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Contaduría y Administración

Accounting & Management

Contaduría y Administración 69 (1), 2024, e433

Construction of conditional vs. traditional portfolios; Application to the Latin American Integrated Market (MILA)

Construcción de portafolios condicionales vs tradicionales; aplicación al Mercado Integrado Latinoamericano (MILA)

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Received December 7, 2022; accepted April 24, 2023
Available online April 27, 2023

Abstract

This paper aims to propose the construction of portfolios using conditional parameters obtained with univariate and multivariate GARCH models under the t-Student distribution. For the design of the optimal portfolios, the MILA (Latin American Integrated Market) indexes from 2017 to 2022 are used. The results reveal that conditional portfolios have a better risk-return ratio and lower risk exposure (measured by Value at Risk) compared to traditional portfolios. Empirical evidence is crucial for developing international investment strategies in emerging markets.

JEL Code: G11, G15, C58
Keywords: conditional portfolios; Latin American integrated market; GARCH models; dynamic conditional correlation model

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Peer Review under the responsibility of Universidad Nacional Autónoma de México.

http://dx.doi.org/10.22201/fca.24488410e.2023.4911

Resumen

El objetivo de este trabajo es construir portafolios, a partir del cálculo de parámetros no condicionales (tradicionales) y condicionales, estos últimos mediante modelos Generalizados Autoregresivos con Heteroscedasticidad Condicional (GARCH) univariados y de Correlación Condicional Dinámica (GARCH-DCC), bajo una distribución t-Student. Una vez realizada la estimación con ambos tipos de parámetros, se comparan los portafolios tradicionales con respecto a los condicionales, determinando cuál de ellos resulta en estimar una mejor relación riesgo-rendimiento. Para el diseño de los portafolios óptimos se emplean los índices bursátiles del Mercado Integrado Latinoamericano (MILA) constituido por Colombia, Chile, México y Perú, precios de cierre diarios de enero 2017 a junio 2022. Los resultados señalan que, los portafolios condicionales tienen mejor desempeño que los portafolios construidos de manera tradicional. Los hallazgos tienen importantes implicaciones en términos del desarrollo de estrategias de inversión internacional en mercados emergentes.

Código JEL: G11, G15, C58
Palabras clave: portafolios condicionales; mercado integrado latinoamericano; modelos GARCH; modelos de correlación condicional dinámica

Introduction

Over the last three decades, foreign portfolio investment directed to emerging countries has been increasing. The financial markets have shown a positive trend after the big drop in stock markets due to the COVID-19 pandemic. In particular, Latin American economies, especially those linked to producing raw materials and oil, have shown recovery in their stock market indicators (Bloomberg, 2022). The capital market offers a series of instruments to build investment portfolios, and it is also an important source of financing, which is why it is key for the region to have access to resources from it.

Financing allows companies to carry out projects that promote the demand for goods and services and job creation, resulting in economic growth. Thus, the availability of resources should be promoted through various sources, including stock exchanges.

The construction of investment portfolios in the context of the Latin American integrated market is important for several reasons: (i) more resources in Latin American markets can increase the region's economic growth potential, as it facilitates the flow of goods, services, capital, and people between countries, which can lead to more investment, more employment, and increased trade; (ii) investment can also increase the competitiveness of Latin American companies, by enabling them to take advantage of economies of scale, reduce costs, and improve efficiency in the production and distribution of goods and services; iii) it can help investors diversify their risks by accessing a wide range of investment opportunities in different countries and sectors; iv) it can provide the region's companies with access to new markets, which can increase their client base and expand their geographic reach.

Given the growing interest shown by international investors in Latin American markets, it is necessary to perform accurate analyses that truly capture the dynamics of financial indicators. As the results of such analysis become more accurate, decision-making will also become more accurate. To this end, an extension of Markowitz's (1952) model is used, incorporating conditional parameters for developing optimal investment portfolios.

The theoretical bases of this work are based on the rational choice theory which states that, in financial terms, higher profit is always preferred to lower profit (Darraz & Bernasconi, 2012). Also, the profit theory is relevant when considering that there is a decreasing marginal profit before such gain since individuals are risk-averse, and it is known that the higher the profit, the higher the risk will be. Both approaches are the basis for portfolio theory, which was formulated from Markowitz's model, which is based on the principle of diversification, allowing investors to maximize their profit at a given level of risk or minimize their risk at a given level of return (Agudo & Marzal, 2002).

The main contribution of Markowitz's model (op. cit.) is that the individual risk level of each instrument that makes up a portfolio is not so important but rather the interrelation between each asset and the rest of the elements included in the portfolio. Thus, originally, it was proposed that the measure of risk of a basket of assets is the covariance of their returns. The standard deviation and pairwise correlation are necessary metrics to estimate this indicator. Nevertheless, given the characteristics of financial series (non-normality in the distribution of returns, time-inconsistent variance, volatility sets, long memory in returns, and volatility, to mention only the most important ones), the use of unconditional parameters, assuming normality, and statics has been intensely debated.

Thus, with the development of computer programs and the increase in the capacity of artificial intelligence, models have been proposed to capture the dynamics of financial series better. Generalized Autoregressive Regression with Conditional Heteroscedasticity (GARCH) models are one of the most widely used approaches in modeling the behavior of financial series. The GARCH (1,1) model developed by Bollerslev, Engle, and Wooldridge (1988) makes it possible to capture the ARCH effect and model the changing variance over time.

