)VAR system is estimated utilizing the conditional variance series so to deal with endogeneity problems and to realize the way volatility is transmitted among stock indexes during bad times versus good times.

4) Once we have dealt with endogeneity, Granger Tests were applied to identify the direction of volatility movements, this means, if volatility movements have been unidirectional or bidirectional. After this we can conclude if there has been volatility co-movement among Latin American stock exchanges.

5)Finally and based on the VAR and Granger results, impulse-response functions were estimated as an aid to verify the transmission of shocks among markets and graphically show the behavior of variables as response of shocks.

The data utilized were daily closing stock index prices of: Mexico (IP&C), Colombia (IBSA), Venezuela (IBC), Chile (IPSA), Argentine (Merval), and Brazil (IBovespa). The period of study is from December 30, 1992 up to March 31, 2005, and is divided into two sub-periods: bad times and good times.[1]

[1] It is meant as bad times the period of financial crises during the 90's and good times the last 5 years in which there has not been evidence of events that could have destabilize financial markets.

Stock index returns were generated as log returns:

$$r_{et} = \ln\frac{S_t}{S_0} \tag{3.1}$$

Data were taken from Economatica and Estimations performed in E-viems release 5.

4. Empirical Results

If stock indexes returns are not normally distributed then we would expect that standardized errors neither should be.[2] Table 1 shows kurtosis of Latin American stock exchanges returns on the complete period, and bad and good times.

Table 1. Kurtosis of Stock Index Returns.

Index	Complete Period	Bad Times	Good Times
IPC&	9.866077	10.14846	6.657292
IGBC	12.93897	9.65317	16.89857
IBC	44.27918	44.4685	11.96227
IPSA	8.868715	8.503369	4.760227
Merval	8.858194	9.839469	7.710344
Ibovespa	11.03967	9.600086	5.028418

In each of the three periods there is evidence of excess of kurtosis since the respective statistical results are greater than 3, and we would infer that the standardized errors of the GARCH estimation would not be normally distributed. It is stated that this wouldn't have been a great problem since GARCH models may capture excess of kurtosis.[3] Also it has been found (Ruppert(2001)) that the marginal distributions of the GARCH process are a mix of normal distributions but with infinite components and with a continuous distribution of the conditional variance. In Appendix A, are shown the Q-Q plots which also give evidence of fat-tailed distributions, in which the quantile of indexes returns take an "S" form.

Then, the GARCH model may be estimated taking in account non-normality otherwise the estimated errors would not be appropriate. Virtually we would have solved this problem by estimating the GARCH model under the option "Hetersokedasticity Consistent Covariance", method described by Bollerslev and Wooldridge (1992).

Firstly we estimated the GARCH model by two methods in such a way to compare the value of the parameters and their statistical significance: 1) On the assumption that residuals were normally distributed and 2) applying the method developed by Bollerslev and Wooldridge. Table 2 shows the results, in which the ARCH and GARCH coefficients values were the same for both methods.

[2] Fama (1965) showed that indexes returns exhibited non-normal sample conditional distributions as excess of kurtosis.

[3] Properties of GARCH models are: zero conditional mean; normal conditional distribution; marginal mean and variance are constants; and, the marginal distribution is heavy-tailed.

Table 2. GARCH(1,1) Estimation.

	Complete Period		Bad Times		Good Times	
Index	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH
IP&C	0.097450	0.894889	0.127219	0.845724	0.065232	0.925805
IGBC	0.545463	0.426142	0.634195	0.258692	0.179899	0.834866
IBC	0.447826	0.568601	0.369861	0.694213	0.351363	0.245828
IPSA	0.136680	0.834451	0.149702	0.819146	0.116734	0.819412
Merval	0.123076	0.854716	0.142587	0.837595	0.101711	0.868925
Ibovespa	0.123095	0.861580	0.166363	0.828365	0.042749	0.932283

It is shown that the method developed by Bollerslev and Wooldridge does not solve the problem of non-normality, the only change was in the variance-covariance matrix. In Appendix B.1, the var-cov matrix is shown for both methods. Bollerslev (1987) suggests that heavy-tails on errors should be treated as a student-t distribution, since such phenomenon stills present even on the standardized errors just as Milhoj (1985) and Bollerslev (1986) show.[4] Another way has been to assume the conditional distribution of errors as a Generalized Error Distribution (GED) described by Box and Tiao (1973).[5]

Based on the above research conclusions, we estimated the GARCH (1,1) model assuming a student-t distribution on the errors. Table 3 shows the results on the complete period and each sub-period.

Table 3. GARCH(1,1) estimation with Student-t Distribution.

	Complete Periodo		Bad Times		Good Times	
Index	ARCH	GARCH	ARCH	GARCH	ARCH	GARCH
IP&C	0.081310	0.906176	0.091138	0.870996	0.076416	0.911770
IGBC	0.609655	0.456221	0.736927	0.342055	0.456862	0.0572104
IBC	0.195519	0.812550	0.189390	0.828634	0.383697	0.337869
IPSA	0.157739	0.797335	0.197178	0.739678	0.118489	0.822876
Merval	0.114899	0.862526	0.121699	0.851986	0.114131	0.865269
Ibovespa	0.093613	0.894328	0.137280	0.861268	0.033810	0.950422

[4] Baillie and Bollerslev (1989) found in exchange rate data that the student-t distribution is well compared with the exponential distribution which captures the excess of kurtosis. Also Baillie and Degennaro (1990) and Jong, Kemma, and Kloeck (1990) assumed a conditional student-t distribution on the residuals jointly specifying a GARCH (1,1) model and found that if heavy-tails are not properly modeled the results could be spurious in terms of the estimated risk-return tradeoff.

[5] Nelson (1989) estimated an EGARCH model with a generalized exponential distribution in which models the conditional excess of kurtosis of stock indexes returns.

Finally, the conditional variance series were generated and plotted, so to realize the magnitude of each financial event in each market. In Appendix B.2, these series are plotted in and we observe that each market reacted different to each financial event. On these series, the VAR system was estimated and the Granger Tests were applied.

The results of the VAR estimations show that IGBC and IBC were the only two indexes not to be statistically significance in each of the VAR equations. The decision rule to reject its significance was a t-statistic less than (2). This means that IGBC and IBC cannot be treated as exogenous neither as endogenous variables that determine the volatility behavior on the rest of the indexes. In Appendix C are shown the VAR equations for the complete period and each sub-period. This conclusion is sustained by Granger Tests from which we have the following results:

1)Complete Period. Null hypothesis was rejected on the following pairs: IPSA-IBovespa, IP&C-IBovespa, Merval-IBovespa, IP&C-IPSA and Merval-IPSA. We mean by this that in the whole period volatility movements have been bidirectional on these stock exchanges. A unidirectional movement was shown on Merval-IGBC and Merval-IP&C, this means that IGBC and IP&C hold information from Merval, but Merval do not from them. (See Appendix D.1)

2) Bad Times. Null hypothesis was rejected on the following pairs: IPSA-IBovespa, IP&C-IBovespa, Merval-IBovespa, Merval-IPSA. So volatility movements were bidirectional on these stock exchanges during the financial crises period. Unidirectional movements were on IPSA-IGBC, IP&C-IPSA and Merval-IP&C. This means, in the first case, that IGBC held information from IPSA but IPSA did not from IGBC. (See Appendix D.2)

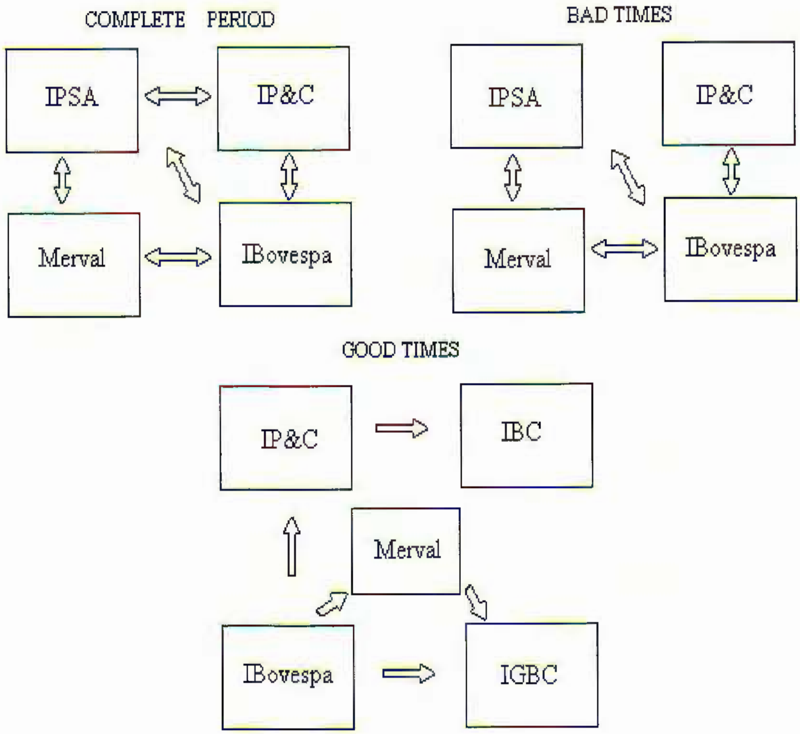
3)Good Times. There is no evidence that volatility movements were bidirectional and only the following pairs showed unidirectional movements: IP&C-IBC, IBovepsa-IGBC, IBovespa-IP&C, IBovespa-Merval and Merval-IGBC.

This means as in the first case that, IBC holds information from IP&C but IP&C does not from IBC. (See Appendix D.3)

Finally, Impulse-Response functions were performed only on those pairs that in the complete period showed bidirectional movements. Besides bidirectional movements, impulse-response is not the same inside each pair. An example is IP&C-IBovespa, in which innovations on IP&C, IBovespa responds slowly. But IP&C responds faster against innovations on IBovespa. In Appendix D.4 the Impulse-Response functions are plotted on the complete period for those markets that showed more integration or bidirectional movement.

The transmission mechanism of shocks based on the above results can be mapped as follows:

Figure 1.

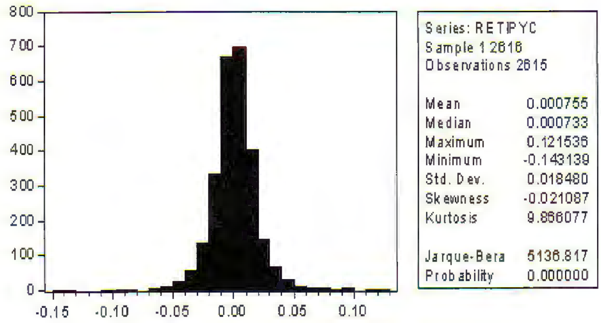


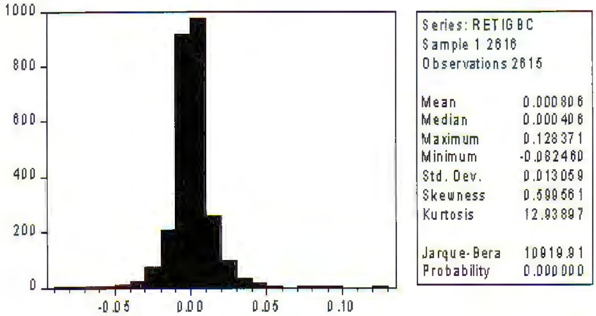
5. Conclusions

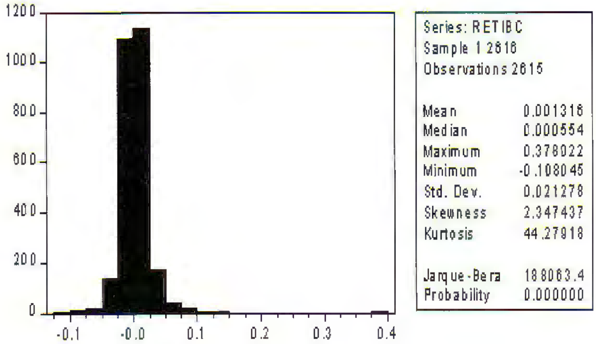
At least utilizing stock index prices, the selected period and the proposed methodology, it can be inferred that the type of financial contagion is one of increasing correlation of shocks which could be observed in mainly four stock indexes named as Latin American strong markets: IBovespa, Merval, IPSA and IP&C. So volatility co-movement increases during financial crises and is almost null during stabilize periods, this means: volatility is correlated among specific markets, increases during turbulence periods and decreases during tranquil periods. The volatility model had to be performed considering a student-t distribution on the standardized errors in such a way to capture the effect of fat-tails of stock index returns. We do not underestimate the existing of other transmission mechanisms of shocks among stock exchanges that could better describe volatility co-movement among emerging markets.

