ARCH models for Value at Risk forecasting in Latin American stock and Forex markets*

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Abstract

Using stock and Forex markets daily returns, a set of ARCH models with three different mean specifications and four error distributions are used to forecast the one-day ahead Value at Risk (VaR) at 1% and 5% confidence level for a group of Latin American countrys. The main results are: (i) in general, FIGARCH volatility process and leptokurtic distributions are able to produce better one-step-ahead VaR forecasts (ii) the models that best fit the full series in-sample are not necessarily the ones that obtain the most accurate VaR forecasts out-of-sample and (iii) the models producing the most accurate forecasts vary by market and country.

JEL Classification: C22, C52, C53.

Keywords: ARCH models, Value at Risk, Backtest, Volatility, Latin American markets, Stock, Forex.

*The source data and procedures to replicate the results in this research are available in the supplementary material.

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1 Introduction

Volatility is a key input in financial risk management methods like Value at Risk (VaR) so its study has been a field of interest within finance and econometrics. One of the most popular class of models for study the volatility are the autoregressive conditional heteroskedasticity (ARCH) that since its development by Engle (1982) have been widely extended to capture the complexity of financial data. The better the model fits and forecast the financial series, the more accurate the risk metric will be. In this context, the empirical literature has identified a set of stylized facts of the financial returns, some of these are *i*) correlated volatility, *ii*) leptokurtic distribution of the disturbance term, *iii*) leverage effect, *iv*) negative skewness and *v*) long memory in r_t^δ or other transformations; see Franses and Dijk (2000).

In this research a group of five ARCH volatility models with three different specifications for the mean equation, and four error distributions are used to model and forecast stock and Forex market return volatility of a group of Latin American countrys. Then, from a risk management perspective, the forecasted volatility is used to estimate the one-day ahead Value at Risk (VaR) at 1% and 5% confidence level. The accuracy of the forecasts are evaluated through backtest tests from which the following results are obtained: (i) in general, FIGARCH volatility process and leptokurtic distributions are able to produce better one-step-ahead VaR forecasts (ii) the models that best fit the full series in-sample are not necessarily the ones that obtain the most accurate VaR forecasts out-of-sample and (iii) the models producing the most accurate forecasts vary by market and country.

The document proceeds as follows. Section 2 contains the literature review. Section 3 briefly presents the models and backtest procedures that are used in the empirical section. Section 4 analyze the empirical findings.

2 Literature review

The theoretical literature on the study of volatility with ARCH models is extensive and a great interest to financial risk managers[1]. The starting point is often considered to be Engle (1982), who formally introduces the autoregressive conditional heteroskedasticity (ARCH) univariate model to explain the dynamic of inflation in the United Kingdom. Following this line, Bollerslev (1986) developed a generalization of the ARCH model by allowing past conditional variances to be integrated as regressors within the current conditional variance equation.

The GARCH model has been extended to capture additional stylized facts observed in financial returns. One of the most studied is the so-called financial leverage effect, which refers that volatility responds asymmetrically to negative and positive past returns. In this sense, it is more likely to observe high volatility when past returns have been negative; see Black (1976). In this regard, Nelson (1991) developed the exponential GARCH (EGARCH), which captures the leverage effects through a dummy variable and remove the restrictions of the non-negativity of the variance present in the GARCH model. In the same line, Glosten et al. (1993) developed the GJR model witch incorporates an asymmetry parameter in the GARCH equation that exacerbates the volatility when past returns were negative.

Another stylized fact is the long memory of volatility. To capture this effect Baillie et al. (1996) introduce the fractionally integrated GARCH (FIGARCH) which allows to conditional variance decay at a slow hyperbolic rate determined by the parameter of fractional differentiation. Similarly, Ding et al. (1993) proposed the asymmetric power ARCH (APARCH) that allows an estimation of the long memory parameter in the volatility.