The multivariate parameterization was developed from the univariate GARCH models, known as the VECH form of the multivariate GARCH model. Since this model involves estimating many parameters, its diagonal form was extended and formulated to simplify the analysis. Although the reduction of parameters was achieved, when the sample size increases, the computational burden also increases, and finding a feasible estimate becomes complex (Tolgahan, 2010).

To alleviate the problem of over-parameterization, in 1990, Bollerslev proposed the GARCH Constant Conditional Correlation (GARCH-CCC) model, which estimates the conditional standard deviations of assets using a univariate GARCH process and assumes that the conditional correlation between each pair of items is constant. Nevertheless, Tse and Tsui (2002) proved that such a model may not be valid when the estimated process is multivariate.

To superimpose the issue of constant conditional correlation, the BEKK and DCC models were proposed. The first was a proposal by Engle and Kroner (1995) that surmises that the covariance between assets is not constant. Nevertheless, the difficulty in estimating the conditional covariances increases as the sample size increases. The GARCH dynamic conditional correlation model (GARCH-DCC) enabled coping with these major challenges, resulting in fewer parameters that are easy to analyze and the analysis of the evolution of covariances and conditional correlations over time.

In terms of this paper, the objective is to compare the construction of efficient portfolios from non-conditional (traditional) and conditional parameters. First, conditional standard deviations and conditional means are estimated using univariate GARCH t-Student models to achieve this objective. Then, the pairwise time-varying conditional correlations between the indices composing the portfolio are modeled using GARCH DCC t-Student models. From these estimates, the conditional covariance matrix is constructed, and the optimal portfolios are designed to optimize the risk level for the minimum variance portfolio and maximize the return for the rest of the portfolios on the efficient frontier. Finally, to test the hypothesis that the estimation of conditional portfolios is more feasible not only for the risk-return relation but also for the potential risk exposure, both the Value at Risk and the conditional Value at Risk are estimated.

The construction of conditional optimal portfolios is performed using the indices of the stock exchanges that compose the Latin American Integrated Market: Chile-IPSA, Colombia-COLCAP, Mexico-IPC (IPC), and Peru-IGBVL[1] during 2017-2022. The contribution of this research lies in the estimation of non-normal conditional portfolios that better capture the dynamics of stock market returns concerning portfolios that use unconditional, normal, and static metrics, which guarantees a better diversification strategy, obtaining portfolios with better performance. The results are important for foreign investors interested in diversifying their resources internationally in emerging countries.

The paper is organized into four sections in addition to this introduction. Section two presents the review of the literature on using GARCH models to determine the risk and performance of financial investments and the construction of investment portfolios. The third section describes the methodology and data used. Section four discusses the results, and the last section concludes the research.

[1] It is assumed that such a strategy is possible thanks to the development of financial engineering and the design of Exchange Traded Funds (ETFs) or American Depositary Receipts (ADRs), which are instruments/portfolios that replicate a known index and are quoted in dollars.

Review of the literature

GARCH models have been widely used to analyze the risk-return of financial assets. Volatility is one of the measures of greatest interest to investors since it indicates how much variation there will be in the expected return. Thus, conditional approaches have sought to measure historical volatility and make predictions of volatility values in certain financial assets.

Applications of GARCH models have been extended to investigate the conditional volatility of various instruments: cryptocurrencies (Fakhfekh & Jeribi, 2020; Cheikh, Zaied, & Chevallier, 2020; Cerqueti, Giacalone, & Mattera, 2020; Fung, Jeong, & Pereira, 2022), commodity prices (Bouri, Jalkh, & Roubaud, 2019; Fałdziński, Fiszeder, & Orzeszko, 2020), stock returns (Nugroho et al. 2019; Mohsin et al., 2020; Oloko, Adediran, & Fadiya, 2022), and stock indices, which is the case of the present article (Kim & Won, 2018; Aliyev, Ajayi, & Gasim, 2020; Endri et al., 2020; Yadav, Singh, & Tandon, 2023).

Regarding the Latin American Integrated Market (MILA; Spanish: Mercado Integrado Latinoamericano), Riaño, Mejía, and Jaramillo (2023) analyze volatility and value creation within the bloc. The authors state that this agreement has been essential to boost the growth of the stock exchanges, generating new investment opportunities and diverse alternatives for investors. Their findings highlight the inverse relation between value creation and volatility, i.e., the lower the value, the higher the volatility.

Another widely researched indicator is the risk-return relation, for which several GARCH approaches have been used, enabling the dynamic movement between risk and return to be measured in various emerging markets such as South Africa (Morahanye, 2019; Dwarika, Moores-Pitt, & Chifurira, 2021), India (Patel, 2021), Nigeria (Nageri, 2021), China (Zhao & Wen, 2022), Hong Kong (Wang & Hartzell, 2021), to mention a few.

Regarding investment portfolios, conditional heteroscedasticity models have been used to measure the potential loss and value at Risk (VaR). Such is the case of the research conducted by Nasini, Labbe, and Brotcorne (2022), who optimize a multi-market portfolio, ensuring regulatory compliance regarding the potential loss estimated through the Conditional Value at Risk (CVaR). Similarly, Nurrahmat, Noviyanti, and Bachrudin (2017) calculate the Value at Risk of a foreign exchange portfolio using asymmetric GARCH models and copula theory.