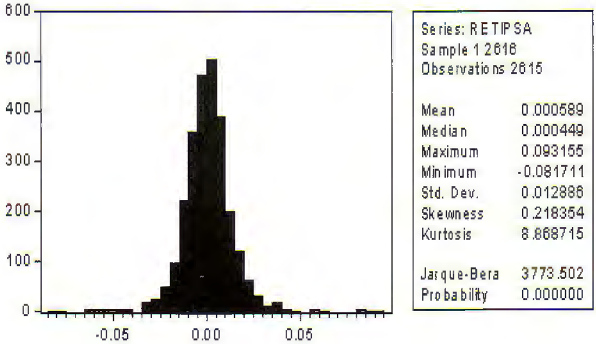
The importance of this document is for investment purposes so that fund managers can best allocate resources among emerging markets. Nowadays we are working on a copula method approach to identify dependence among emerging stock exchanges.

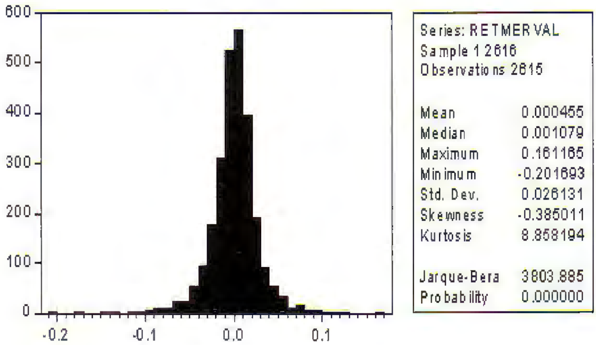
Appendix A.1
Descriptive Statistics and Histograms. Complete Period

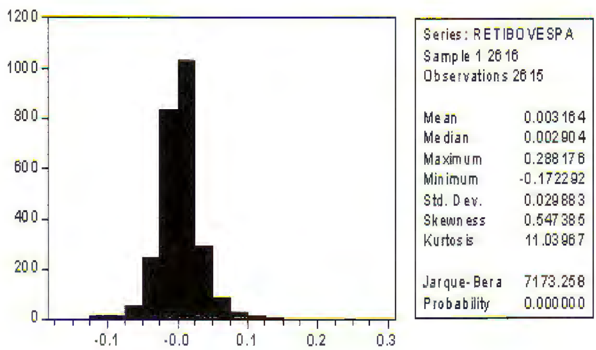




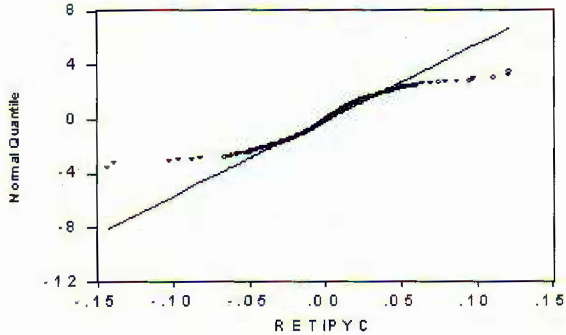



Series: RETIPSA
Sample 1 2616
Observations 2615
Mean 0.000589
Median 0.000449
Maximum 0.093155
Minimum -0.081711
Std. Dev. 0.012886
Skewness 0.218354
Kurtosis 8.868715
Jarque-Bera 3773.502
Probability 0.000000
600
500
400
300
200
100
0
-0.05
0.00
0.05

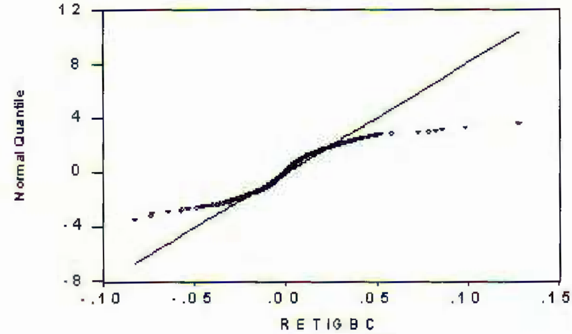

Series: RETMERVAL
Sample 1 2616
Observations 2615
Mean 0.000455
Median 0.001079
Maximum 0.161165
Minimum -0.201693
Std. Dev. 0.026131
Skewness -0.385011
Kurtosis 8.858194
Jarque-Bera 3803.885
Probability 0.000000
600
500
400
300
200
100
0
-0.2
-0.1
0.0
0.1


Series: RETIBOVESPA
Sample 1 2616
Observations 2615
Mean 0.003164
Median 0.002904
Maximum 0.288176
Minimum -0.172292
Std. Dev. 0.029883
Skewness 0.547385
Kurtosis 11.03967
Jarque-Bera 7173.258
Probability 0.000000
1200
1000
800
600
400
200
0
-0.1
-0.0
0.1
0.2
0.3

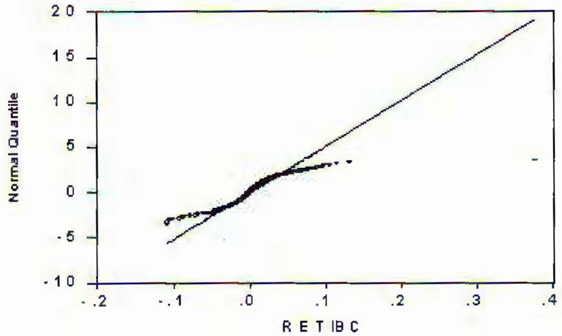
Theorical Quantile-Quantile



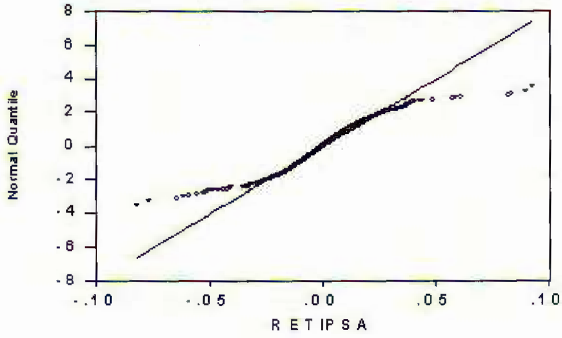
Theorical Quantile-Quantile



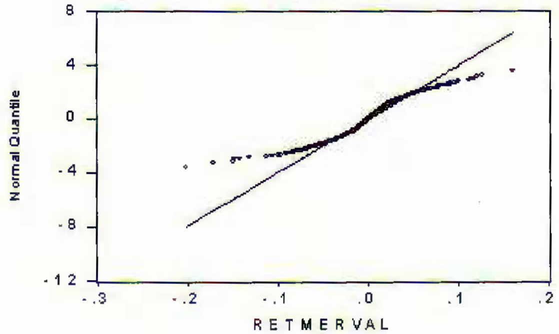
Theorical Quantile-Quantile



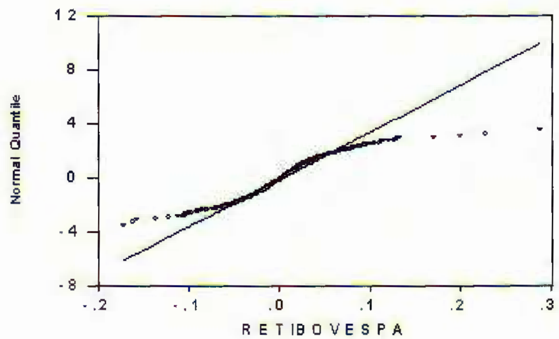
Theorical Quantile-Quantile



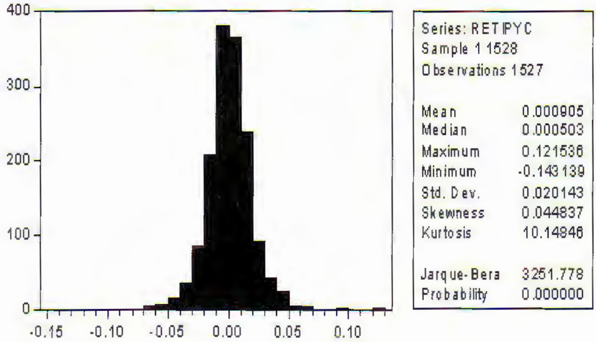
Theorical Quantile-Quantile

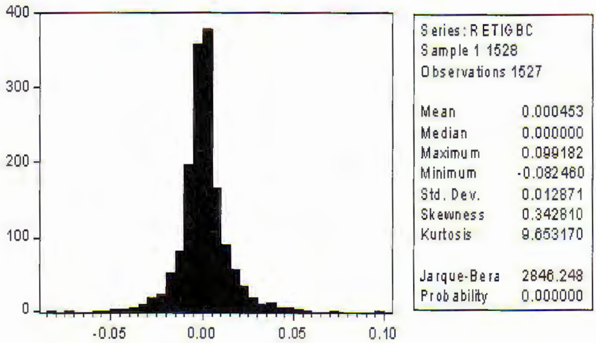


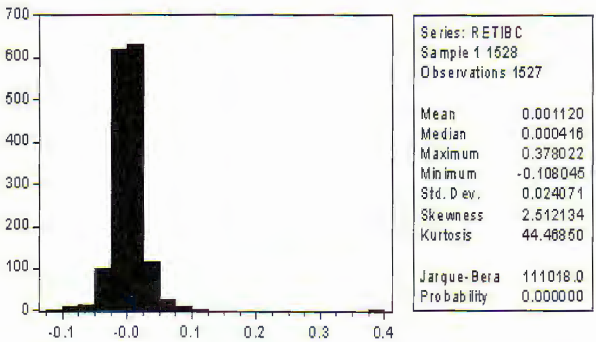
Theorical Quantile-Quantile

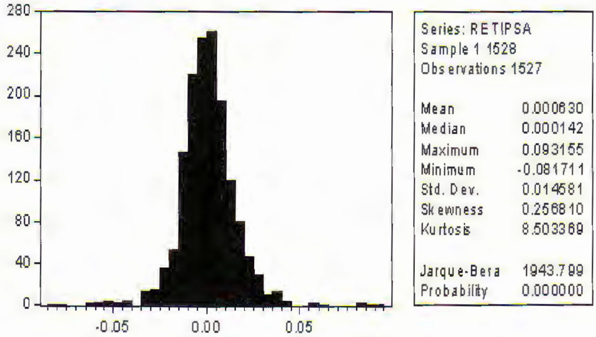


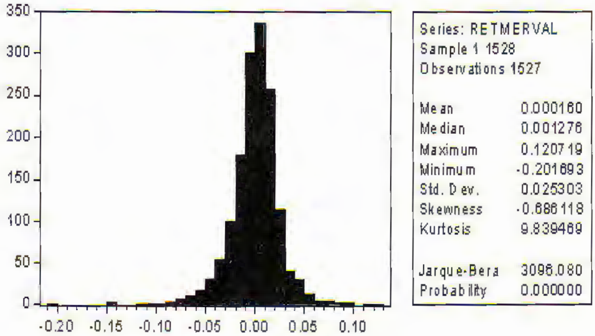
Appendix A.2
Descriptive Statistics and Histograms. Bad Times