On the side of empirical research, Vlaar (2000) found that the GARCH-$\mathcal{N}$ outperform other distributions such as student-$\mathcal{S}$ and the historical simulation models in VaR estimation for the Dutch bond interest rates. On the other hand, Brooks and Persand (2003) compare symmetric and asymmetric arch-type models on VaR accuracy for a selection of Southeast Asian stock indices. They found that models ignoring asymmetrical effects lead to inappropriately small VaR estimates compared to models taking the asymmetries in account. In addition, Angelidis et al. (2004) evaluate through backtest procedures the performance of an extensive family of ARCH models with different error distributions and sample sizes in forecasting one-day ahead VaR of a selection of major stock indices. The results don't reveal a clearly superior model but concluded that heavy-tail

[1]See Engle and Manganelli (2004) and Bollerslev (2008) for a survey on the theoretical development of the ARCH models, and Poon and Granger (2003) and Andersen et al. (2005) for empirical application in forecasting volatility.

distributions lead to more accurate VaR forecasts than the Normal distribution and that there is no consistent relation between the sample sizes and the optimal models. Ane (2006) compares different VaR specifications in an Asymmetric Power ARCH framework for the japanesse stock market and found that include a optimal power parameter provides little improvements for risk management. Orhan and Koksal (2012) compare a comprehensive list of ARCH models in quantifying VaR for of stock market indices of emerging (Brazil and Turkey) and developed (Germany and the USA) markets. They concluded that leptokurtic error distributions yielded the best results for VaR estimations.

Other documents with empirical applications of ARCH models in VaR forecast are Fan et al. (2008), who analyze the crude oil price incorporating a GED distribution; Liu and Hung (2010), who study the Standard & Poor's 100 with asymmetric distributions and ARCH models; and Ardia and Hoogerheide (2014), who analyze the impact of the estimation frequency on one-day ahead forecasts of risk metrics.

3 Methodology

A set of ARCH models is used to forecast the one-day ahead VaR at 1% and 5% confidence level for a group of Latin American countrys. This is done through a four-step out-of-sample analysis. First, an ARCH-type model is estimated for a given window of 250 observations equivalent to a trading year. Second, with the fitted model the one-day-ahead volatility and distribution of returns is obtained. Third, VaR is computed from forecasted volatility and distribution parameters. Fourth, the accuracy of the VaR forecasts is analyzed by backtest tests. Additionally, as a previous step, an in-sample analysis is performed where the models are specified and its parameters estimated with the full available series.

A complete ARCH model is divided into three components: mean specification, volatility model and distribution of the disturbance term. This research consider three different mean equation specifications (zero, constant, AR(1)), five volatility process (ARCH, GARCH, GJR, FIGARCH and APARCH) and four error distributions (Normal, Student-$\mathcal{S}$, Skeweed Student-$\mathcal{S}$, and Generalized error distribution (GED)).

Regarding the volatility models, two symmetric models are consideres.The ARCH model of Engle (1982) witch can be expressed as

$$\sigma_t^2 = \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-P}^2 \tag{1}$$

Secondly, the GARCH model of Bollerslev (1986) witch reduces the number of estimated parameters by imposing restrictions so that the conditional variance is positive: $\omega > 0$, $\beta \geq 0$ and $\beta_1 \geq 0$ to ensure a positive conditional variance σ^2, and $\alpha + \beta < 1$ to ensure that the unconditional variance is defined. It can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

In third place, on the side of asymmetric models to capture the leverage effect, the GJR (1993) of Glosten et al. (1993) allows the conditional variance to respond differently to the past negative and positive error through the incorporation of a dummy variable $I_{[\varepsilon_{t-i}<0]}$. This model may be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i I_{[\varepsilon_{t-i}<0]} \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{3}$$

The FIGARCH of Baillie et al. (1996) hyperbolic rate of decay for the lagged squared or absolute innovations in the conditional variance function using fractional orders of integration in the autoregressive polynomial:

$$\sigma_t^2 = \omega + \left[1 - \beta L - \phi L \left(1 - L\right)^d\right] \varepsilon_t^2 + \beta \sigma_{t-1}^2 \tag{4}$$

In the APARCH of Ding et al. (1993) parameterizes the non-linearity including a δ parameter to estimate. Adicionally the APARCH nests another seven ARCH models as special cases of its parameters. It is given by

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i I_{[o \geq i]} \varepsilon_{t-i} \right)^\delta + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^\delta \tag{5}$$

Regarding the innovations of the disturbance term, three symmetric distributions around the mean are used. A normal distribution, because it is the most used among practitioners mainly because of its practical advantages. The corresponding density function given by

$$\mathcal{N}(\epsilon_t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{6}$$