Extensions of GARCH models have not only been implemented to measure the conditional VaR of portfolios but also to construct dynamic portfolios, for which Diaz and Esparcia (2021) employ various conditional heteroscedasticity approximations. Ali et al. (2019) employ symmetric and asymmetric GARCH models to model the interdependence between stock and oil markets in the G-7 countries. They also employ the estimated parameters to construct conditional portfolios, concluding that including oil instruments is important to achieve the objectives of diversification and adequate hedging objectives.

Joyo and Lefen (2019) analyze the integration process and portfolio diversification options between Pakistan and its main trading partners using DCC-GARCH models under the t-Student distribution. The results suggest that Pakistan was strongly integrated with its partners during the 2008 crisis, but this phenomenon has declined, opening up possibilities for portfolio diversification among these economies.

Similarly to Joyo and Lefen (op. cit.), this article analyzes the conditional volatility of the Latin American indices belonging to the MILA, measuring the co-movements over time for each pair of markets. It also analyzes the possibilities of diversification in investments that incorporate instruments whose origin is the countries of this stock market alliance.

Methodology and data

This work aims to analyze the volatility of the stock indices of the countries that make up the Latin American Integrated Market, in addition to proposing the construction of conditional portfolios based on these indices to measure the dynamic relation between them. The aim is to prove that the optimization of portfolios from the incorporation of conditional parameters enables better performance in the return of the investments by adequately capturing the dynamics of the series and the coefficients referring to the risk return of the same.

To achieve this objective, univariate GARCH models are first estimated under the t-Student distribution to obtain the conditional variance and mean of the series. Secondly, the pairwise dynamic correlation is modeled from the DCC models. Thus, the conditional variance, covariance matrix, and dynamic correlation between the series are obtained. Once the parameters have been estimated, the parametric optimization model is used for portfolio construction.

Markowitz model

Following the Markowitz model, the expected return of each portfolio is the weighted sum of the expected returns of the assets comprising each portfolio:

$$E(r_p)=\sum_{j=1}^{n} w_j E(r_j) \tag{1}$$

http://dx.doi.org/10.22201/fca.24488410e.2023.4911

where:

$E(r_p)$= Expected return on portfolio p

p= Asset portfolio

w_j= Ratio of the investment made in each asset of the portfolio

$E(r_j)$= Expected return on each asset in portfolio

With the budget constraint that the sum of the weights = 1.

On the other hand, the risk of a portfolio is measured by the standard deviation of the returns of the assets included in the portfolio. The variance of portfolio returns is the weighted average of the covariances of all the pairs included in the portfolio (Luenberger, 1998):

$$\sigma_{rp}^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{2}$$

where:

σ_p^2= Variance of portfolio returns p

$w_i w_j$= Ratio of investment in assets i and j

σ_{ij}= Covariance between the returns of assets i and j

The variance of the portfolio can also be obtained through its matrix form:

$$\sigma_{rp}^2 = [w_1 \quad w_2 \quad \cdots \quad w_n] \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix} \tag{3}$$

The standard deviation of the portfolio is determined as follows:

$$\sigma_{rp} = \sqrt{\sum_{i=1}^{n} w_i^2 \, \sigma_i^2} + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \;\; i \neq j \tag{4}$$

where:

σ_{rp}= Standard deviation of the portfolio p

σ_p^2= Variance of portfolio returns p

p= Asset portfolio

$w_i w_j$= Ratio of investment in assets i and j

σ_{ij}= Covariance between the returns of assets i and j

The extension of the Markowitz model proposed in this research incorporates conditional parameters instead of conventional ones. Thus, the conditional standard deviation and the conditional dynamic correlation are estimated from the following univariate and multivariate GARCH models.

Univariate GARCH models

The GARCH models developed by Bollerslev (1986) describe the conditional variance as a function of the squares of the disturbances and the conditional variances of previous periods.

The relevance of these models lies in the fact that they capture the main characteristics of financial series (Francq & Zakoian, 2010, p. 19). In line with the above and according to Bollerslev (1986, p. 308), the GARCH (p,q) process is described as:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t) \tag{5}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i} \tag{6}$$

Where ε_t represents a discrete-time stochastic process, ψ_{t-1} is a set of information through time t, and h_t is the conditional volatility under the singularities of $p \geq 0, q > 0, \alpha_0 > 0, \alpha_i \geq 0, i = 1,2,\dots,q$ and $\beta_i \geq 0$ $i = 1,2,\dots,p$. If $p = 0$ one has the ARCH process (q) in regression.

The condition $\alpha + \beta < 1$ indicates that this is a stationary GARCH process, indicating that the variance does not grow indefinitely. Likewise, where $\beta > \alpha$ it is interpreted that volatility does not decrease rapidly in the face of shocks with long-run effects, i.e., there is persistence in volatility.

Multivariate GARCH DCC model

The Dynamic Conditional Correlation (DCC) model proposed by Engle (2002) directly parameterizes the conditional correlations using the standardized residuals (ε_{it}) of the volatility modeled by some univariate GARCH application. It is assumed that the standardized residuals ε_{it} follow a multivariate t-Student distribution with v degrees of freedom, giving the information available at time t-1. The t-Student distribution is used to model non-normality; heavy tails, and sharp distributions, usually drawn by economic and financial series returns.

