THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Practitioners' Challenge 2024
Technical Report
Team 1

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*Note: Please refer to our team's **GitHub Repository** for data, code, and referenced papers.*

Introduction

Latin America and the Caribbean is a region that encompasses various economies from Guatemala to Argentina. This brings very diverse macroeconomic dynamics for the region which has become significantly volatile following the pandemic period. Post-pandemic period being the main driver of this economic downturn in the region, the economic agents, particularly the firms, face challenges that affect their financial outlook. One of the parameters that would allow us to observe the financial health of the firms is to evaluate the firms' debt structure and understand capture credit default risks. This is a significant concern as, given the recent macroeconomic outlook of the region, the firms are seeking financing opportunities either in the form of debt or equity. Our study aims to understand the dynamics of credit default and capture the credit default correlation estimates between the firms operating under the Latin America and the Caribbean region.

Objective

Our objective is to produce a model methodology and model results of credit default correlation factors for the Latin American and Caribbean region. We designed these correlation factors to reflect the strength of the relationship between the credit quality of two different companies in the Latin American and Caribbean region. The correlation factors that we aim to capture are the following.

I. Global correlation coefficient:

Average Correlation coefficient between the returns of any 2 companies selected from different countries and different sectors in the Latin American and Caribbean region.

II. Country Correlation coefficient:

Average Correlation coefficient between the returns of any 2 companies selected from the same country, but from different industry sectors, in the Latin American and Caribbean region.

III. Financial sector correlation coefficient:

Average Correlation coefficient between the returns of any 2 companies selected in the Financial sector and from the same country in the Latin American and Caribbean region.

IV. Non Financial sector correlation coefficient:

Average Correlation coefficient between the returns of any 2 companies selected in the same Non-Financial Industry Sector and from the same country in the Latin American and Caribbean region.

Methodology

Overview

Our model methodology suggests to use stock returns as a proxy to credit default correlations by capturing the return correlations through the Dynamic Conditional Correlation (DCC) model that implements GJR-GARCH and puts the output into DeepAR to yield a extensive estimation and forecast of credit default correlations. *Figure 1* shows the framework used to model default correlations of companies.

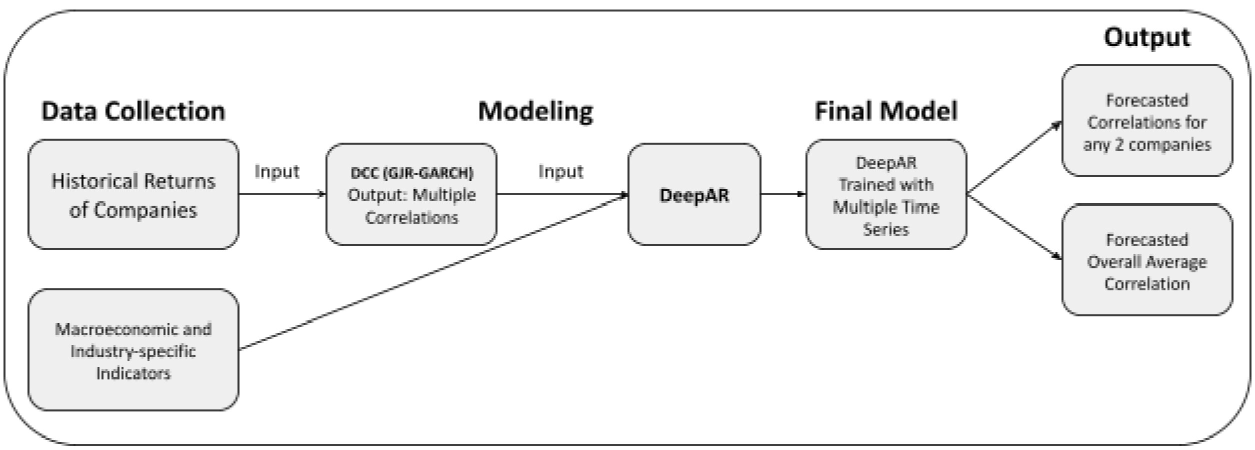


Figure 1: Modeling Pipeline.