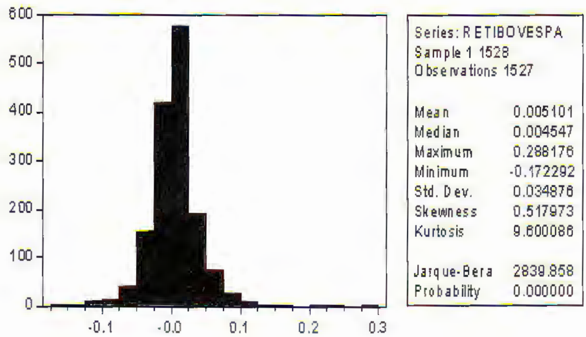




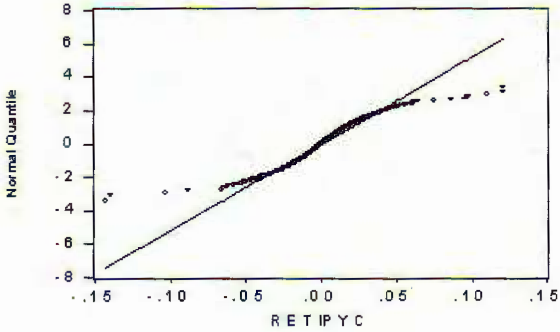



Series: RETIPSA
Sample 1 1528
Observations 1527
Mean 0.000630
Median 0.000142
Maximum 0.093155
Minimum -0.081711
Std. Dev. 0.014581
Skewness 0.256810
Kurtosis 8.503369
Jarque-Bera 1943.799
Probability 0.000000
-0.05
0.00
0.05

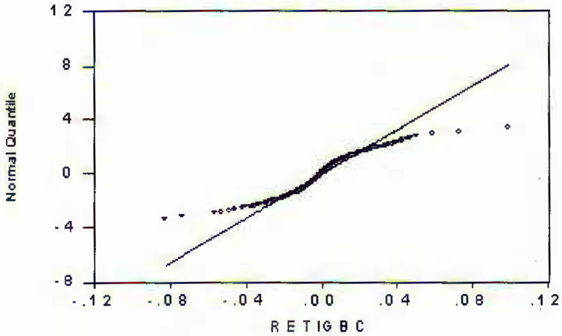

Series: RETMERVAL
Sample 1 1528
Observations 1527
Mean 0.000160
Median 0.001276
Maximum 0.120719
Minimum -0.201693
Std. Dev. 0.025303
Skewness -0.686118
Kurtosis 9.839469
Jarque-Bera 3096.080
Probability 0.000000
-0.20 -0.15 -0.10 -0.05 0.00 0.05 0.10


Series: RETIBOVESPA
Sample 1 1528
Observations 1527
Mean 0.005101
Median 0.004547
Maximum 0.288176
Minimum -0.172292
Std. Dev. 0.034876
Skewness 0.517973
Kurtosis 9.600086
Jarque-Bera 2839.858
Probability 0.000000
-0.1 -0.0 0.1 0.2 0.3

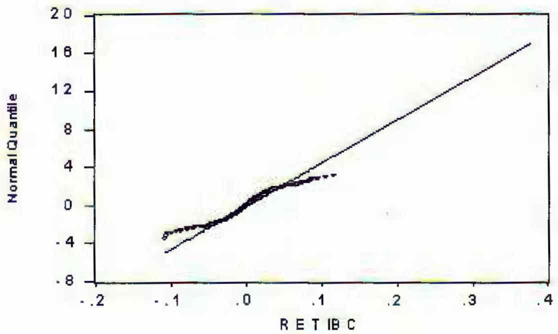
Theorical Quantile-Quantile



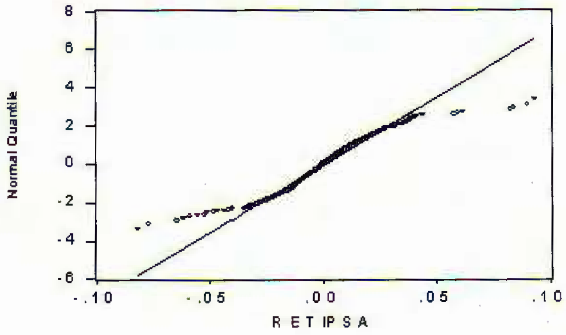
Theorical Quantile-Quantile



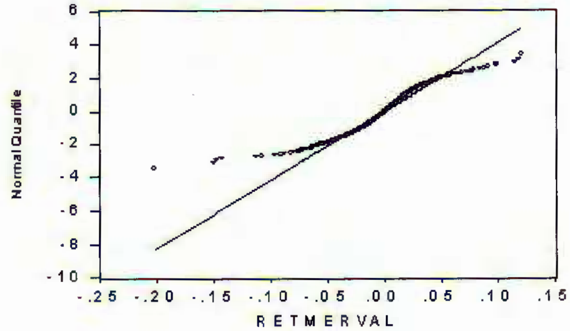
Theorical Quantile-Quantile



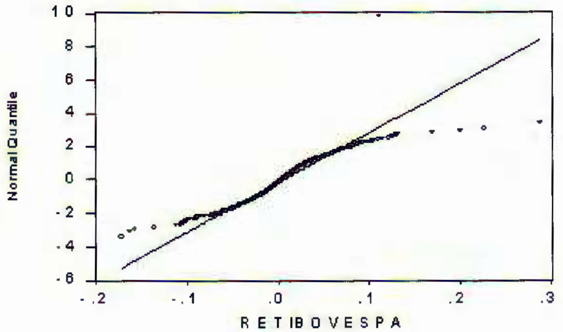
Theorical Quantile-Quantile



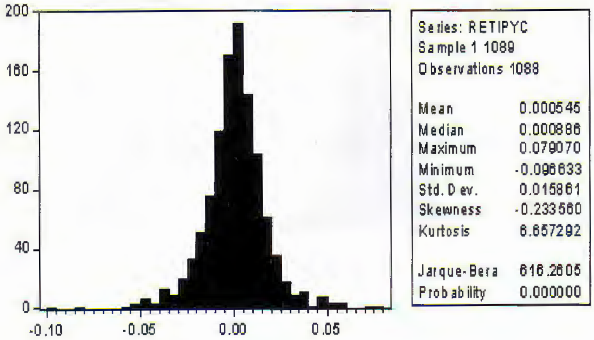
Theorical Quantile-Quantile

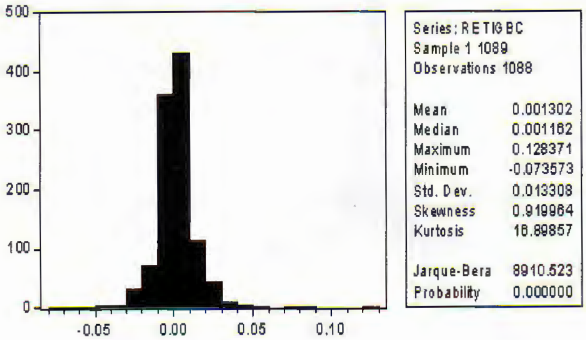


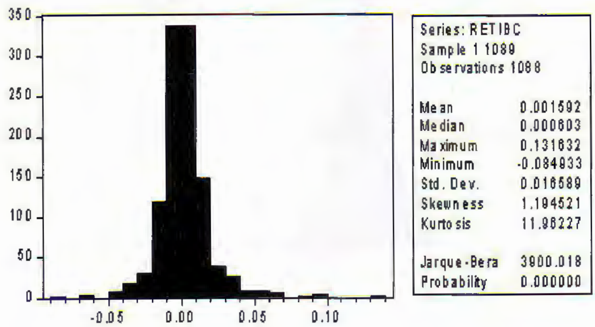
Theorical Quantile-Quantile

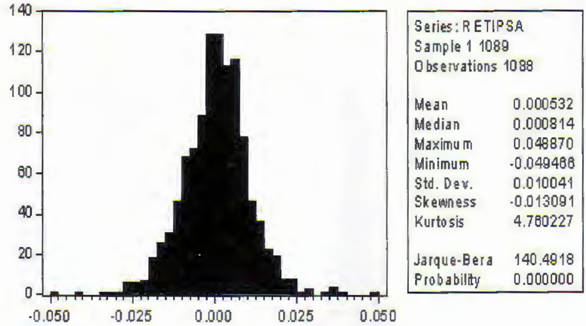


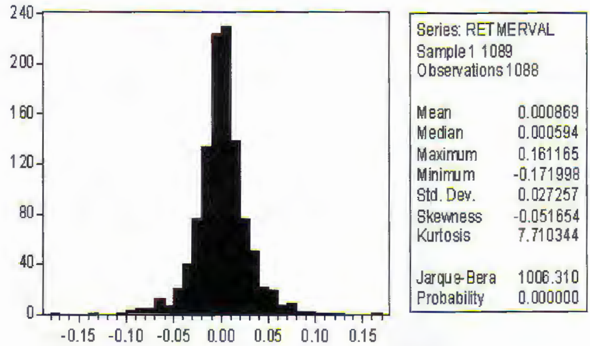
Appendix A.3
Descriptive Statistics and Histograms. Good Times

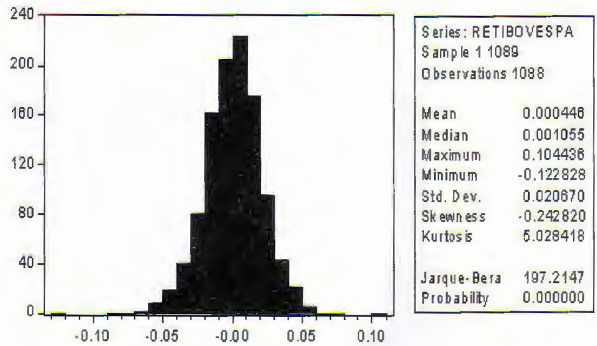




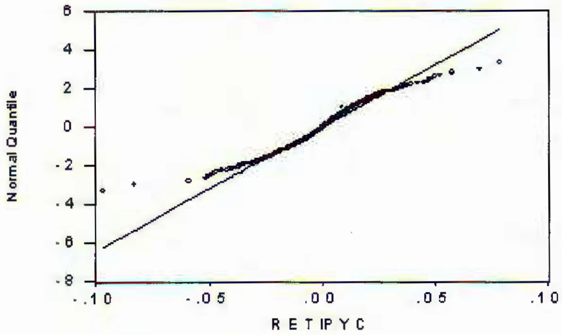



Series: RETIPSA
Sample 1 1089
Observations 1088
Mean 0.000532
Median 0.000814
Maximum 0.048870
Minimum -0.049466
Std. Dev. 0.010041
Skewness -0.013091
Kurtosis 4.760227
Jarque-Bera 140.4918
Probability 0.000000