The advantage of using this GARCH extension is that the number of parameters to be estimated is independent of the number of correlated series, unlike other models such as BEKK in which, as the sample size increases, the difficulty of estimation and interpretation also increases due to the growing number of parameters (Engle, 2002, p. 3)

According to Engle (2002, p. 10) and Aielli (2013, p. 283), the DCC process equation is as follows:

$$H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}} \tag{7}$$

$$Q_t = (1 - a - b)\overline{Q} + a\varepsilon_{t-1}\varepsilon_{t-1}' + bQ_{t-1} \tag{8}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{9}$$

Where, in Equation 7, for the definition of the conditional covariance matrix (H_t), D_t is the conditional variances matrix comprising the diagonal elements of the estimation of a univariate GARCH model $\mathrm{diag}(h_{1t}, \dots, h_{Nt})$. Then, $R_t = [\rho_{ij,t}]$ represents the conditional correlation matrix composed by the matrix of quasi-correlations $Q_t = [q_{ij,t}]$ and $Q_t^* = \mathrm{diag}(q_{11,t}, \dots, q_{NNN,t})$. Finally, a and b are scalars and $\overline{Q} = E[\varepsilon_t \varepsilon_t']$.

Value at Risk (VaR) and Conditional VaR (cVaR)

Value at Risk measures the maximum possible loss over an investment horizon (t days) at a given confidence horizon (1-α). Thus, VaR is a percentile determined from a probability distribution of the expected variations in the market value of an asset or investment portfolio. It is usually estimated in terms of the distribution of the profitability presented by the portfolio in past periods. This methodology is called “historical.” This estimate has certain advantages over parametric methods, in which a probability distribution is assumed.

For a univariate distribution, Fh(x) and a probability p; 0 < p < 1; the *p*-th quantile of $F_h(x)$ is:

$$x_p = inf\{x|F_h(x) \geq p\} \tag{10}$$

where *inf* denotes the smallest quantity that satisfies the above inequality. If the distribution $F_h(x)$ were known, then the VaR of the portfolio would simply be the *p*-th quantile of $F_h(x)$. Nevertheless, this distribution is unknown in practice, and the calculation of VaR requires estimating $F_h(x)$or its *p*-th quantile (Novales, 2016).

Based on VaR, the conditional VaR, also known as the Expected Tail Loss (ETL) at *100 %*, is the Conditional VaR defined by:

$$ETL_h^P = -E\left(R_h \middle| R_h < -VaR_h^p\right)W \tag{11}$$

Where R_h denotes the discounted return of the portfolio *h* days, and *W* is the present value

Taking the one-day horizon as a reference, then

$$ES_{t+1}^P = -E\left[R_{t+1}|R_{t+1} < -VaR_{t+1}^p\right] \tag{12}$$

Measured in terms of logarithmic returns, not in nominal terms, the Expected Shortfall (ES) is the conditional VaR benchmark defined by

$$ES_h^P = -E\left(RA_h \middle| RA_h < -BVaR_h^p\right)W \tag{13}$$

Where *RA* denotes the portfolio's active return, and BVAR is the *VaR benchmark* (Novales, 2016).

Data

The Latin American integrated market comprises four of Latin America's most important stock exchanges: the Santiago Stock Exchange, the Colombian Stock Exchange, the Mexican Stock Exchange, and the Lima Stock Exchange. It is the main market regarding securities supply and second in market capitalization (BVL, 2022). Thus, it has become an ideal alternative for investment in emerging markets, providing international diversification opportunities.

The MILA is a stock market created in 2011. Since its creation, the MILA has experienced an evolution in terms of issuers, volume, and market capitalization (BMV, 2023).

In 2011, the MILA had 562 issuers. In 2021, the MILA had 1 215 issuers, i.e., the number of companies listed on these exchanges has more than doubled. Most of the issuers are small and mid-cap companies. In terms of volume, in 2011 MILA's trading volume was around USD 100 million, while by 2021 MILA's trading volume was around USD 8 billion, i.e., the volume grew nearly 80 times. In terms of market capitalization, when the MILA was created, it was USD 600 billion, while in 2021, it was already around USD 2.8 trillion, i.e., it grew five times. It should be noted that the volume and capitalization are concentrated in the largest and most liquid issuers (BVL, 2023).

It is important to remember that the MILA has faced challenges and limitations in its integration process, such as regulatory and cultural differences among member countries. Nevertheless, the MILA is expected to grow and consolidate as an integrated stock market in Latin America, as it has done so far.

Based on the above, this paper proposes the application of an investment portfolio that integrates the stock market index of each market. As stated in the introduction, the strategy is feasible thanks to the development of financial engineering and the design of Exchange Traded Funds (ETFs) or American Depositary Receipts (ADRs), which are instruments/portfolios that replicate a known index and are quoted in dollars. The study period is from January 3, 2017, to June 2, 2022.