Data Collection

The data gathering process followed a methodology to capture both historical stock returns and macroeconomic variables that can improve our understanding in credit default dynamics. A thorough research of the International Monetary Fund (IMF), World Bank, Statista, S&P Capital IQ and most importantly Yahoo Finance was carried out. Restricting the domain of companies to the ones that are actively traded on the US or South American Exchanges, the main data that was collected was the historical stock data, complemented with the total market cap and face value of debt. We extracted the equity price data from Yahoo Finance using the **getSymbols** function from the **quantmod** package in R. A sample length of 5 years was chosen so that any results and forecasting methods would capture accurate market dynamics. This duration was chosen to capture a sufficiently robust dataset while ensuring that the analysis and forecasting methodologies employed would accurately reflect prevailing market dynamics.

Data Preprocessing

Effective data preprocessing is crucial for ensuring the reliability and accuracy of our Dynamic Conditional Correlation (DCC) estimation. This section outlines the steps undertaken to prepare the financial time series data for analysis, focusing on standardizing comparisons across countries by addressing exchange rate variations, trading day discrepancies, and ensuring data quality before applying advanced econometric models. By standardizing data across different markets, addressing discrepancies in trading activities, and refining the data quality, we lay a solid foundation for accurately estimating dynamic correlations and volatilities using the DCC-GJR-GARCH framework.

Exchange Rate and Trading Days Normalisation

Given the geographic diversity of our dataset and the need to compare assets across different countries, a key preprocessing step involved the standardization of financial time series data using exchange rates. This adjustment is critical for making meaningful comparisons across markets. We began by extracting daily exchange rates to convert all financial data into a common currency. This step ensures that asset prices and returns are comparable across different countries. For stock data, we identified non-trading days specific to each country's stock exchange calendar. Due to the international scope of our dataset, discrepancies in active trading days across exchanges necessitated careful alignment. We addressed these discrepancies by carrying forward the last available stock price for non-trading days, ensuring a continuous time series. This approach also applied to exchange rates, where markets might be closed on days stocks traded, thereby standardizing data availability across our dataset.

Log Returns, Null Values and Averaging

Transforming price data into log returns and ensuring data cleanliness were our next steps, crucial for the subsequent econometric modeling. We converted stock prices into log returns, a common practice in financial time series analysis to stabilize variance and make series increments stationary. After conversion, we scanned the dataset for null values, removing any instances to prevent distortions in our analysis. For each stock, we calculated the Average Return (Avg Ret), providing a baseline measure of performance over the analysis period.

Demeaned Returns and Model Identification

The final preprocessing step involved preparing the data for ARIMA and GJR-GARCH modeling, focusing on removing linear autocorrelations and ensuring stationarity. We demeaned the log returns to eliminate any mean-reverting patterns, facilitating a more accurate estimation of volatility and correlation dynamics in the subsequent GJR-GARCH modeling. Utilizing the **auto.arima** function from the **forecast** package in R, we analyzed the demeaned log returns to identify the best-fitting ARIMA model for the mean equation of each time series. This function assesses various combinations of Auto-Regressive (AR) and Moving-Average (MA) components, selecting the model that minimizes information criteria such as AIC or BIC. This step is instrumental in capturing and eliminating linear autocorrelations, ensuring the residuals are suitable for volatility modeling through GJR-GARCH.

Models

Estimation of Dynamic Correlations using DCC & GJR-GARCH

We introduce the Dynamic Conditional Correlation (DCC) model combined with the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) model in capturing the dynamic correlations and volatility clustering in financial time series to capture equity correlations as a proxy for default correlations, emphasizing its necessity due to observed leverage effects and asymmetries in the Latin America and Caribbean market.