Likewise, a student-$\mathcal{S}$ distribution is considered because its thick-tailed seems to correspond more closely to financial returns. Under this distribution the density function is given by

$$\mathcal{S}(\epsilon_t; \nu) = \frac{\Gamma((\nu+1))}{\Gamma\left(\frac{\nu}{2}\right)\sqrt{\pi(\nu-2)}} \left(1 + \frac{z_t^2}{\nu-2}\right)^{-\frac{\nu+1}{2}}$$

Where ν is the kurtosis parameter controlling the thickness of the tails. Nelson (1991) recommended the use of a Generalized error distribution (GED) witch is expressed by

$$GED(\epsilon_t; \nu, \lambda) = \frac{e^{(-0.5|z_t/\lambda|^\nu)\nu}}{2^{\left(1+\frac{1}{\nu}\right)}\Gamma(\nu^{-1})\lambda} \tag{7}$$

Finally, the skewed Student's t-distribution proposed by Hansen (1994) is considered to capture asymmetry in conjunction with leptokurtosis with a λ asymmetric parameter. The corresponding density function expressed by

$$f(\epsilon_t; \nu, \lambda) = \begin{cases} bc\left(1 + \frac{1}{\nu-2}\left(\frac{b\epsilon_t + \sigma_t a}{\sigma_t(1-\lambda)}\right)^2\right)^{-(\nu+1)/2} & \epsilon_t < -a/b \\ bc\left(1 + \frac{1}{\nu-2}\left(\frac{b\epsilon_t + \sigma_t a}{\sigma_t(1+\lambda)}\right)^2\right)^{-(\nu+1)/2} & \epsilon_t \geq -a/b \end{cases} \tag{8}$$

Regarding the risk management perspective, the Value-at-Risk (VaR) is a market risk metric defined as the maximum loss that will be incurred on an asset or portfolio with a given level of confidence α over a specified period and is given by

$$\widehat{VaR}_{t+1}^{\alpha} = -\hat{\mu}_{t+1} - \widehat{\sigma}_{t+1} q_\alpha \tag{9}$$

Where σ_{t+1} is the forecasted 1-day ahead volatility which will be obtained through the ARCH models, and q_α corresponds to the α^{th} quantile of the cumulative distribution function of the errors distribution. The accuracy of VaR forecasts are measured in terms of unconditional coverage and independence distribution of the failures. A VaR failure occurs when the return is less than the forecasted VaR value $r_{t+1} < \widehat{VaR}_{t+1}^{\alpha}$. For example, if the confidence level used for calculating daily VaR is 99%, we expect an exception to occur once in every 100 days on average. Conditional coverage refers that the percentage of failures should be equal to the α confidence level it is measured by the Unconditional coverage (UC) test of Kupiec (1995) (also known as the Proportion of Failures (POF) test) . This is a likelihood ratio test χ^2-distributed with one degree of freedom and a null hypothesis is that the the forecasting model is correct and the observed proportion of tail losses is consistent with the confidence level of the model. The test is given by

$$LR_{UC} = -2\log\left(\frac{(1-p)^{N-x} p^x}{\left(1-\frac{x}{N}\right)^{N-x}\left(\frac{x}{N}\right)^x}\right) \tag{10}$$

where x is the number of VaR failures, N the number of observations and and $p = 1 - \alpha$.

On the other hand, independence refers that the VaR violations are serially independent and is analyzed by the Conditional Coverage (CC) test of Christoffersen (1998) and the Dynamic Quantile (DQ) test of Engle and Manganelli (2004).

The Christoffersen (1998) jointly test the unconditional coverage and the independence through the sum of the individual test statistics for the properties as $LR_{CC} = LR_{UC} + LR_{IND}$. This mean, test both unconditional coverage and the independence null hypotheses combined. The likelihood ratio statistic LR_{CC} has an asymptotically Chi-square distribution with two degree of freedom. It is given by

$$LR_{CC} = -2\log\left(\frac{(1-\pi)^{n00+n10}\,\pi^{n01+n11}}{(1-\pi_0)^{n00}\,\pi_0^{n01}\,(1-\pi_1)^{n10}\,\pi^{n11}}\right) \tag{11}$$

4 Empirical evidence

4.1 Data

The daily closing price of the stock indices and exchange rates of Argentina, Brazil, Chile, Colombia, Mexico and Peru are obtained from Bloomberg Financial Data. Returns are calculated as the percentage change in logarithms of the price (p_t) according to $y_t = 100 * [\log(p_t) - \log(p_{t-1})]$. The series are taken from different dates according to availability. For stock markets the start dates are December 26, 1991 (Argentina); March 16, 1995 (Brazil); August 9, 1990 (Chile); July 26, 2001 (Colombia); March 31, 1994 (Mexico) and February 7, 2002 (Peru). In case of Forex markets the start dates are March 6, 2014 (Argentina); June 03, 1999 (Brazil); January 18, 1990 (Chile); September 3, 1992 (Colombia); May 9, 1996 (Mexico) and May 25, 1995 (Perú). The samples for all countries and markets end on August 31, 2021.