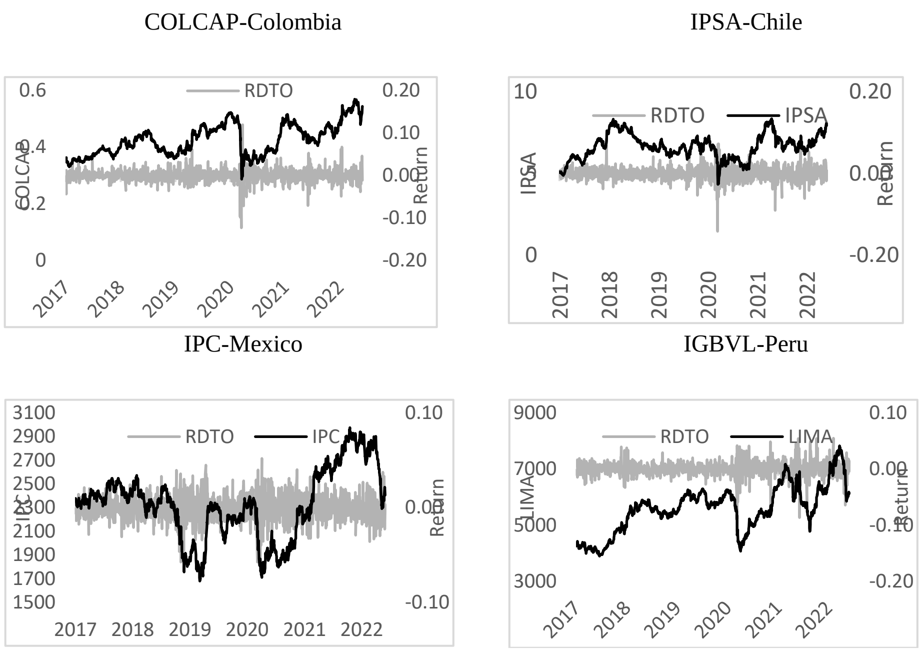


Figure 1. MILA index prices and returns (2017-2022) in USD

Source: created by the authors with data from Yahoo Finance

http://dx.doi.org/10.22201/fca.24488410e.2023.4911

The graphs in Figure 1 show the stock market indices and their respective daily returns. A common drop was observed in 2020 due to the beginning of the lockdown imposed as a measure against the COVID-19 pandemic. In 2021, with the reactivation of the economy, a positive trend is shown, interrupted in 2022 by the international uncertainty caused by the beginning of the war between Russia and Ukraine.

Results analysis

Table 1 shows the descriptive statistics of the series, as well as the results of the Jarque-Bera normality and ARCH-LM heteroscedasticity tests. Thus, a preliminary analysis of the characteristics of the series can be performed. The mean for all the indices is positive, which means that despite the negative events, investors who held positions during the study period had profits. The best-performing index was the Chilean index (IPSA), with an average annual return of almost 13%, followed by the Colombian index (COLCAP) with 11.5%, and the worst-performing index was the Mexican index (IPC) with 0.6%.

Table 1
Descriptive statistics of stock market returns in US dollars

	COLCAP_USD_	IPC_USD_	IPSA_USD_	LIMA_USD_
Mean	0.000317	0.000016	0.000355	0.000300
Median	0.000338	0.000212	0.000116	0.000630
Maximum	0.118739	0.051836	0.089600	0.054740
Minimum	-0.123124	-0.058179	-0.141522	-0.111186
Std. dev.	0.015534	0.013460	0.016254	0.012843
Skewness	-0.473680	-0.213253	-0.771652	-0.904599
Kurtosis	16.205740	4.322476	13.939020	12.181130
Jarque-Bera	9202.669	101.3697	6407.308	4597.233
ARCH-LM[1/]	230.415***	25.381***	257.478***	52.275***

Note: [1/] The ARCH-LM statistical test is the Lagrange multiplier used to detect the ARCH effect. Under the null hypothesis of no heteroscedasticity, this term is distributed as λ 2(k). ***significant at 1%

Regarding the maximum daily variations, the COLCAP index presented a variation of almost 12% in a single day, followed by the IPSA index (8.9%), Chile's IBVL (5.4%), and, lastly, the IPC (5.2%). The Chilean index (IPSA) had the largest one-day loss with 14%, followed by COLCAP (12%), BVL (11%), and IPC (6%). As for the volatility of the indices, the one with the highest standard deviation was the Chilean index, followed by the Colombian, Mexican, and Peruvian indices.

All series are distinguished by their negative bias, which can be explained by the repeated and large drops that occurred due to the events previously mentioned: COVID-19 and the Ukraine vs. Russia war. As is characteristic of economic and financial series, they do not present normality but leptokurtosis, and the distributions present long and heavy tails and sharp structures.

Likewise, the absence of homoscedasticity is tested through the ARCH-LM test, where the null hypothesis of non-heteroscedasticity is accepted. This last finding justifies using the GARCH methodology for modeling the volatility and correlation of the stock returns in question as a better approximation than the linear one proposed by Markowitz (1952).

Table 2
ADF and PP unit root tests

INDEX	TEST		Levels		1st Diff.	
			t-Stat	Prob.	t-Stati	Prob.
COLCAP	ADF	Int	-16.64	***	-20.84	***
		Int and Ten	-16.63	***	-20.83	***
		None	-16.63	***	-20.85	***
	PP	Int	-32.69	***	-361.06	***
		Int and Ten	-32.68	***	-358.12	***
		None	-32.69	***	-361.03	***
IPC	ADF	Int	-34.90	***	-15.98	***
		Int and Ten	-34.89	***	-15.98	***
		None	-34.92	***	-15.99	***
	PP	Int	-34.91	***	-635.71	***
		Int and Ten	-34.90	***	-634.87	***
		None	-34.92	***	-635.75	***
IPSA	ADF	Int	-33.90	***	-19.71	***
		Int and Ten	-33.89	***	-19.70	***
		None	-33.90	***	-19.72	***
	PP	Int	-33.91	***	-190.10	***
		Int and Ten	-33.90	***	-189.99	***
		None	-33.91	***	-190.20	***
IBVL	ADF	Int	-34.64	***	-18.05	***
		Int and Ten	-34.63	***	-18.05	***
		None	-34.63	***	-18.06	***
	PP	Int	-34.97	***	-423.83	***
		Int and Ten	-34.96	***	-422.47	***
		None	-34.97	***	-424.07	***