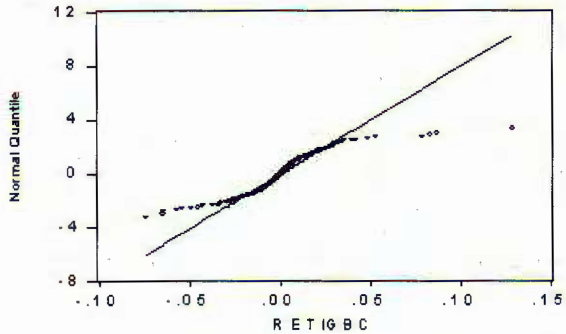

Series: RETMERVAL
Sample 1 1089
Observations 1088
Mean 0.000869
Median 0.000594
Maximum 0.161165
Minimum -0.171998
Std. Dev. 0.027257
Skewness -0.051654
Kurtosis 7.710344
Jarque-Bera 1006.310
Probability 0.000000


Series: RETIBOVESPA
Sample 1 1089
Observations 1088
Mean 0.000446
Median 0.001055
Maximum 0.104436
Minimum -0.122828
Std. Dev. 0.020670
Skewness -0.242820
Kurtosis 5.028418
Jarque-Bera 197.2147
Probability 0.000000

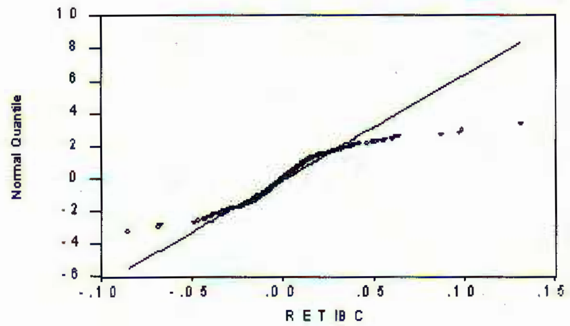
Theorical Quantile-Quantile



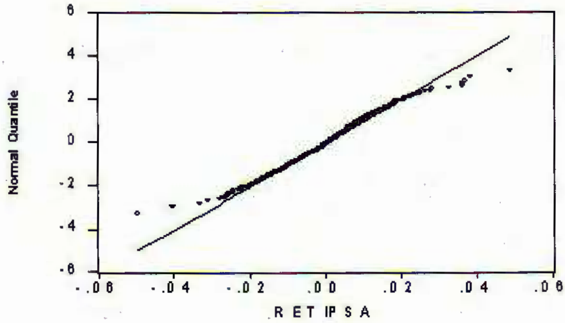
Theorical Quantile-Quantile



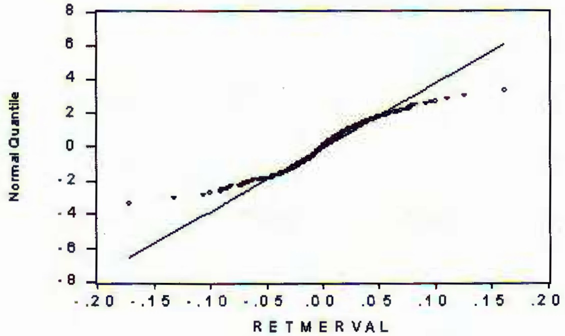
Theorical Quantile-Quantile



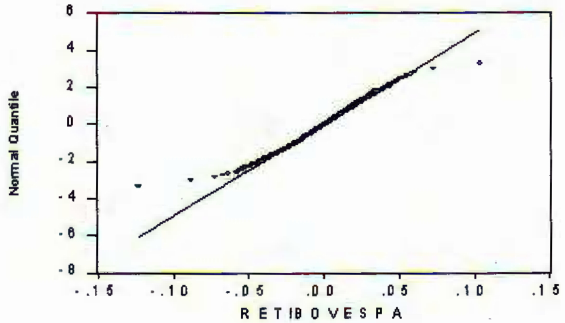
Theorical Quantile-Quantile



Theorical Quantile-Quantile



Theorical Quantile-Quantile



Appendix B.1 GARCH (1,1) Variance-Covariance Matrix Complete Period.

Normality on Residuals Assumption				
IPC& México				
	C	C	resid(-1)^2	garch(-1)
C	8.48E-08	3.08E-12	-2.49E-07	1.30E-07
C	3.08E-12	7.67E-13	1.34E-09	-3.96E-09
resid(-1)^2	-2.49E-07	1.34E-09	3.30E-05	-3.13E-05
garch(-1)	1.30E-07	-3.96E-09	-3.13E-05	4.29E-05

Bollerslev-Wooldridge Method				
IPC& México				
	C	C	resid(-1)^2	garch(-1)
C	7.52E-08	1.59E-11	4.45E-07	3.11E-07
C	1.59E-12	7.95E-12	7.64E-09	-1.36E-09
resid(-1)^2	4.45E-07	7.64E-09	0.00043	-0.000332
garch(-1)	-3.11E-07	-1.36E-08	-0.000332	0.000304

Normality on Residuals Assumption				
IGC Colombia				
	C	C	resid(-1)^2	garch(-1)
C	2.74E-08	6.55E-11	1.58E-07	-5.87E-07
C	6.55E-11	1.91E-12	2.86E-10	-1.12E-08
resid(-1)^2	1.58E-06	2.86E-10	0.000471	-0.000168
garch(-1)	-5.87E-07	-1.12E-08	-0.000168	0.000159

Bollerslev-Wooldridge Method				
IGC Colombia				
	C	C	resid(-1)^2	garch(-1)
C	5.62E-08	-5.06E-10	-1.13E-05	5.14E-06
C	-5.06E-10	3.25E-11	3.09E-07	-3.22E-07
resid(-1)^2	-1.13E-05	3.09E-07	0.009998	-0.005177
garch(-1)	5.14E-06	-3.22E-07	-0.005177	0.004495

Normality on Residuals Assumption				
IBC Venezuela				
	C	C	resid(-1)^2	garch(-1)
C	5.82E-08	1.66E-10	-1.23E-08	-6.20E-07
C	1.66E-10	8.88E-12	1.88E-08	-3.44E-08
resid(-1)^2	-1.23E-08	1.88E-08	0.00025	-0.000194
garch(-1)	6.20E-07	-3.44E-08	-0.000194	0.000225

Bollerslev-Wooldridge Method				
IBC Venezuela				
	C	C	resid(-1)^2	garch(-1)
C	1.28E-07	-7.16E-10	8.05E-06	1.77E-08
C	-7.16E-10	7.08E-11	1.25E-07	-2.40E-07
resid(-1)^2	8.05E-06	1.25E-07	0.010003	-0.003574
garch(-1)	1.77E-08	-2.40E-07	-0.003574	0.002093

Normality on Residuals Assumption				
IPSA Chile				
	C	C	resid(-1)^2	garch(-1)
C	4.54E-08	2.02E-11	8.90E-08	8.70E-08
C	2.02E-11	6.31E-13	2.10E-09	6.09E-09
resid(-1)^2	-8.90E-08	2.10E-09	0.000146	-0.000119
garch(-1)	-8.70E-08	-6.09E-09	-0.000119	0.000136

Bollerslev-Wooldridge Method				
PISA Chile				
	C	C	resid(-1)^2	garch(-1)
C	3.33E-08	-2.80E-11	-3.72E-08	2.39E-07
C	-2.80E-11	2.31E-12	1.27E-08	-2.88E-08
resid(-1)^2	-3.72E-08	1.27E-08	0.00036	-0.000426
garch(-1)	2.39E-07	-2.88E-08	0.000365	0.000545

Normality on Residuals Assumption				
MERVAL Argentina				
	C	C	resid(-1)^2	garch(-1)
C	1.71E-07	4.16E-11	-2.86E-07	2.06E-07
C	4.16E-11	5.14E-12	4.61E-09	-1.36E-08
resid(-1)^2	-2.86E-07	4.61E-09	6.90E-05	-6.08E-05
garch(-1)	2.06E-07	-1.36E-08	-6.08E-05	7.88E-05

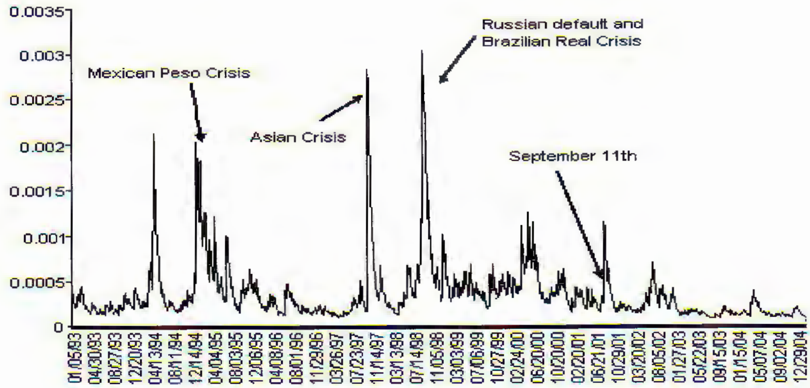
Bollerslev-Wooldridge Method				
MERVAL Argentina				
	C	C	resid(-1)^2	garch(-1)
C	1.36E-07	-1.73E-11	-3.33E-07	1.47E-07
C	-1.73E-11	2.73E-11	4.81E-08	-9.14E-08
resid(-1)^2	-3.33E-07	4.81E-08	0.000476	-0.000426
garch(-1)	1.47E-07	-9.14E-08	-0.000426	0.00051

Normality on Residuals Assumption				
IBOVESPA Brazil				
	C	C	resid(-1)^2	garch(-1)
C	1.91E-07	-1.21E-10	-9.21E-07	9.95E-07
C	-1.21E-10	6.50E-12	6.58E-09	-1.78E-08
resid(-1)^2	-9.21E-07	6.58E-09	7.57E-05	-7.14E-05
garch(-1)	9.95E-07	-1.78E-08	-7.14E-05	9.70E-05

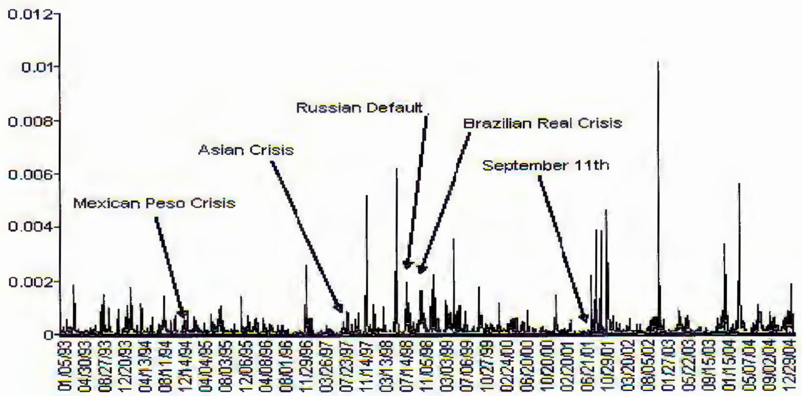
Bollerslev-Wooldridge Method				
IBOVESPA Brazil				
	C	C	resid(-1)^2	garch(-1)
C	1.57E-07	5.71E-11	1.20E-06	-1.02E-06
C	5.71E-11	1.40E-11	2.19E-08	-3.80E-08
resid(-1)^2	1.20E-06	2.19E-08	0.000475	-0.000373
garch(-1)	-1.02E-06	-3.80E-08	0.000373	0.000344

Appendix B.2 Condicional Variance (GARCH) Series Complete Period.