Table 1 shows the descriptive statistics of the series. Panel (a) show the information about stock indices returns where the extreme values are between a minimum of -47.69 (Argentina) and a maximum of 28.82 (Brazil). Additionally, the most volatile stock market index in terms of standard deviation is Argentina and the least volatile is Mexico. Only the stock index of Argentina and Mexico show positive asymmetries. Finally, in line with the empirical literature, it is observed that in all markets the returns are leptokurtic.

Panel (b) show the information about Forex returns. In terms of standard deviation, the Forex markets are less volatile than the stock markets and Peru has the least volatile exchange rate among the selected countries. Further, for all countries except Argentina the extreme values of the Forex market are more limited than in the Stock market. Additionally, unlike stock markets, all skew coefficients for Forex markets are positive. Finally, a characteristic in common between both markets is that they have heavy tails.

Figure 1 and 2 show the evolution of Latam stock and Forex market returns, respectively. We can see typical stylized facts such as volatility clusters. For example, periods of higher volatility during the 2008-2009 crisis and the COVID-19 pandemic.

4.2 Results

A set of five ARCH models with three different mean specifications and four error distributions is implemented. This implies estimating 60 models for each market across all countries. Since we have six stock markets and six Forex markets, the total number of models to estimate is 720.

First, an in–sample analysis is considered. In this the models are fitted to the full available series. Table 4.2 show the results for the estimated parameters[2]. The best models are selected using the log likelihood criteria and, in case of controversy, the BIC and the significance of the parameters. A common result between both markets is that the data never validate the symmetric (ARCH, GARCH) or purely asymmetric (GJR) models, nor the normal distribution. Market-specific results are as follow.

Panel (a) show the results for stock markets where the constant mean especification is selected for all markets except for Colombia, where a cero mean is selected. In no case an AR(1) is selected in the mean equation. Regarding the volatility process, the APARCH model is selected for all markets except for Peru, where a FIGARCH is selected. Likewise, in all cases a GED distribution is selected. Regarding the parameters, it is observed that the asymmetry coefficient γ present in the APARCH is high and significant. In addition, the ν parameter of the GED related to the kurtosis is small and significant, reflecting the presence of heavy tails.

[2]Due the large number of estimated models, only two of the 60 models are included for each serie. The complete table and instructions for replication are available in the supplementary material.

Panel (b) show the results for Forex markets where the constant mean specification is selected for all markets except for Chile, where a mean zero is selected. Regarding the volatility process, the APARCH model is selected for Brazil, Chile and Mexico; and the FIGARCH for Argentina, Colombia and Peru. Additionally, the GED distribution is selected for Brazil, Colombia and Peru; the sk$\mathcal{S}$ for Argentina and Mexico; and Chile is the only case where the $\mathcal{S}$ distribution is selected.

Secondly, in the case of out-of-sample analysis, a rolling–window of 250 observations is used to forecast one–day ahead VaR. The accuracy of the forecasts are measured in terms of conditional coverage through the test of Kupiec (1995) and independence through the test of Christoffersen (1998) and the test of Engle and Manganelli (2004). Table 3 shows the results for p-values of the backtest tests used for VaR at 5% (left panel) and 1% (right panel) confidence level. Panel (a) show the results for stock indices. Overall, the backtest results indicate that the models that had the best fit in the in-sample analysis are not necessarily the most effective in the out-of-sample application. For example, at 5% confidence, the specification of the selected mean does not coincide in any case, for the volatility process it only coincides in one (Peru) of six cases; and regarding the distribution in two (Brazil and Peru) of six cases. Further, it is observed that models that capture asymmetries and long memory (GJR, FIGARCH, APARCH) outperform the standard GARCH and ARCH models; and a fat-tailed distribution of the errors leads to a substantial reduction in the rejection frequencies. Finally, it is observed that the models producing the most accurate forecasts vary by market and country.