Note: Null hypothesis is that the series presents unit root.. *** means that the null hypothesis is rejected at 1% statistical significance

Table 2 shows the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, confirming the series' stationarity, a necessary condition for modeling. As can be seen, the null hypothesis of the existence of a unit root is rejected, i.e., it is proven that the series has a stationary behavior.

Once the series are heteroscedastic and stationary, univariate GARCH models are estimated under the t-Student distribution, enabling the conditional variance and mean of the series to be obtained. Secondly, the pairwise dynamic correlation is modeled from the DCC models. Thus, the conditional variance, covariance matrix, and dynamic correlation between the series are obtained. Once the parameters have been estimated, the parametric optimization model is used for portfolio construction.

Table 3
Results of GARCH-Univariate and GARCH-DCC Models

	IPC		COLCAP		IBVL		IPSA	
	Coef	t-prob	Coef	t-prob	Coef	t-prob	Coef	t-prob
C(m)	-0.000047		0.000385		0.000634	**	0.000249	
C(v)	0.062425	**	0.170034	***	0.031649		0.097037	
α_1	0.092613	***	0.168956	***	0.112766	***	0.109321	**
β_1	0.872779	***	0.748262	***	0.874692	***	0.857743	***
$\alpha_1 + \beta_1$	0.965392		0.917218		0.987458		0.967064	

	IPC-COLCAP		IPC-IBVL		IPC-IPSA		COLCAP-IBVL		COLCAP-IPSA		IBVL-IPSA	
	Coef	t-prob	Coef	t-prob	Coef	t-prob	Coef	t-prob	Coef	t-prob	Coef	t-prob
$\rho_{2,1}$	0.3463	***	0.3714	***	0.4259	***	0.2939	***	0.3615	***	0.3204	***
α	0.0149	**	0.0200	***	0.0076	*	0.0436		0.0167	***	0.0257	**
β	0.9279	***	0.9637	***	0.9796	***	0.7956	***	0.9683	***	0.9359	***
df	9.1637	***	7.6204	***	8.8855	***	5.7475	***	6.1060	***	5.3676	***

Source: created by the authors
[1/] $\rho_{2,1}$: correlation between the exchange rate and the stock market index
** ,***significant at 5% and 1%, respectively

Table 3 shows the results of the univariate and bivariate GARCH-DCC models.

As can be observed, the coefficients α_1 and β_1 are statistically significant. Likewise, the condition on the sum of the terms α_1 and β_1, which are smaller and close to unity, is satisfied. The above translates into the presence of a mean reversion process in the volatility of the variables where the shocks are only transitory.

Meanwhile, the term $\rho_{2,1}$ indicates the level of dynamic correlation, which is positive and medium-low between all the stock market indices, around 0.3, with the indices with the strongest relationship being Mexico-Peru (0.43), followed by Colombia-Peru (0.37) and, in third place, Mexico-Colombia. The dynamic relations are statistically significant, as are most of the α and β parameters. Likewise, the parameter df (degrees of freedom) confirms the presence of heavy tails.

Once the results of the DCC-GARCH model are obtained, Hosking and Mcleod-Li are performed to ensure that the model adequately captures the relation dynamics between the series. Thus, Table 4 shows that once the DCC - GARCH (1,1) model is estimated, there are no ARCH effects in the residuals nor serial correlation between the residuals with 20 and 50 lags with a probability of 95% and 99%.

Table 4
Hosking[1/] and Mcleod - Li[2/] test on the square of the standardized residuals up to the lag k

	IPC-COLCAP		IPC-IBVL		IPC-IPSA		COLCAP-IBVL		COLCAP-IPSA		IBVL-IPSA	
Hosking's Multivariate Portmanteau Statistics on Standardized Residuals												
Hosking(20)	95.70	***	96.39	***	98.52	**	85.63	***	89.27	***	75.66	***
Hosking(50)	199.21	***	216.79	***	234.84	*	211.95	***	226.26	**	214.63	***
Li and McLeod's Multivariate Portmanteau Statistics on Standardized Residuals												
Li-McLeod(20)	95.54	***	96.33	***	98.29	**	85.73	***	89.22	***	75.78	***
Li-McLeod(50)	199.41	***	216.67	***	234.10	*	211.77	***	225.72	***	214.17	***

Source: created by the authors
[1/] Null hypothesis: The residuals are not serially correlated
[2/] Null hypothesis: There is no autoregressive conditional heteroscedasticity
*, **, and *** significant at 10%, 5%, and 1%, respectively