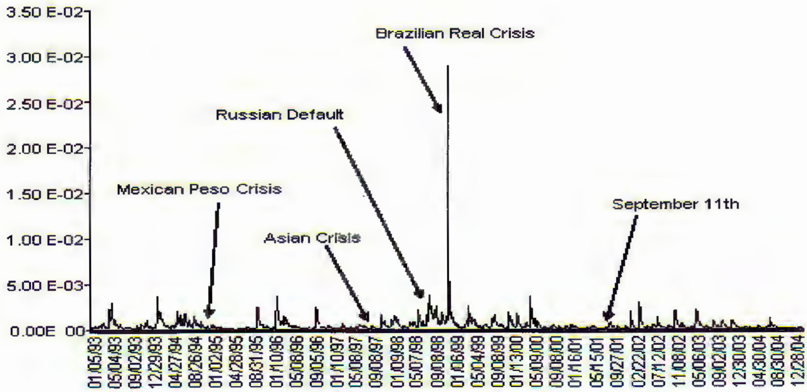
IP&C GARCH Series: 1993-2005



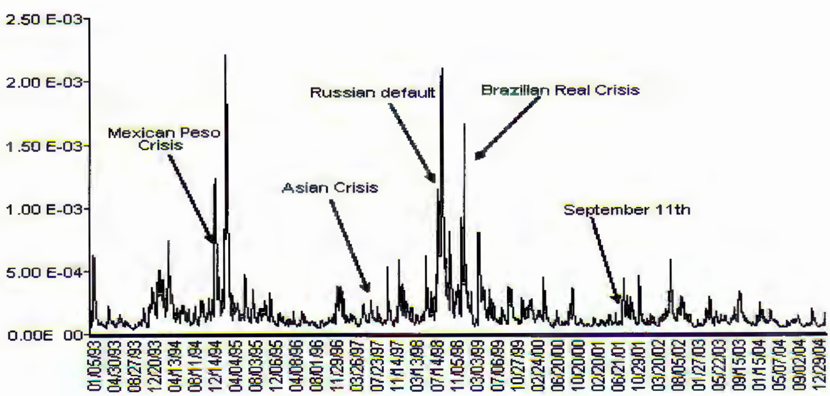
IGBC GARCH Series: 1993-2005



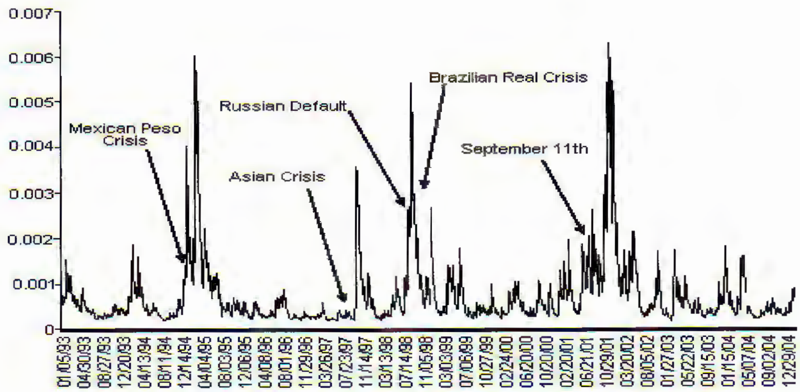
IBC GARCH Series: 1993-2005



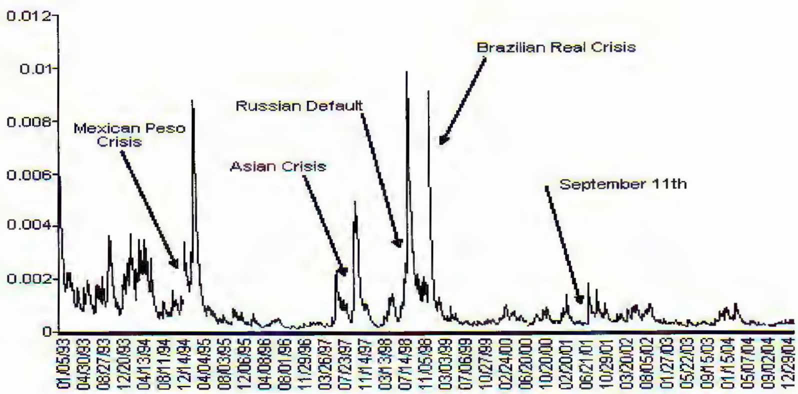
IPSA GARCH Series: 1993-2005



Merval GARCH Series: 1993-2005



Ibovespa GARCH Series: 1993-2005



Appendix C. VAR Estimations.

Table C.1. Vector Autoregression Estimates-Complete period

	G-IBC	G-IBOVESPA	G-IGBC	G-IPSA	G-IPYC	G-MERVAL
G-IBC(-1)	0.909932	-0.005476	-0.006939	-0.000277	-4.27E-05	-0.000412
	-0.01967	-0.00842	-0.012	-0.00233	-0.00268	-0.00707
	[46.2681]	[-0.65042]	[-0.57821]	[-0.11849]	[-0.01595]	[-0.05827]
G-IBC(-2)	-0.051912	0.012813	0.00587	0.002077	-0.000374	0.001541
	-0.01966	0.00842	-0.012	-0.00233	-0.00268	-0.00707
	[-2.64010]	[1.52218]	[0.48923]	[0.89016]	[-0.13965]	[0.21785]
G-IBOV	-0.019392	1.054068	0.001255	0.026332	0.028821	0.036443
ESPA(-1)	-0.05359	-0.02294	-0.0327	-0.00636	-0.0073	-0.01928
	[-0.36187]	[45.9478]	[0.03839]	[4.14056]	[3.94820]	[1.89061]
G-IBOV	0.027621	-0.120482	-0.007641	-0.021858	-0.029093	-0.042845
ESPA(-2)	-0.05265	-0.02254	-0.03213	-0.00625	-0.00717	-0.01894
	[0.52463]	[-5.34550]	[-0.23783]	[-3.49827]	[-4.05649]	[-2.26235]
G-IGBC	0.015997	0.003587	0.603937	-0.000885	-0.000136	0.009821
(-1)	-0.03239	-0.01387	-0.01977	-0.00384	-0.00441	-0.01165
	[0.49381]	[0.25866]	[30.5516]	[-0.23031]	[-0.03076]	[0.84281]
G-IGBC	0.002201	-0.0086	-0.02709	-0.000904	-0.00118	-0.006408
(-2)	-0.03234	-0.01385	-0.01974	-0.00384	-0.00441	-0.01163
	[0.06806]	[-0.62110]	[-1.37254]	[-0.23540]	[-0.26772]	[-0.55079]
G-IPSA	0.00538	0.08224	-0.060099	0.911222	-0.058653	0.181327
(-1)	-0.19348	-0.08283	-0.11806	-0.02296	-0.02636	-0.0696
	[0.02780]	[0.99290]	[-0.50904]	[39.6853]	[-2.22540]	[2.60540]
G-IPSA	0.032752	0.061626	0.136448	-0.029265	0.081956	0.201639
(-2)	-0.19252	-0.08242	-0.11748	-0.02285	-0.02623	-0.06925
	[0.17012]	[0.74772]	[1.16144]	[-1.28087]	[3.12499]	[-2.91164]
G-IPYC	0.00202	0.05708	0.020655	-0.040232	1.04701	0.021238
(-1)	-0.16718	-0.07157	-0.10202	-0.01984	-0.02277	-0.06014
	[0.01208]	[0.79753]	[0.20246]	[-2.02776]	[45.9735]	[0.35315]
G-IPYC	0.052093	-0.034092	-0.041562	0.043604	-0.091237	0.001591
(-2)	-0.1699	-0.07145	-0.10185	-0.01981	-0.02274	-0.06004
	[0.31212]	[-0.47714]	[-0.40808]	[2.20145]	[-4.01295]	[0.02650]
G-MER	-0.043106	0.020754	0.076854	-0.006418	0.023153	0.946028
VAL(-1)	-0.06286	-0.02691	-0.03836	-0.00746	-0.00856	0.02261
	[-0.68573]	[0.77123]	[2.00351]	[-0.86037]	[2.70383]	[41.8372]
G-MER	0.025434	0.000256	-0.050695	0.014637	-0.022409	0.010905
VAL(-2)	-0.06281	-0.02689	-0.03833	-0.00745	-0.00856	-0.02259
	[0.40492]	[0.00952]	[-1.32262]	[1.96354]	[-2.61905]	[0.48263]
C	5.46E-05	7.99E-06	8.56E-05	8.36E-06	1.19E-05	3.05E-05
	-1.90E-05	-8.20E-06	-1.20E-05	-2.30E-06	-2.60E-06	-6.9E-06
	[2.85745]	[0.97679]	[7.33994]	[3.68695]	[4.56543]	[4.44020]

Notes: In both rows and columns, "G-" stands for GARCH. Each set shows the regressor, its standard error, and in brackets, its t-statistic. Sample (adjusted): 4-2616. Included observations: 2613

Table C.1 (continue)

R^2	0.754573	0.946204	0.360346	0.859906	0.938893	0.916897
Adj. R^2	0.753441	0.945956	0.357394	0.85926	0.938611	0.916514
$\sum resids^2$	0.000881	0.000161	0.000328	1.24E-05	1.63E-05	0.000114
S.E. equation	0.000582	0.000249	0.000355	6.91E-05	7.93E-05	0.000209
F-statistic	666.1493	3810.884	122.0583	1329.917	3329.002	2390.548
Log likelihood	15763.04	17979.9	17053.68	21332.28	20971.97	18434.7
Akaike AIC	-12.0551	-13.7519	-13.043	-16.3179	-16.0421	-14.10004
Schwarz SC	-12.026	-13.7227	-13.0138	-16.289	-16.0129	-14.07084
Mean dependent	0.00056	0.000908	0.000244	0.000169	0.000352	0.000711
S.D. dependent	0.001172	0.001072	0.000443	0.000184	0.00032	0.000725
Determinant resid covariance (dof adj)			1.59E-45	Akaike AIC		-86.09414
Determinant resid covariance			1.55E-45	Schwarz criterion		-85.91896
Log likelihood			112560			