In investigating the LAC region we found interesting results on the literature on daily return data from select assets in the Brazilian market, where significant leverage effects and asymmetry in return distributions could be identified. These findings demonstrate the DCC-GJR-GARCH model's superiority in understanding market behaviors and enhancing risk management strategies.

Literature Review

The evolution of GARCH models has been instrumental in financial econometrics, with the GJR-GARCH model addressing asymmetries and leverage effects unaccounted for by its predecessors. The DCC model, introduced by Engle (2002), marked a significant advancement in estimating time-varying correlations, offering insights into the interconnectedness of global financial assets. Recent studies have combined these models to tackle the multifaceted nature of financial data, revealing their potential in comprehensive risk analysis.

Model Specification

1. Univariate GJR-GARCH for variance with a t-distribution

The GJR-GARCH model captures the leverage effect—where negative market shocks increase future volatility more significantly than positive shocks of equal magnitude. Empirical analysis of the Brazilian market corroborates this, highlighting the model's relevance in depicting real-world phenomena. We use a t-distribution to accurately capture tail dependencies.

2. ARMA for mean model

Preliminary analysis using **auto.arima** suggests an ARMA(p,q) order for the mean model which is then inputted into the DCC specification, effectively capturing the autocorrelations in the returns of the studied assets, laying a strong foundation for subsequent volatility modeling.

3. DCC model

The DCC model's flexibility allows for efficient estimation of time-varying correlations across multiple assets. This parsimony ensures the model's applicability to a wide array of financial series, providing a dynamic lens through which market behaviors can be examined. Please refer to the model notebooks on our team’s GitHub repository for the code on how to prepare the data, to model, and to plot the DCC.

Comparative Advantages of DCC

The DCC model's two-step estimation process stands out for its simplicity and reduced computational demand, making it ideal for analyzing across a wide range of assets. Its ability to consistently estimate positive semi-definite covariance matrices ensures the reliability of risk assessments derived from the model. Moreover, the DCC model's implementation in R underscores its accessibility and practicality for financial analysts.

Methodology

Data for this study were sourced from Yahoo Finance, prioritizing quality and consistency. The analysis focused on daily returns of selected Latin American and Caribbean assets from 2015 to 2020. The **rugarch** and **rmgarch** packages in R facilitated the DCC-GJR-GARCH model's application, following data preprocessing to compute log returns and ensure stationarity.

Empirical Results

The DCC-GJR-GARCH model unveiled significant time-varying correlations among the assets, particularly during market downturns, underscoring the model's ability to detect shifts in market dynamics. The GJR component effectively captured the leverage effect, with the DCC model illustrating how correlations intensified during periods of financial stress.

Conclusions and Implications

The application of the DCC-GJR-GARCH model offers nuanced insights into the dynamic correlations and volatility patterns in financial markets. For portfolio managers and risk analysts, these findings highlight the importance of considering time-varying correlations in strategic decision-making. Future research might extend this framework to other emerging markets, exploring the global applicability of the DCC-GJR-GARCH model in financial econometrics.

Visual Illustration of DCC & volatility dynamics of GJR-GARCH

Please refer to Engle (2002) for the formulation of DCC and its correlation and covariance matrices, as well as the model's statistical specification. GJR-GARCH, by including the leverage effects, captures the estimate of the volatility of stock returns. For the formulation of GJR-GARCH, please check NYU Stern's Volatility Laboratory.

DeepAR: Deep Learning for Time Series

Part of the GluonTS library, DeepAR allows us to implement deep-learning-based time series modeling in a simple, fast manner. We first present an overview of DeepAR's model architecture, followed by comparative advantages and tuning suggestions.