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Table 1: Descriptive Statistics for Stock and Forex Markets Returns

Country	Security ID	Start Date	End Date	Obs.	Mean	Std,	Min	Max	Skew	Kurt
(a) Stock Market Returns										
Argentina	MERVAL	1991-12-26	2021-08-31	7744	0.06	2.30	-47.69	16.12	-1.43	27.89
Brasil	IBOV	1995-03-16	2021-08-31	6904	0.05	1.96	-17.23	28.82	0.09	14.05
Chile	IPSA	1990-08-09	2021-08-31	8104	0.05	1.14	-15.22	11.80	-0.32	12.83
Colombia	IGBC	2001-07-26	2021-08-31	5244	0.05	1.14	-11.05	14.69	-0.18	15.73
México	MEXBOL	1994-03-31	2021-08-31	7154	0.04	1.40	-14.31	12.15	0.03	7.56
Perú	SPBLPGPT	2002-02-07	2021-08-31	5104	0.05	1.35	-13.29	12.82	-0.59	12.69
(b) Forex Market Returns										
Argentina	ARS	2014-03-06	2021-08-31	1954	0.13	1.14	-6.03	30.80	12.32	294.71
Brasil	BRL	1999-06-03	2021-08-31	5804	0.02	1.04	-10.34	7.11	0.07	5.90
Chile	CLP	1990-01-18	2021-08-31	8249	0.01	0.60	-4.33	4.68	0.25	7.54
Colombia	COP	1992-09-03	2021-08-31	7564	0.02	0.66	-7.60	6.02	0.17	10.31
México	MXN	1996-05-09	2021-08-31	6604	0.01	0.71	-6.65	7.98	0.85	11.43
Perú	PEN	1995-05-25	2021-08-31	6854	0.01	0.30	-2.85	3.55	0.08	14.54

Table 2: Estimated Parameters for daily Latin American Stock and Forex Markets Return

Model	μ	ω	α	β	γ	δ	ν	λ	BIC	log-lik
Stock Market Returns										
Argentina (MERVAL)										
μ-APARCH-GED	0.0462^a	0.1573^a	0.1120^a	0.8564^a	0.2148^a	1.9847^a	1.0919^a		31888.194	-15912.755
μ-GJR-GED	0.0462^a	0.1592^a	0.0692^a	0.8558^a	0.0955^a		1.0921^a		31879,245	-15912,758
Brazil (IBOV)										
μ-APARCH-GED	0.0503^a	0.0701^a	0.0759^a	0.8980^a	0.4245^a	1.7129^a	1.3592^a		26273.472	-13105.796
μ-GJR-GED	0.0510^a	0.0814^a	0.0275^a	0.8933^a	0.1067^a		1.3594^a		26266,918	-13106,939
Chile (IPSA)										
μ-APARCH-GED	0.0304^a	0.0295^a	0.1411^a	0.8475^a	0.1485^a	1.7939^a	1.3146^a		21853.744	-10895.372
μ-FIGARCH-GED	0.0372^a	0.0400^a	0.2548^a	0.5357^a		0.4905^a	1.3183^a		21845,496	-10895,7481
Colombia (IGBC)										
APARCH-GED		0.0045^a	0.0943^a	0.9203^a	0.2276^a	0.3190^a	1.0853^a		5889.822	-2919.216
μ-APARCH-GED	-0.0000	0.0000	0.1932	0.8068	0.0230	1.8244	1.0100		6023.314	-2981.680
Mexico (MEXBOL)										
μ-APARCH-GED	0.0316^a	0.0160^a	0.0786^a	0.9214^a	0.4290^a	1.4718^a	1.3037^a		22136.973	-11037.422
μ-GJR-GED	0.0331^a	0.0167^a	0.0312^a	0.9131^a	0.0988^a		1.3015^a		22138,601	-11042,674
Peru (SPBLPGPT)										
μ-FIGARCH-GED	0.0397^a	0.0846^a	0.0867	0.3316^a		0.4235^a	1.1342^a		14482.021	-7215.397
μ-APARCH-GED	0.0375^b	0.0394^a	0.1473^a	0.8337^a	0.0743^b	1.9825^a	1.1281^a		14524,715	-7232,475
Forex Market Returns										
Argentina (ARS)										
μ-FIGARCH-sk$\mathcal{S}$	0.0539^a	0.0003	0.0541	0.6814^b	0.8463^a	0.8918^a	3.0927^a	0.0909^b	500.480	-223.718
μ-FIGARCH-S	0.0501	0.0003	0.0768	0.6077^a		0.8463^a	3.0500^a		505,101	-229,817
Brazil (BRL)										
μ-APARCH-GED	0.0022	0.0139^a	0.0968^a	0.9032^a	-0.3064^a	1.4421^a	1.3863^a		14806.536	-7372.936
GJR-GED		0.0101^a	0.1438^a	0.8940^a	-0.0872^a		1.3768^a		14800,927	-7378,798
Chile (CLP)										
APARCH-$\mathcal{S}$		0.0270^a	0.1300^a	0.8686^a	-0.4153^a	0.2499^a	2.8537^a		8009.367	-3977.630
APARCH-sk$\mathcal{S}$		0.0177^a	0.0884^a	0.9099^a	0.2023^a	0.3396^a	3.0470^a	0.0971^a	8837.625	-4387.250
Colombia (COP)										
μ-FIGARCH-GED	0.0000	0.0024^c	0.2664^a	0.5728^a		0.4672^a	1.0100^a		10252.889	-5099.651
FIGARCH-GED		0.0024^c	0.2662^a	0.5730^a		0.4675^a	1.0100^a		10244,165	-5099,754
Mexico (MXN)										
μ-APARCH-sk$\mathcal{S}$	0.0117^a	0.0120^a	0.0966^a	0.9034^a	-0.4849^a	1.1410^a	7.3379^a	0.1336^a	11378.144	-5653.890
μ-GJR-GED	0.0331^a	0.0167^a	0.0312^a	0.9131^a	0.0988^a		1.3015^a		22138,601	-11042,674
Peru (PEN)										
μ-FIGARCH-GED	-0.0000	0.0002	0.1766^a	0.6098^a		0.6468^a	1.0100^a		-2873.629	1463.312
μ-APARCH-GED	-0.0000	0.0004	0.1618^a	0.8382^a	-0.1393	2.0107	1.0100^a		-2844,943	1453,385