Notes: Sample (adjusted): 4-2616. Included observations: 2613

Table C.2. Vector Autoregression Estimates - Bad times

	G-IBC	G-IBOV ESPA	G-IGBC	G-IPSA	G-IPYC	G-MERVAL
G-IBC(-1)	0.921207	-0.008999	-0.00485	-0.000644	-0.00016	0.00028
	-0.02575	-0.01636	-0.01244	-0.00381	-0.00381	-0.0079
	[35.7756]	[-0.54994]	[-0.38996]	[-0.16899]	[-0.04198]	[0.03540]
G-IBC(-2)	-0.051445	0.020448	0.005826	0.002807	-0.000299	0.002331
	-0.02575	-0.01636	-0.01244	-0.00381	-0.00381	-0.0079
	[-1.99807]	[1.24964]	[0.46849]	[0.73709]	[-0.07839]	[0.29520]
G-IBOV ESPA(-1)	-0.015603	1.011864	0.012666	0.019413	0.01672	0.026857
	-0.04839	-0.03075	-0.02337	-0.00716	-0.00716	-0.01484
	[-0.32243]	[32.8944]	[0.54185]	[2.71209]	[2.33471]	[1.80969]
G-IBOV ESPA(-2)	0.021846	-0.121935	-0.0181	-0.019112	-0.017773	-0.033258
	-0.04753	-0.03021	-0.02296	-0.00703	-0.00703	-0.01458
	[0.45961]	[-4.0367]	[-0.78838]	[-2.71847]	[-2.52689]	[-2.28172]
G-IGBC (-1)	0.040198	0.041955	0.567253	0.000393	0.010847	0.010624
	-0.05344	-0.03396	-0.02581	-0.0079	-0.00791	-0.01639
	[0.75222]	[1.23536]	[21.9762]	[0.04978]	[1.37168]	[0.64826]
G-IGBC (-2)	0.001184	-0.02146	-0.05791	0.006071	-0.005153	-0.005228
	-0.05344	-0.03396	-0.02581	-0.0079	-0.00791	-0.01639
	[0.02216]	[-0.63187]	[-2.16134]	[0.76798]	[-0.65165]	[-0.319]

Notes: In both rows and columns, "G-" stands for GARCH. Each set shows the regressor, its standard error, and in brackets, its t-statistic. Sample (adjusted): 4-1528. Included observations: 1525

Table C.2. (continue)

	G-IBC	G-IBOVESPA	G-IGBC	G-IPSA	G-IPYC	G-MERVAL
G-IPSA (-1)	-0.001535	-0.016454	-0.00498	0.826373	-0.079996	0.167296
	-0.2091	-0.13288	-0.101	-0.03093	-0.03094	-0.06412
	[-0.00734]	[-0.12382]	[-0.04931]	[26.7190]	[-2.58532]	[2.60901]
G-IPSA (-2)	0.038185	0.049119	0.16735	-0.039704	0.070551	-0.16677
	-0.207	-0.13155	-0.09998	-0.03062	-0.03063	-0.06348
	[0.18447]	[0.37339]	[1.67378]	[-1.29676]	[2.30321]	[-2.62720]
G-IPYC (-1)	-0.003738	0.084325	0.089101	-0.064265	1.008063	0.0015
	-0.20765	-0.13197	-0.1003	-0.03071	-0.03073	-0.06368
	[-0.018]	[0.639]	[0.88837]	[-2.09237]	[32.8058]	[0.02356]
G-IPYC (-2)	0.045741	-0.149404	-0.074558	0.030844	-0.096782	0.052003
	-0.20867	-0.13261	-0.10079	-0.03086	-0.03088	-0.06399
	[0.21921]	[-1.12663]	[-0.73975]	[0.99933]	[-3.13427]	[0.81267]
G-MERVAL(-1)	-0.039335	0.070158	-0.036475	0.004902	0.052383	0.916515
	-0.10815	-0.06873	-0.05224	-0.016	-0.016	-0.03317
	[-0.36371]	[1.02077]	[-0.69826]	[0.30642]	[3.27313]	[27.6348]
G-MERVAL(-2)	0.020047	0.102108	0.017209	0.048767	-0.030503	0.022065
	-0.10875	-0.06911	-0.05253	-0.01609	-0.01609	-0.03335
	[0.18434]	[1.47740]	[0.32761]	[3.03168]	[-1.8954]	[0.66162]
C	6.14E-05	3.53E-05	9.64E-05	2.18E-05	2.44E-05	2.32E-05
	-3.20E-05	-2.00E-06	-1.50E-05	-4.70E-06	-4.70E-06	-9.80E-06
	[1.91979]	[1.73814]	[6.23572]	[4.60269]	[5.14930]	[2.36543]
R^2	0.771587	0.915223	0.305837	0.801158	0.901052	0.905503
Adj. R^2	0.769774	0.91455	0.300328	0.79958	0.900267	0.904753
$\sum resids^2$	0.000794	0.000321	0.000185	1.74E-05	1.74E-05	7.46E-06
S.E. equation	0.000725	0.00046	0.00035	0.000107	0.000107	0.000222
F-statistic	425.6315	1360.252	55.51365	507.6696	1147.401	1207.378
Log likelihood	8868.328	9559.644	9978.09	11782.81	11782.81	10670.9
Akaike AIC	-11.61355	-12.52019	-13.06897	-15.43581	-15.4349	-13.97757
Schwarz SC	-11.56811	-12.47475	-13.02354	-15.39038	-15.38947	-13.93214
Mean dependent	0.000705	0.001313	0.000243	0.000218	0.000408	0.00065
S.D. dependent	0.00151	0.001575	0.000418	0.000239	0.00034	0.00072
Determinant resid covariance (dof adj)			3.15E-44	Akaike AIC		-83.08744
Determinant resid covariance			2.99E-44	Schwarz criterion		-82.81483
Log likelihood			63432.17			

Notes: In both rows and columns, "G-" stands for GARCH. Each set shows the regressor, its standard error, and in brackets, its t-statistic. Sample (adjusted): 4-1528. Included observations: 1525

Table C.3. Vector Autoregression Estimates - Good times

	G-IBC	G-IBOV ESPA	G-IGBC	G-IPSA	G-IPYC	G-MERVAL
G-IBC(-1)	0.539714	0.00119	-0.03845	0.002103	0.001211	-0.007662
	-0.03171	-0.00264	-0.02919	-0.00208	-0.004	-0.01896
	[17.0178]	[0.45083]	[-1.31706]	[1.01284]	[0.30260]	[-0.40417]
G-IBC(-2)	-0.064383	-0.004515	0.004618	-0.001933	-0.004627	-0.004423
	-0.03133	-0.00261	-0.02884	-0.00205	-0.00395	-0.01873
	[-2.05513]	[-1.73138]	[0.16013]	[-0.94257]	[-1.17079]	[-0.23623]
G-IBOV ESPA(-1)	-0.066583	0.975092	0.631454	-0.000749	0.192309	0.506762
	-0.43749	-0.03642	-0.40272	-0.02864	-0.05519	-0.26151
	[-0.15219]	[26.7762]	[1.56798]	[-0.02616]	[3.48459]	[1.93786]
G-IBOV ESPA(-2)	0.017057	-0.007798	-0.397005	0.002327	-0.19824	-0.374548
	-0.43738	-0.03641	-0.40261	-0.02863	-0.05517	-0.26144
	[0.039]	[-0.21419]	[-0.98607]	[0.08126]	[-3.593]	[-1.43265]
G-IGBC (-1)	-0.049804	-0.003867	0.6655	-0.001073	-0.006824	0.004087
	-0.0345	-0.00287	-0.03176	-0.00226	-0.00435	-0.02062
	[-1.44366]	[-1.34652]	[20.9563]	[-0.47498]	[-1.56804]	[0.19818]
G-IGBC (-2)	0.024673	0.002419	-0.014704	-0.000874	0.002367	-0.007435
	-0.03449	-0.00287	-0.03175	-0.00226	-0.00435	-0.02062
	[0.71539]	[0.84270]	[-0.46317]	[-0.38714]	[-0.54415]	[-0.36068]
G-IPSA (-1)	-0.29819	-0.006195	-0.04313	0.962461	-0.075495	0.305374
	-0.50749	-0.04224	-0.46715	-0.03322	-0.06402	-0.30334
	[-0.58724]	[-0.14665]	[-0.09232]	[28.9695]	[-1.17928]	[1.00669]
G-IPSA (-2)	0.415596	0.012993	-0.100546	-0.077773	0.094426	-0.4406
	-0.50531	-0.04206	-0.46515	-0.03308	-0.06374	-0.30204
	[0.82246]	[0.3089]	[-0.21616]	[-2.25101]	[1.48135]	[-1.45874]
G-IPYC (-1)	0.140033	-0.02148	-0.119373	0.022975	0.973799	0.102384
	-0.26911	-0.0224	-0.24772	-0.01762	-0.03395	-0.16086
	[0.52036]	[-0.95891]	[-0.48189]	[1.30409]	[28.6855]	[0.63649]
G-IPYC (-2)	-0.000656	0.02788	0.066947	-0.017149	-0.004239	-0.157047
	-0.26841	-0.02234	-0.24707	-0.01757	-0.03386	-0.16044
	[-0.00244]	[1.24787]	[0.27096]	[-0.97592]	[-0.12519]	[-0.97887]
G-MER VAL(-1)	-0.08461	0.009029	0.129026	-0.003727	0.00511	0.957106
	-0.0532	-0.00443	-0.04897	-0.00348	-0.00671	-0.0318
	[-1.59052]	[2.03916]	[2.63491]	[-1.07013]	[0.76143]	[30.1001]
G-MER VAL(-2)	0.091275	-0.007878	-0.110719	0.004615	-0.00522	-0.005043
	-0.05303	-0.00441	-0.04882	-0.00347	-0.00669	-0.0317
	[1.72109]	[-1.78458]	[-2.268]	[1.32923]	[-0.78028]	[-0.15909]
C	0.000152	1.19E-05	8.31E-06	9.33E-06	1.00E-05	1.58E-05
	-3.90E-05	-3.20E-06	-3.60E-05	-2.50E-06	-4.90E-06	-2.30E-05
	[3.9268]	[3.68423]	[0.23296]	[3.68092]	[2.04957]	[0.68415]

Notes: In both rows and columns, "G-" stands for GARCH. Each set shows the regressor, its standard error, and in brackets, its t-statistic. Sample (adjusted): 4-1089. Included observations: 1086

Table C.3. (continue)

R^2	0.26495	0.951902	0.464429	0.818797	0.955375	0.922551
Adj. R^2	0.25673	0.951364	0.458439	0.81677	0.954876	0.921685
$\sum \text{resids}^2$	0.00013	8.98E-07	0.00011	5.56E-07	12.06E-06	4.63E-05
S.E. equation	0.000348	2.89E-05	0.00032	2.28E-05	4.38E-05	0.000208
F-statistic	32.23041	1769.617	77.5391	404.0445	1914.329	1065.111
Log likelihood	7115.016	9814.862	7204.962	10075.7	9363.372	7673.879
Akaike AIC	-13.07922	-18.05131	-13.24486	-18.53167	-17.21984	-14.10843
Schwarz SC	-13.01948	-17.99158	-13.18513	-18.47193	-17.1601	-14.0487
Mean dependent	0.000342	0.000427	0.000238	0.000103	0.00026	0.000814
S.D. dependent	0.00403	0.000131	0.000435	5.32E-05	0.000206	0.000742
Determinant resid covariance (dof adj)			2.49E-49	Akaike AIC		-94.81764
Determinant resid covariance			2.31E-49	Schwarz criterion		-94.45923
Log likelihood			51563.98			