Model Architecture

$$\mathcal{L} = \sum_{i=1}^{N} \sum_{t=t_0}^{T} \log \ell(z_{i,t}|\theta(\mathbf{h}_{i,t}))\,.$$

Figure 1 (Salinas, Flunkert, Gasthaus 2019)

We have multiple target time series (correlations in our case) and optional associated covariates as inputs to the model. As presented by the original DeepAR paper (Salinas, Flunkert, Gasthaus 2019), the model utilizes an

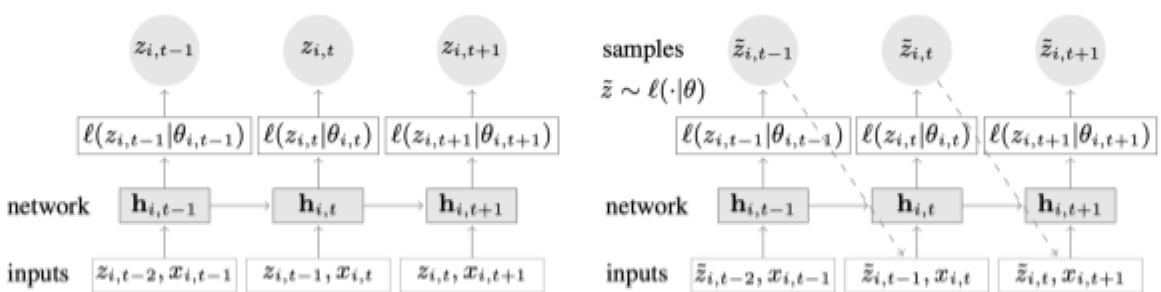


Figure 2: Summary of the model. Training (left): At each time step t, the inputs to the network are the covariates $x_{i,t}$, the target value at the previous time step $z_{i,t-1}$, as well as the previous network output $\mathbf{h}_{i,t-1}$. The network output $\mathbf{h}_{i,t} = h(\mathbf{h}_{i,t-1}, z_{i,t-1}, \mathbf{x}_{i,t}, \Theta)$ is then used to compute the parameters $\theta_{i,t} = \theta(\mathbf{h}_{i,t}, \Theta)$ of the likelihood $\ell(z|\theta)$, which is used for training the model parameters. For prediction, the history of the time series $z_{i,t}$ is fed in for $t < t_0$, then in the prediction range (right) for $t \geq t_0$ a sample $\hat{z}_{i,t} \sim \ell(\cdot|\theta_{i,t})$ is drawn and fed back for the next point until the end of the prediction range $t = t_0 + T$ generating one sample trace. Repeating this prediction process yields many traces representing the joint predicted distribution.

Figure 2 (Salinas, Flunkert, Gasthaus 2019)

autoregressive recurrent neural network (see Stanford RNN for a detailed introduction) in order to model the conditional distribution of the future of our time series. To achieve this, we compute the network output in each time step, use the output to compute the parameters of the likelihood function (see Figure 2), and then train the model by optimizing the log-likelihood (see Figure 1).

Using DeepAR to Forecast Default Correlations

We use DeepAR to forecast four different correlation coefficients. We first train four global models that take as input the DCC correlation estimates of relevant companies. We then train the model on those companies and make predictions for a single time series—that is, the correlation coefficients between any two companies. We present examples for each correlation type in the results section below.

Training DeepAR

Using the GluonTS API's, DeepAR can be trained using ~20 lines of code. Please refer to the model notebooks on our team's GitHub repository for the code on how to prepare the data, train, and plot DeepAR.

Tuning DeepAR

As usually is the case with deep learning models, even though DeepAR has many tuning parameters, most of them have values that have been empirically shown to work well in different settings. We list the tuning parameters below with their usual values or the values we chose, if there isn't a widely accepted value.

1. **Dropout probability:** p = 0.5 is used in general.
2. **Learning rate of the optimizer:** Learning rates between 0.01 and 0.05 usually work well. With DeepAR and our scenario, we found that the learning rate of 0.05 is the most successful in terms of test accuracy.
3. **Number of layers for the recurrent neural network:** 3 or 4 work well in general. We use 4 layers.
4. **Number of epochs:** 5 to 10 work well in general. Since it is not costly to train a DeepAR model with the amount of data we have, we set the maximum number of epochs to 10.