a, b, c denote significance level at 1%, 5% and 10% respectively

Table 3: Accuracy of VaR predictions for Stock and Forex Markets Returns

VaR 5% risk level					VaR 1% risk level				
Model	% Failures	UC	CC	DQ	Model	% Failures	UC	CC	DQ
(a) Stock Market Returns									
Argentina (MERVAL)									
AR(1)-GARCH-$\mathcal{S}$	0.0653	0.0373*	0.0078*	0.0000*	AR(1)-FIGARCH-GED	0,0179	0.0272*	0.0518	0.0000*
AR(1)-GJR-$\mathcal{N}$	0.0674	0.0185*	0.0061*	0.0011*	GARCH-$\mathcal{N}$	0,0189	0.0133*	0.0331*	0.0000*
Brazil (IBOV)									
μ-GJR-GED	0.055285	0.0749	0.0066*	0.0155*	APARCH-$\mathcal{S}$	0.0167	0.0000*	0.0000*	0.0000*
μ-APARCH-GED	0.055286	0.0748	0.0067*	0.0155*	APARCH-GED	0.0167	0.0000*	0.0000*	0.0000*
Chile (IPSA)									
GJR-$\mathcal{S}$	0,0568	0.0058*	0.0000*	0.0000*	FIGARCH-sk$\mathcal{S}$	0,0166	0.0000*	0.0000*	0.0000*
APARCH-$\mathcal{S}$	0,0569	0.0058*	0.0000*	0.0000*	GARCH-GED	0,0166	0.0000*	0.0000*	0.0000*
Mexico (MEXBOL)									
FIGARCH-$\mathcal{S}$	0,044	0.3030	0.0047*	0.0121*	GJR-$\mathcal{N}$	0,0146	0.0690	0.0003*	0.0000*
FIGARCH-GED	0,045	0.3030	0.0003*	0.0002*	APARCH-$\mathcal{N}$	0,0147	0.0690	0.0002*	0.0000*
Peru (SPBLPGPT)									
FIGARCH-GED	0,0569	0.0312*	0.0000*	0.0000*	FIGARCH-sk$\mathcal{S}$	0,0165*	0.0000*	0.0000*	0.0000*
μ-GARCH-$\mathcal{S}$	0,0571	0.0266*	0.0000*	0.0000*	FIGARCH-GED	0,0173*	0.0000*	0.0000*	0.0000*
(b) Forex Market Returns									

UC refers to the Unconditional coverage test of Kupiec (1995), CC to the Conditional coverage (CC) test of Christoffersen (1998) and DQ to the Dynamic quantile test of Engle and Manganelli (2004). Likewise, * denote the p–values below 5%.