Notes: Sample (adjusted): 4-1089. Included observations: 1086

Appendix D. Granger Causality Tests

Table D.1. Pairwise Granger Causality Test - Complete period

Null hypothesis	Observations	F-Statistic	Probability
G-IBOVESPA does not Granger Cause G-IBC	2613	1.65355	0.19157
G-IBC does not Granger Cause G-IBOVESPA		2.6899	0.06808
G-IGBC does not Granger Cause G-IBC	2613	0.20831	0.81197
G-IBC does not Granger Cause G-IGBC		0.1537	0.85753
G-IPSA does not Granger Cause G-IBC	2613	1.20751	0.29911
G-IBC does not Granger Cause G-IPSA		1.34601	0.26046
G-IPYC does not Granger Cause G-IBC	2613	1.82971	0.16067
G-IBC does not Granger Cause G-IPYC		0.00035	0.99965
G-MERVAL does not Granger Cause G-IBC	2613	0.5971	0.55048
G-IBC does not Granger Cause G-MERVAL		0.03016	0.97029
G-IGBC does not Granger Cause G-IBOVESPA	2613	0.28952	0.74865
G-IBOVESPA does not Granger Cause G-IGBC		1.08455	0.33821
G-IPSA does not Granger Cause G-IBOVESPA	2613	13.5554	1.40E-06
G-IBOVESPA does not Granger Cause G-IPSA		11.3237	1.30E-05
G-IPYC does not Granger Cause G-IBOVESPA	2613	5.06054	0.0064
G-IBOVESPA does not Granger Cause G-IPYC		10.485	2.90E-05
G-MERVAL does not Granger Cause G-IBOVESPA	2613	8.78762	0.00016
G-IBOVESPA does not Granger Cause G-MERVAL		5.70981	0.00335
G-IPSA does not Granger Cause G-IGBC	2613	2.4502	0.08648
G-IGBC does not Granger Cause G-IPSA		0.06881	0.9335

Notes: "G-" stands for GARCH. Sample: 1-2616. Lags: 2

Table D.1. (continue)

Null hypothesis	Observations	F-Statistic	Probability
G-IPYC does not Granger Cause G-IGBC	2613	0.81859	0.44117
G-IGBC does not Granger Cause G-IPYC		0.00686	0.99317
G-MERVAL does not Granger Cause G-IGBC	2613	5.40755	0.00453
G-IGBC does not Granger Cause G-MERVAL		0.41342	0.66143
G-IPYC does not Granger Cause G-IPSA	2613	4.42139	0.01211
G-IPSA does not Granger Cause G-IPYC		3.09221	0.04557
G-MERVAL does not Granger Cause G-IPSA	2613	9.83138	5.60E-05
G-IPSA does not Granger Cause G-MERVAL		7.46136	0.00059
G-MERVAL does not Granger Cause G-IPYC	2613	6.22785	0.002
G-IPYC does not Granger Cause G-MERVAL		1.74481	0.17488

Notes: "G-" stands for GARCH. Sample: 1-2616. Lags: 2

Table D.2. Pairwise Granger Causality Test - Bad times

Null hypothesis	Observations	F-Statistic	Probability
G-IBOVESPA does not Granger Cause G-IBC	1525	0.63747	0.52877
G-IBC does not Granger Cause G-IBOVESPA		1.60668	0.20089
G-IGBC does not Granger Cause G-IBC	1525	0.49429	0.6101
G-IBC does not Granger Cause G-IGBC		0.2436	0.78383
G-IPSA does not Granger Cause G-IBC	1525	0.4496	0.63797
G-IBC does not Granger Cause G-IPSA		0.74234	0.47617
G-IPYC does not Granger Cause G-IBC	1525	0.51662	0.59664
G-IBC does not Granger Cause G-IPYC		0.00327	0.99673
G-MERVAL does not Granger Cause G-IBC	1525	0.46822	0.62621
G-IBC does not Granger Cause G-MERVAL		0.22323	0.79996
G-IGBC does not Granger Cause G-IBOVESPA	1525	1.07175	0.34267
G-IBOVESPA does not Granger Cause G-IGBC		0.85634	0.42492
G-IPSA does not Granger Cause G-IBOVESPA	1525	7.90587	0.0.00038
G-IBOVESPA does not Granger Cause G-IPSA		7.61613	0.00051
G-IPYC does not Granger Cause G-IBOVESPA	1525	3.29425	0.03736
G-IBOVESPA does not Granger Cause G-IPYC		6.21157	0.00206
G-MERVAL does not Granger Cause G-IBOVESPA	1525	19.5173	4.30E-09
G-IBOVESPA does not Granger Cause G-MERVAL		3.80756	0.02241
G-IPSA does not Granger Cause G-IGBC	1525	3.9851	0.01879
G-IGBC does not Granger Canse G-IPSA		0.21148	0.80941
G-IPYC does not Granger Cause G-IGBC	1525	1.00844	0.36503
G-IGBC does not Granger Cause G-IPYC		0.7874	0.45521
G-MERVAL does not Granger Cause G-IGBC	1525	1.10542	0.33134
G-IGBC does not Granger Cause G-MERVAL		0.33899	0.71254

Notes: "G-" stands for GARCH. Sample: 1-1528. Lags: 2

Table D.2. (continue)

Null hypothesis	Observations	F-Statistic	Probability
G-IPYC does not Granger Cause G-IPSA	1525	3.13775	0.04366
G-IPSA does not Granger Cause G-IPYC		1.71307	0.18066
G-MERVAL does not Granger Cause G-IPSA	1525	24.0999	5.00E-11
G-IPSA does not Granger Cause G-MERVAL		5.14705	0.00592
G-MERVAL does not Granger Cause G-IPYC	1525	9.98451	4.90E-05
G-IPYC does not Granger Cause G-MERVAL		1.84986	0.15761

Notes: "G-" stands for GARCH. Sample: 1-1528. Lags: 2

Table D.3. Pairwise Granger Causality Test - Good times

Null hypothesis	Observations	F-Statistic	Probability
G-IBOVESPA does not Granger Cause G-IBC	1086	0.76914	0.46367
G-IBC does not Granger Cause G-IBOVESPA		1.39236	0.24893
G-IGBC does not Granger Cause G-IBC	1086	1.47791	0.22857
G-IBC does not Granger Cause G-IGBC		0.66838	0.51275
G-IPSA does not Granger Cause G-IBC	1086	1.52628	0.21781
G-IBC does not Granger Cause G-IPSA		0.49873	0.60744
G-IPYC does not Granger Cause G-IBC	1086	3.49178	0.03079
G-IBC does not Granger Cause G-IPYC		0.83975	0.4321
G-MERVAL does not Granger Cause G-IBC	1086	1.99686	0.13626
G-IBC does not Granger Cause G-MERVAL		0.4371	0.64602
G-IGBC does not Granger Cause G-IBOVESPA	1086	0.62504	0.53544
G-IBOVESPA does not Granger Cause G-IGBC		4.9074	0.00756
G-IPSA does not Granger Cause G-IBOVESPA	1086	0.12012	0.88682
G-IBOVESPA does not Granger Cause G-IPSA		0.669	0.51243
G-IPYC does not Granger Cause G-IBOVESPA	1086	1.07501	0.34166
G-IBOVESPA does not Granger Cause G-IPYC		6.31905	0.00187
G-MERVAL does not Granger Cause G-IBOVESPA	1086	1.69979	0.18321
G-IBOVESPA does not Granger Cause G-MERVAL		4.343422	0.01322
G-IPSA does not Granger Cause G-IGBC	1086	0.28589	0.7514
G-IGBC does not Granger Cause G-IPSA		0.44695	0.63969
G-IPYC does not Granger Cause G-IGBC	1086	0.19428	0.82346
G-IGBC does not Granger Cause G-IPYC		1.71253	0.1809
G-MERVAL does not Granger Cause G-IGBC	1086	6.15005	0.00221
G-IGBC does not Granger Cause G-MERVAL		0.22308	0.80008
G-IPYC does not Granger Cause G-IPSA	1086	2.06707	0.12706
G-IPSA does not Granger Cause G-IPYC		0.13426	0.87438

Notes: "G-" stands for GARCH. Sample: 1-1089. Lags: 2

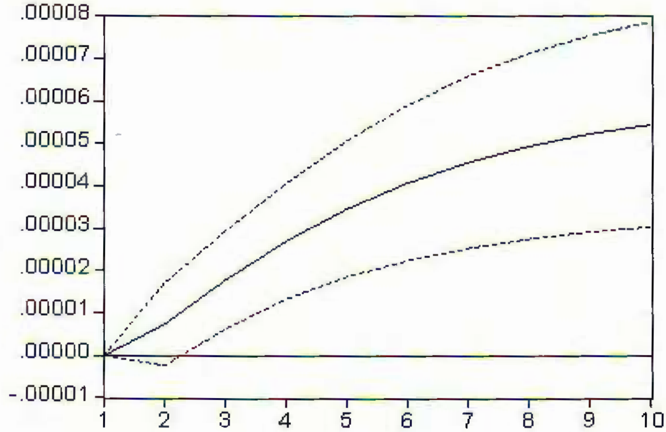
Table D.3. (continue)

Null hypothesis	Observations	F-Statistic	Probability
G-MERVAL does not Granger Cause G-IPSA	1086	0.69173	0.50093
G-IPSA does not Granger Cause G-MERVAL		2.74072	0.06497
G-MERVAL does not Granger Cause G-IPYC	1086	0.79138	0.45348
G-IPYC does not Granger Cause G-MERVAL		2.41932	0.08946

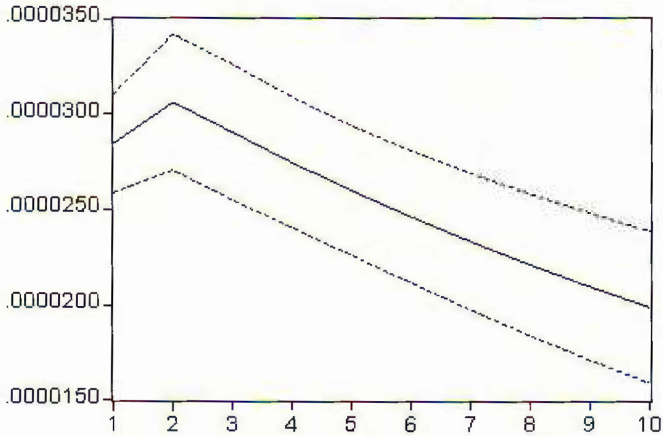
Notes: "G-" stands for GARCH. Sample: 1-1089. Lags: 2

Appendix D.4 Impulse-Response Funtions Integrated Markets in Complete Period.