5. **Prediction length and windows:** Depends on how sudden the target variable changes. If there are instant and unexpected changes happening frequently, using a smaller prediction length with greater number of windows makes sense to capture the changes. This is why we use prediction length of 5 with 48 windows (as our test set has 240 days, prediction length * windows should be equal to 240, so windows are determined by prediction length). If our data had a perfect pattern, we would rather choose a larger prediction length with less number of windows.

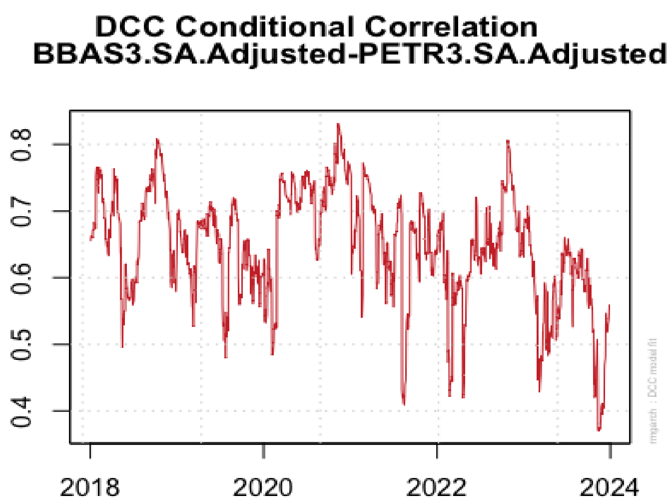
Comparative Advantages of DeepAR

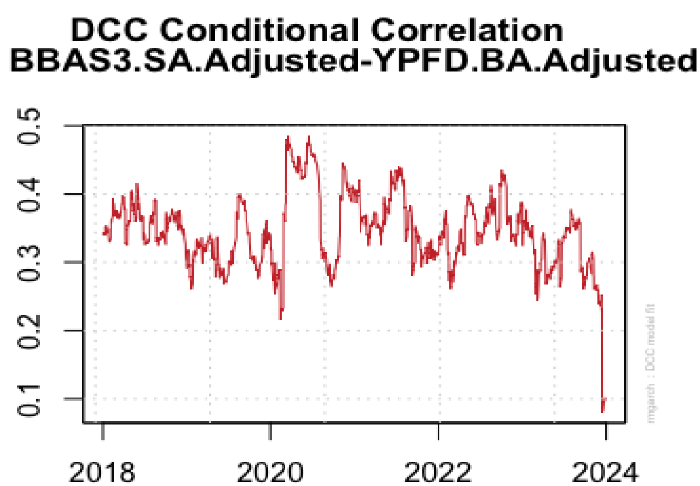
1. **Learning global models from multiple time series**: DeepAR is trained with multiple time series so that it captures global and complex patterns in order to forecast for any individual time series.
2. **Forecasting for companies with little history**: As DeepAR learns a global model, it is able to provide accurate forecasts for companies with little or no history, which means we can incorporate companies with less public record to our model.
3. **Multiple covariates to reflect different scenarios:** DeepAR is able to integrate multiple dynamic and static covariates when modeling the target time series without the need to do separate inference and preprocessing for each variable. This feature can be used to accommodate for different scenarios at hand, such as global, country, financial, non-financial cases for correlation coefficients.
4. **Probabilistic forecasting:** DeepAR is a probabilistic forecasting model, and, in contrast to point forecasting models, it outputs a range of plausible values for the variable we are interested in. This is equivalent to having a prediction interval for each future time step t.
5. **No inference required:** Every input we need in order to compute the log-likelihood is observed (correlations and other possible covariates), which means we do not need to do inference as in state-space time series models. This makes DeepAR very convenient to use and less prone to possible modeling errors.
6. **Ease of model training and deployment:** DeepAR is based on the GluonTS library, which is flexible for various scenarios, data types and distributions and is integrated with libraries like Pandas, NumPy, SciPy, PyTorch, and scikit-learn, all of which are required to train and test deep learning models.