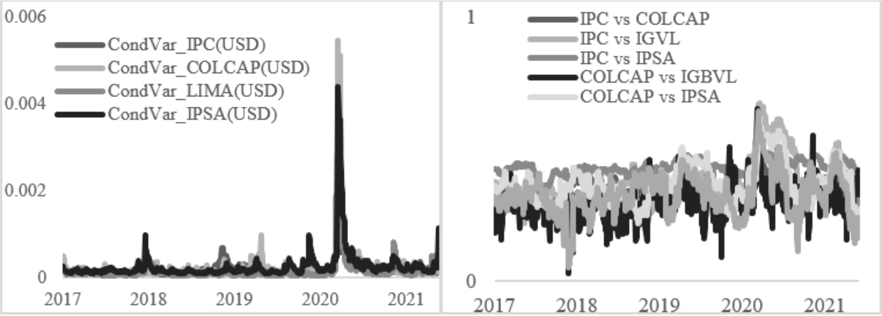
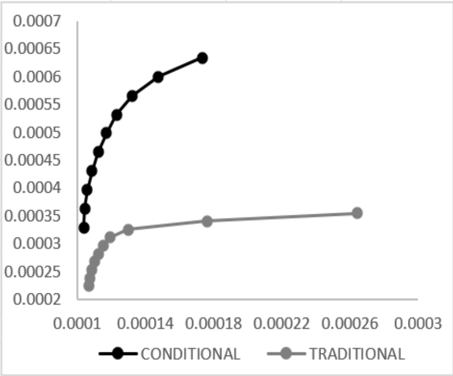


Figure 2. Conditional Volatility (left side) and Dynamic Conditional Correlation (right side)
Source: created by the authors based on estimation data

As a result of the application of the univariate and multivariate GARCH models, the conditional variance and DCC series are obtained. Thus, the graphs in Figure 2 show the conditional volatility of each stock index (on the left) and the pairwise dynamic correlations (on the right). As can be seen, the declaration of the pandemic by the World Health Organization in March 2020 had important effects on the volatility of the Latin American markets under study. The substantial increase in the dynamic conditional correlation between the markets also demonstrated this effect.



CONDITIONAL		TRADITIONAL	
Var(P)	R(P)	Var(P)	R(P)
0.00010378	0.0003293	0.00010706	0.0002242
0.00010432	0.00036313	0.00010739	0.00023873
0.00010593	0.00039696	0.00010839	0.00025326
0.00010861	0.00043079	0.00011006	0.00026779
0.00011237	0.00046463	0.00011239	0.00028232
0.0001172	0.00049846	0.00011539	0.00029685
0.00012314	0.00053229	0.00011905	0.00031138
0.00013235	0.00056612	0.00012979	0.00032591
0.00014767	0.00059995	0.00017616	0.00034044
0.00017324	0.00063378	0.00026397	0.00035497

Figure 3. Conditional efficient frontier vs. traditional (daily risk and return)
Source: created by the authors with estimation data

Once the results of the models are obtained and the proper modeling fit is verified, the conditional efficient frontier is estimated and compared with the traditional efficient frontier; Figure 3 shows the result. Thus, as expected, since the mean, volatility, and conditional covariance models capture more adequately the behavior of the series, the measurement of the risk and return parameters is also more accurate, permitting the parametric optimization to give better results. As shown in black, the conditional efficient frontier dominates the traditional efficient frontier, i.e., it enables the investor to obtain better results for the same risk levels.

The results imply that if an investor had constructed their portfolio considering the conditional parameters and had a high-risk propensity, i.e., had chosen the portfolio with the maximum return (the one farthest from the origin on the black line), they would obtain an annual return of 22.8%, versus an investor who had constructed their portfolio based on conventional calculations which would have a 10.2% annual return.

Thus, the evolution of the conditional portfolio versus the traditional one would look as shown in Figure 4. As can be seen, the conditional portfolio has higher returns and volatility. Nevertheless, the graphical analysis may not be conclusive in determining risk. Thus, to compare the potential loss of both portfolios, the Value at Risk (VaR) and the Conditional VaR are estimated for the most usual confidence levels (99, 95, and 90%).

As seen in Table 5, for both the VaR measure and the conditional VaR (cVaR), the conditional portfolio has a lower potential loss at one year at all confidence levels. In monetary terms, an individual who invested in the conditional portfolio of MXN 100 million would have a maximum loss of MXN 2.3 and 2.88 million (according to VaR and cVaR, respectively) with 99% confidence in one year. If this individual had constructed the portfolio based on the traditional parameters, the loss would have amounted to MXN 2.36 and 2.9 million (according to the VaR and cVaR, respectively) under the same conditions. Thus, it is demonstrated that the conditional portfolio also offers better results regarding potential losses.