Figure 1: Latin American Stock Markets Returns

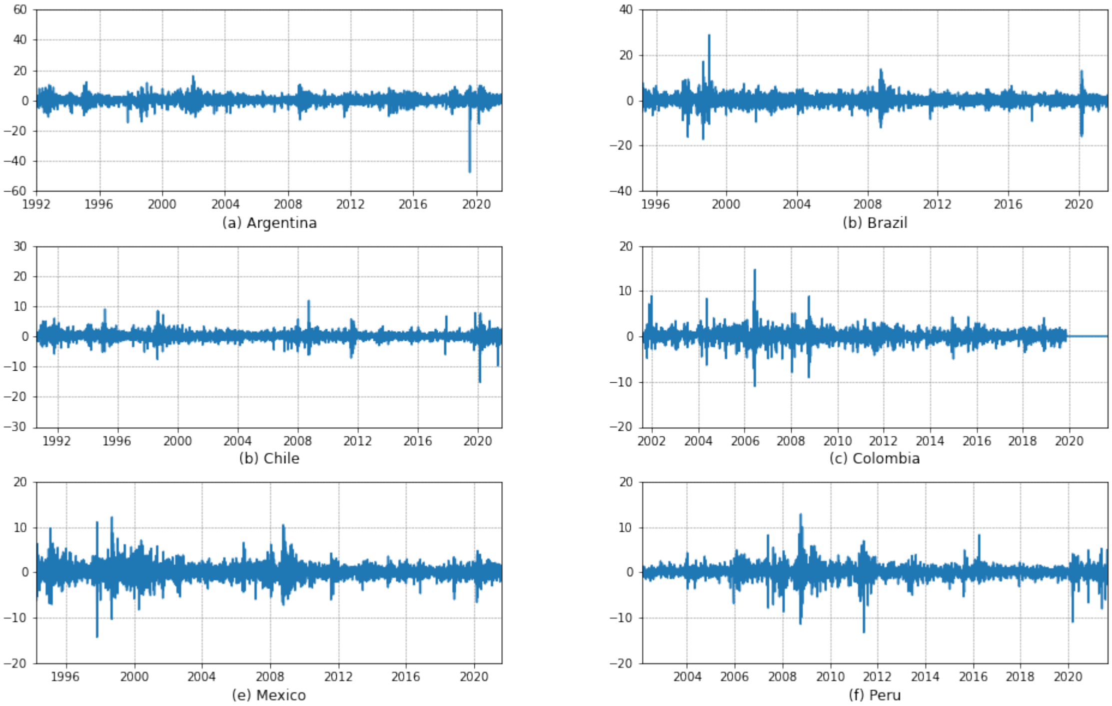

Figure 2: Latin American Forex Markets Returns

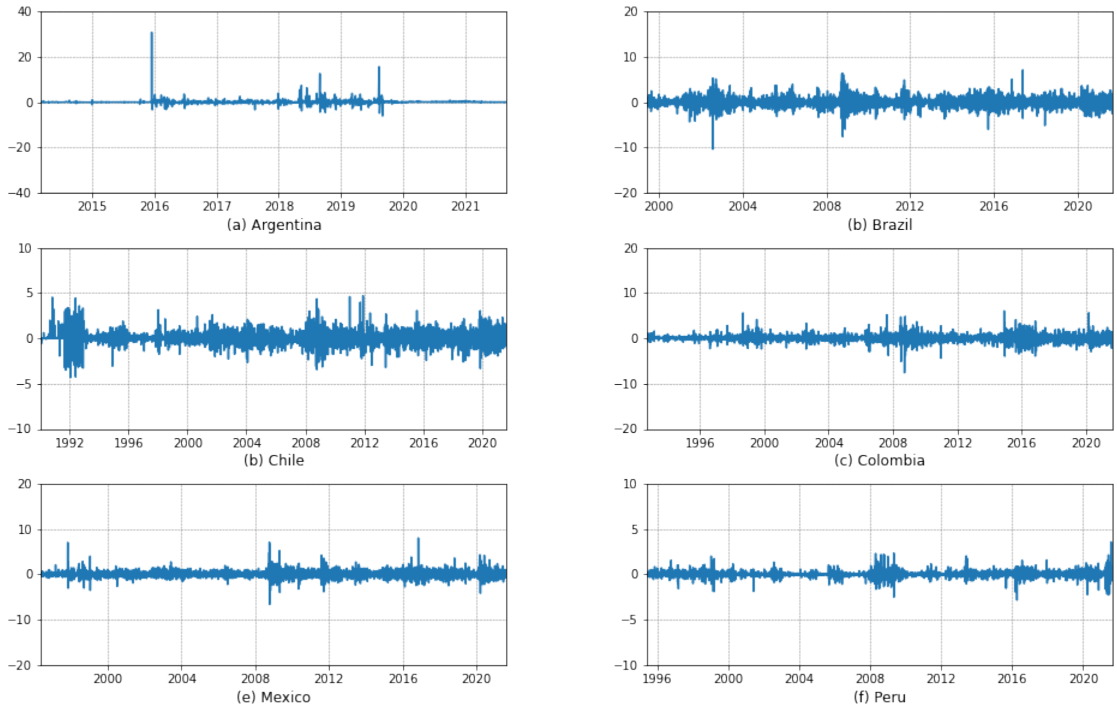