7. **Minimal tuning required:** RNNs have many tuning parameters, but most of them have widely-accepted default values that work well. So, training DeepAR is not time consuming and does not require heavy computing power. Training a DeepAR model on 10 epochs with 5 years of time series data for 100 combinations of companies takes around 2 minutes on a Macbook Pro without using a GPU, for example.

Results

Outputs of DCC

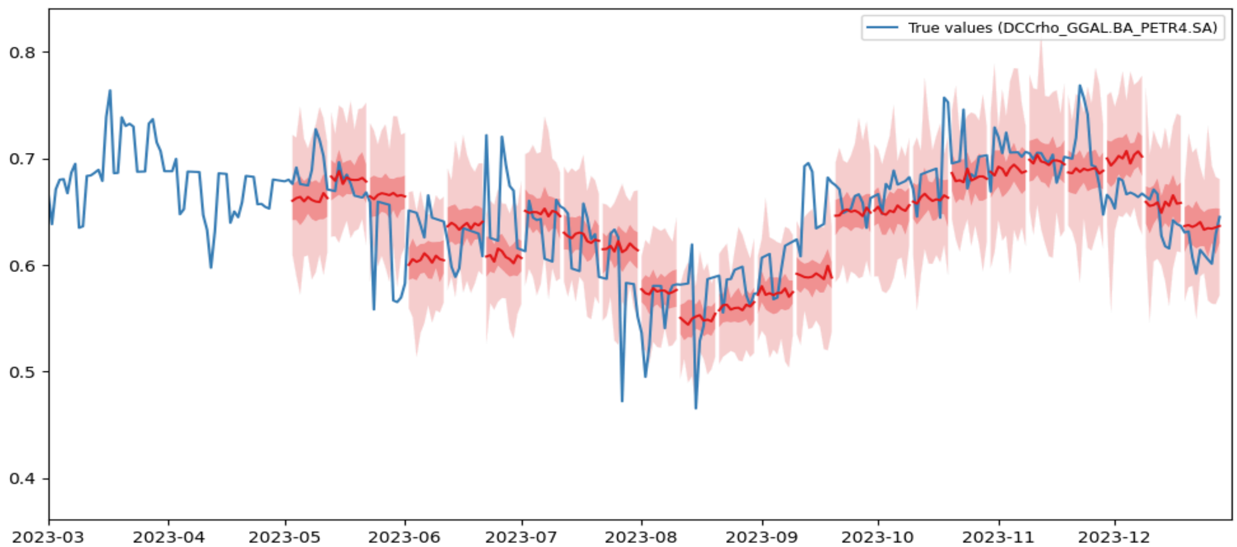




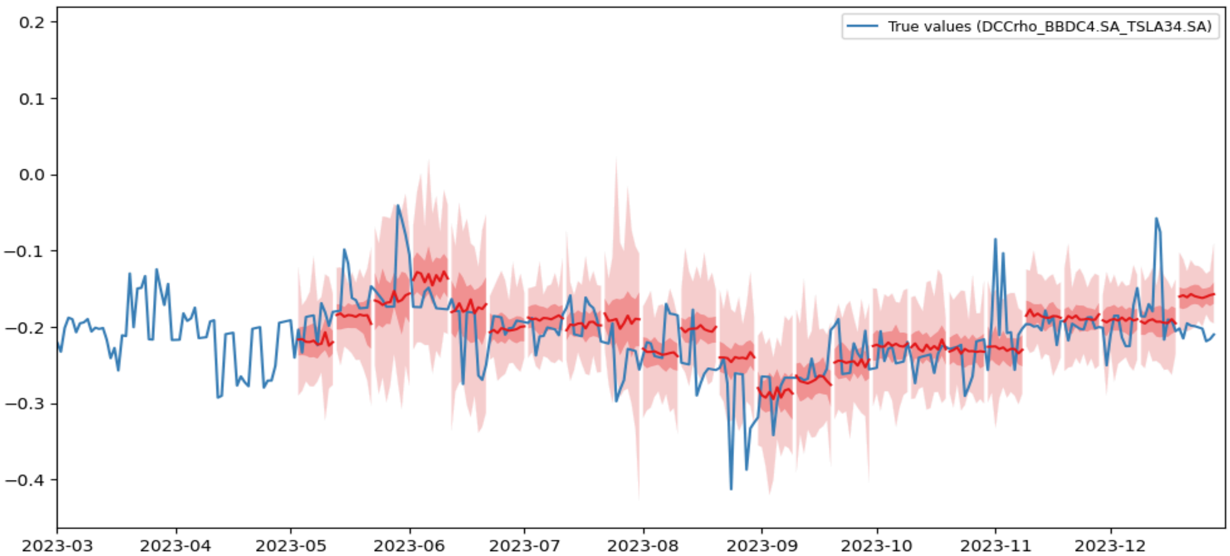
Outputs of DeepAR and Final Results