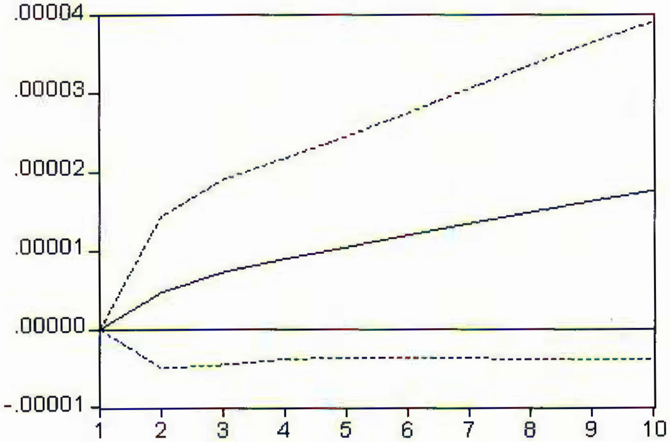
Response of GARCHIBOVESPA to Cholesky
One S.D. GARVHIPSA Innovation



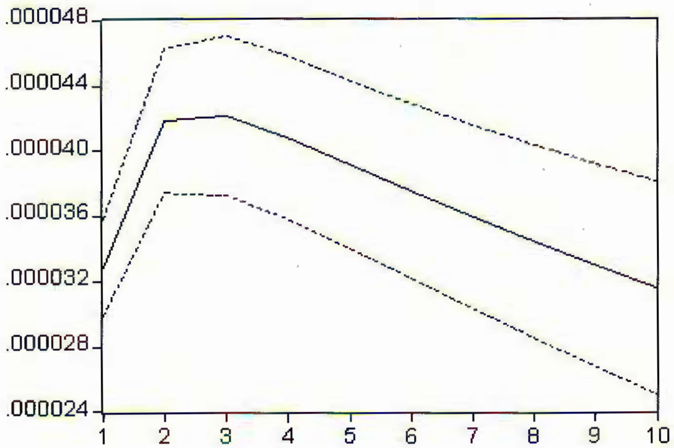
Response of GARCHIPSA to Cholesky
One S.D. GARCHIBOVESPA Innovation



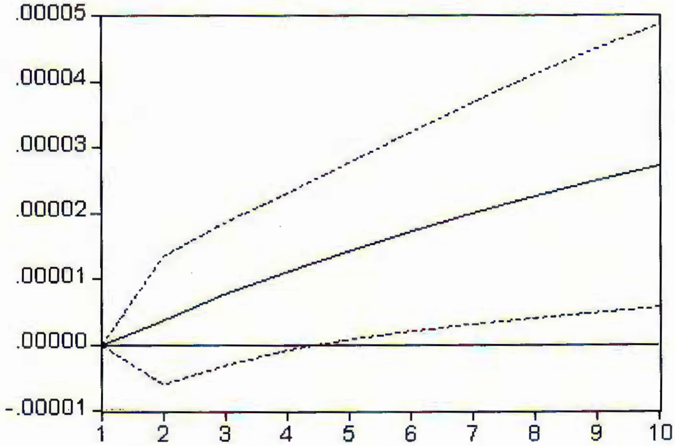
Response of GARCHIBOVESPA to Cholesky
One S.D. GARCHIPYC Innovation



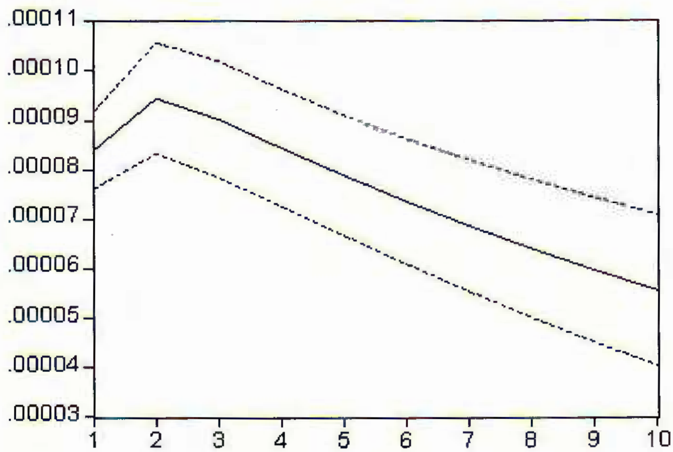
Response of GARCHIPYC to Cholesky
One S.D. GARCHIBOVESPA Innovation



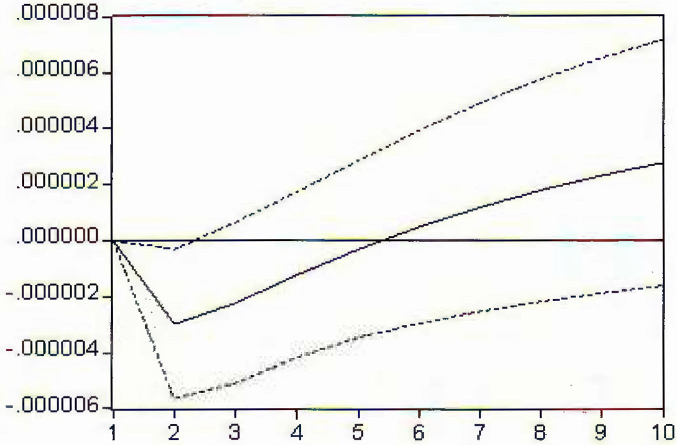
Response of GARCHIBOVESPA to Cholesky
One S.D. GARCHMERVAL Innovation



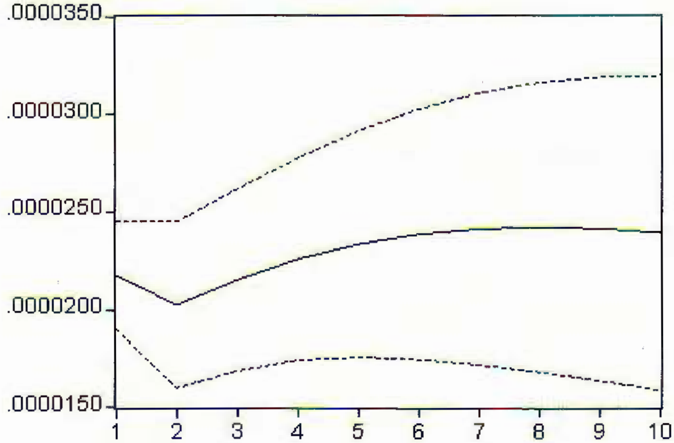
Response of GARCHMERVAL to Cholesky
One S.D. GARCHIBOVESPA Innovation



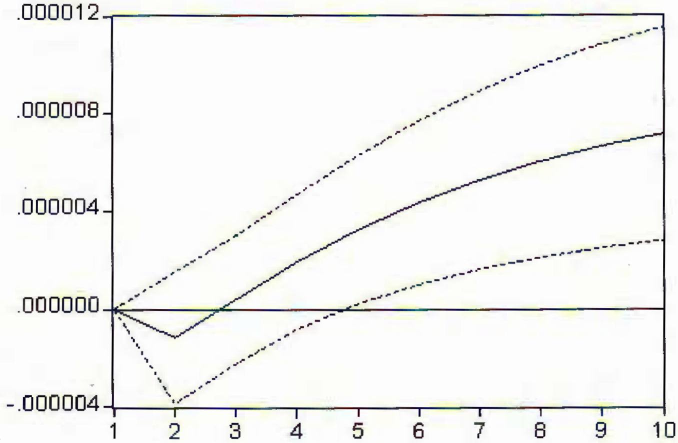
Response of GARCHIPSA to Cholesky
One S.D. GARCHIPYC Innovation



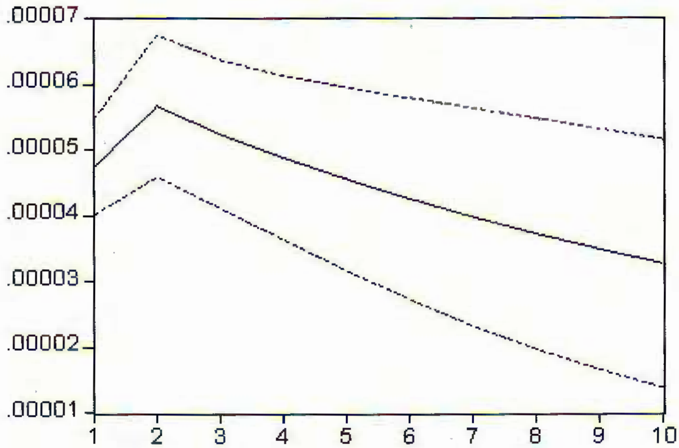
Response of GARCHIPYC to Cholesky
One S.D. GARCHIPSA Innovation



Response of GARCHIPSA to Cholesky
One S.D. GARCHMERVAL Innovation



Response of GARCHMERVAL to Cholesky
One S.D. GARCHIPSA Innovation



References

Bera, A., and Higgins, M. (1993). A Survey of ARCH Models: Properties, Estimation and Testing. Journal of Economic Surveys, Vol 7, No. 4.

Bollerslev, T., Chou, R., and Kroner, K. (1992). ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence. Econometrics, Vol. 52.

Bollerslev. T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 31, 307-327.

Bollerslev, T., Chou, R., and Kroner, K. (1992). ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence. Econometrics, Vol. 52.

Bollerslev. T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics, 31, 307-327.

Brooks, C. (2002). Introductory Econometrics for Finance. Cambridge University Press.

Edwards, S. (2000). Contagion. University of California, Los Angeles and National Bureau of Economic Research.

Enders, W. (2004). Applied Econometric Time Series. 2nd Edition, Wiley Series in Probability and Statistics.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, Vol. 50, No. 4, 987-1008.

Kaminsky, G., Reinhart, C., and Végh, C. (2003). The Unholy Trinity of Financial Contagion. Journal of Economic Perspectives, 17, 4, 51-74.

Pericoli, M., and Sbracia, M. (2001). A Primer on Financial Contagion. Banca d' Italia.

Rijckeghem, C., and Weder, B. (1999). Sources of Contagion: Finance or Trade? International Monetary Fund, WP/99/146.

Ruppert, D. (2001). Lecture Notes for ORIE 473: Empirical Methods in Financial Engineering. Cornell University.

Brooks, C. (2002). Introductory Econometrics for Finance. Cambridge University Press.

Edwards, S. (2000). Contagion. University of California, Los Angeles and National Bureau of Economic Research.

Edwards, S. (2000). Contagion. University of California, Los Angeles and National Bureau of Economic Research.

Enders, W. (2004). Applied Econometric Time Series. 2nd Edition, Wiley Series in Probability and Statistics.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, Vol. 50, No. 4, 987-1008.

Kaminsky, G., Reinhart, C., and Végh, C. (2003). The Unholy Trinity of Financial Contagion. Journal of Economic Perspectives, 17, 4, 51-74.

Pericoli, M., and Sbracia, M. (2001). A Primer on Financial Contagion. Banca d' Italia.

Rijckeghem, C., and Weder, B. (1999). Sources of Contagion: Finance or Trade? International Monetary Fund, WP/99/146.

Ruppert, D. (2001). Lecture Notes for ORIE 473: Empirical Methods in Financial Engineering. Cornell University.

Enders, W. (2004). Applied Econometric Time Series. 2nd Edition, Wiley Series in Probability and Statistics.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, Vol. 50, No. 4, 987-1008.

Kaminsky, G., Reinhart, C., and Végh, C. (2003). The Unholy Trinity of Financial Contagion. Journal of Economic Perspectives, 17, 4, 51-74.

Pericoli, M., and Sbracia, M. (2001). A Primer on Financial Contagion. Banca d' Italia.

Rijckeghem, C., and Weder, B. (1999). Sources of Contagion: Finance or Trade? International Monetary Fund, WP/99/146.

Ruppert, D. (2001). Lecture Notes for ORIE 473: Empirical Methods in Financial Engineering. Cornell University.

Ruppert, D. (2001). Lecture Notes for ORIE 473: Empirical Methods in Financial Engineering. Cornell University.

Enders, W. (2004). Applied Econometric Time Series. 2nd Edition, Wiley Series in Probability and Statistics.

Engle, R. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica, Vol. 50, No. 4, 987-1008.

Kaminsky, G., Reinhart, C., and Végh, C. (2003). The Unholy Trinity of Financial Contagion. Journal of Economic Perspectives, 17, 4, 51-74.

Pericoli, M., and Sbracia, M. (2001). A Primer on Financial Contagion. Banca d' Italia.

Rijckeghem, C., and Weder, B. (1999). Sources of Contagion: Finance or Trade? International Monetary Fund, WP/99/146.

Ruppert, D. (2001). Lecture Notes for ORIE 473: Empirical Methods in Financial Engineering. Cornell University.