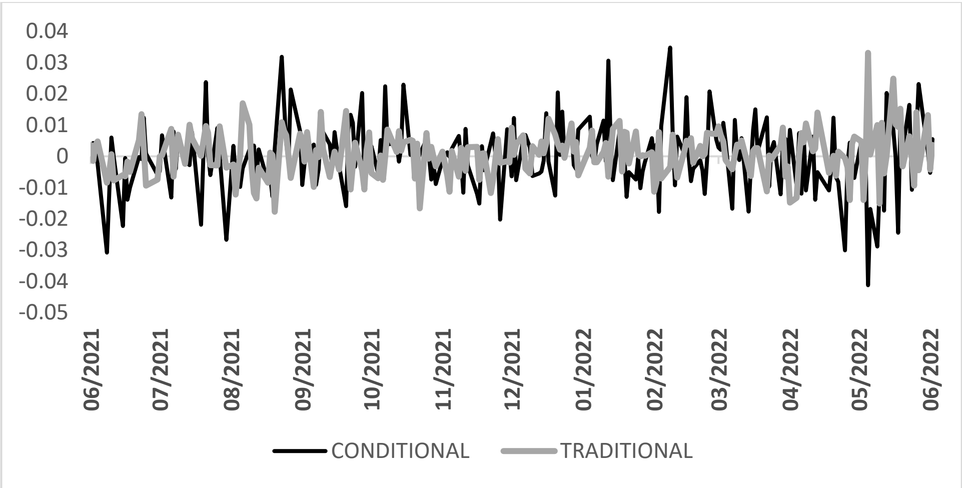


Figure 4. Performance of the Traditional vs. one-year Conditional Portfolio (2021-2022)
Source: created by the authors with estimation data.

Table 5
VaR and cVaR for conditional and traditional maximum return portfolio (2017-2021)

	Model			
α	VaR		cVaR	
	Portfolio			
	Conditional	Traditional	Conditional	Traditional
1%	2.30%	2.36%	2.88%	2.90%
5%	1.61%	1.66%	2.30%	2.50%
10%	1.25%	1.29%	2.07%	1.74%

Source: created by the authors with estimation data

Once the VaR is estimated, the results are validated, i.e., whether the estimate is correct or the loss was over or underestimated. Such analysis is crucial for financial institutions, for example, banks, investment funds, and pension funds, since an inaccurate measurement would lead to erroneous decisions on the level of reserves of high-quality assets, causing sanctions by regulatory and supervisory institutions or an excessive reserve, the opportunity cost of which could be reflected in profits.[2]

[2] The backtesting test is only performed on the VaR, not on the cVaR or ES (Expected Shortfall) because the latter, according to Gneiting (2011), lacks a mathematical property called elicitability, which is necessary for any risk measure to undergo a rigorous backtest, i.e. the cVaR, in a rigorous sense, is not backtestable. In addition, it should be noted

Thus, the Kupiec test is carried out in-sample (2017-2021), which is over the period when the values at risk are calculated, and out-of-sample (2021-2022). Table 6 shows the results of the backtesting adjustment. For the in-sample results, the estimation of both portfolios presents adequate adjustment at 95% but not at 99% statistical confidence since the loss for the conditional portfolio is underestimated, while at 90%, the traditional portfolio overestimates the VaR.

Regarding the out-of-sample results, the VaR on the traditional portfolio adequately estimates the potential loss at 99% confidence, while the VaR on the conditional portfolio is adequate at all significance levels. That is, better fits are obtained during the out-of-sample period, which could be explained by the fact that the in-sample period included the COVID-19 era, during which higher outliers were present than the relative recovery era (2021-2022).

Table 6
VaR backtesting with in-sample and out-of-sample Kupiec test

	17-21			21-22	
	CONDITIONAL	TRADITIONAL		CONDITIONAL	TRADITIONAL
1%	18	15***	1%	5***	2***
5%	44***	42***	5%	15***	3
10%	82***	80	10%	20***	10

Note: *** denotes adequate fit
Source: created by the authors with estimation data

Conclusions

This paper aims to construct traditional and conditional portfolios by estimating univariate and multivariate GARCH models to demonstrate that the design of portfolios based on conditional parameters (standard deviation, variance, covariance, correlation, and conditional mean) provides better results than traditional parameters. This is because GARCH models provide a better fit to the behavior of the financial series by capturing volatility sets and changes in variance and, assuming t-Student distribution, non-normality can also be captured. The results align with other studies' results (Hoga, 2019; Ullah *et al.*, 2022), indicating that estimation from conditional parameters or using other distributions provides better results.

Hoga (2019) analyzes the returns of six stock indices: NASDAQ, DJIA, Nikkei 225, Hang Seng (HSI), CAC 40, and DAX 30. The author points out that the results of the AR-GARCH models prove that the distributions have heavy tails, thus justifying that the theory of extreme values can be used to estimate

that since the cVaR is the average risk of the tail of the distribution, the fit of the cVaR depends on the VaR estimate, any fit test performed on the cVaR will also be performed on the VaR and vice versa.

the conditional Value at Risk (VaRc) and the conditional Expected Shortfall, which improves the results of the forecasts of both indicators, for the various indices under analysis.

Ullah et al. (op. cit.) estimate Value At Risk (VaR) and conditional VaR by employing the heavy-tailed Laplace distribution instead of the normal distribution to manage changes in the price of a stock, using GARCH models. The results prove that using the Laplace distribution provides better results than the normal or Gumbel distribution for risk management.

Thus, the present work contrasts the hypothesis, proving that conditional investment portfolios provide better risk/return ratios to the investor and have lower risk exposure, measured through VaR and conditional VaR.

The results are of great importance for individual investors, investment managers, hedgers, and financial institutions, as they suggest an alternative way of portfolio construction that offers higher returns and lower risk. In addition, the findings are of special relevance for Latin American economies, as they show positive results in terms of international diversification through investment in four of the main markets in the region, suggesting the use of instruments created from financial engineering (ETFs or ADRs) that allow hedging against foreign exchange risk.

Future research lines could include new Latin American markets in the construction of portfolios, incorporating methodologies to measure correlation, such as copulas, and constructing portfolios for shorter periods, for example, assuming quarterly or annual rebalancing.

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