Figure 3: Squared of Latin American Stock Markets Returns

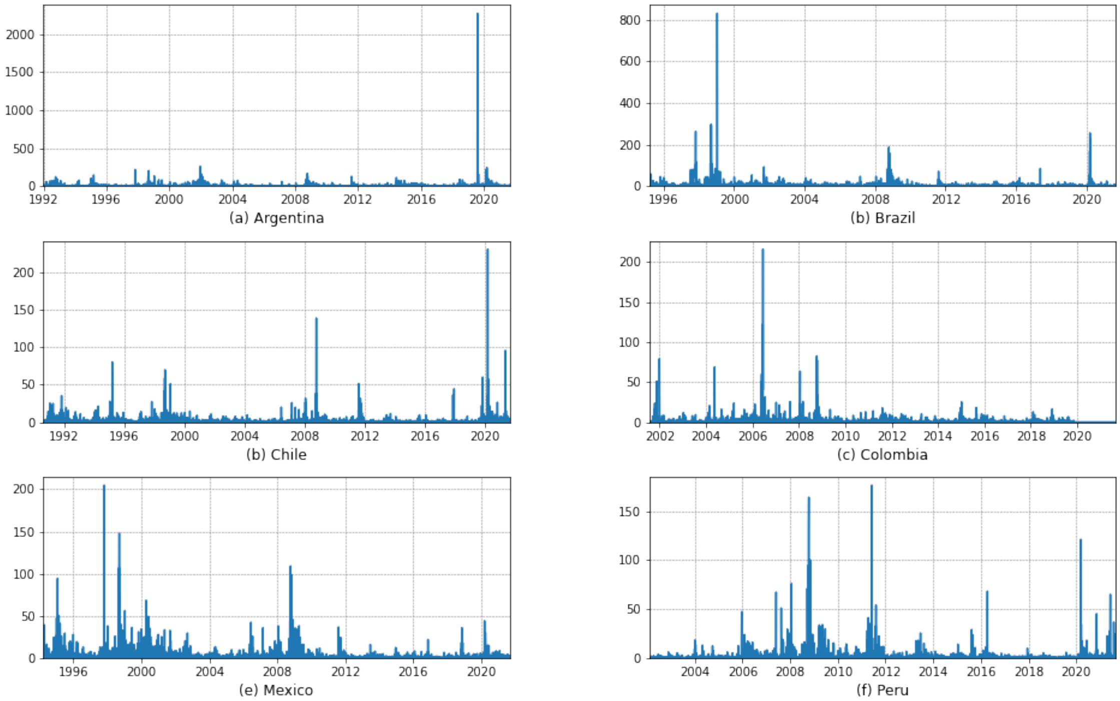

Figure 4: Squared of Latin American Forex Markets Returns