We observe that DeepAR forecasts are able to capture the true correlations between companies almost all of the time. Note that the shaded areas are 50 and 90% prediction intervals.

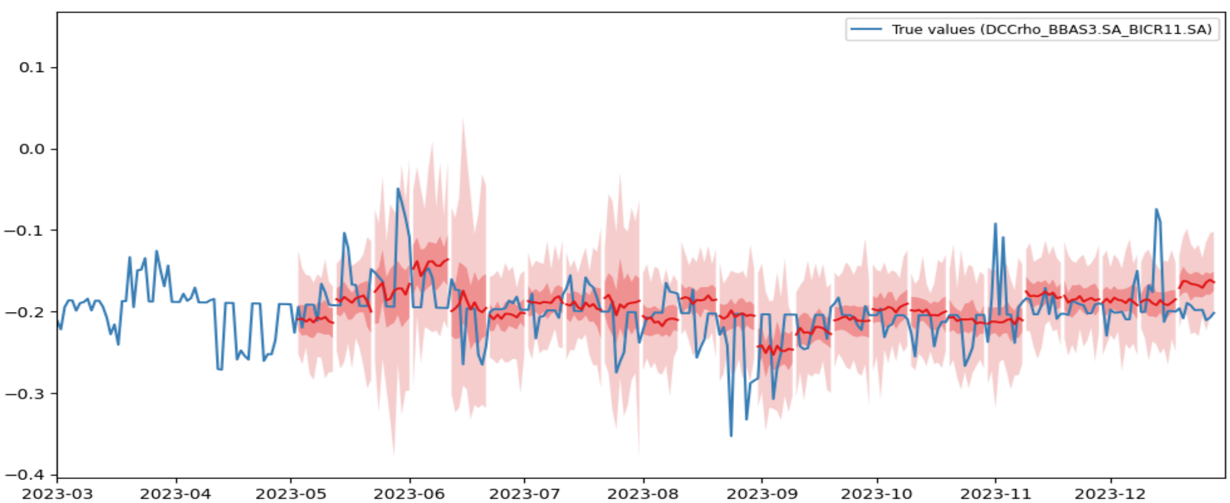
Global correlation coefficient: Below is a graph depicting the forecasted correlations between Grupo Financiero Galicia (Argentina) and Petroleo Brasileiro (Brazil). The model was trained on multiple time series data of companies in Brazil and Argentina from 2018-01 to 2023-05 and is able to forecast correlations from 2023-05 to 2024-01.



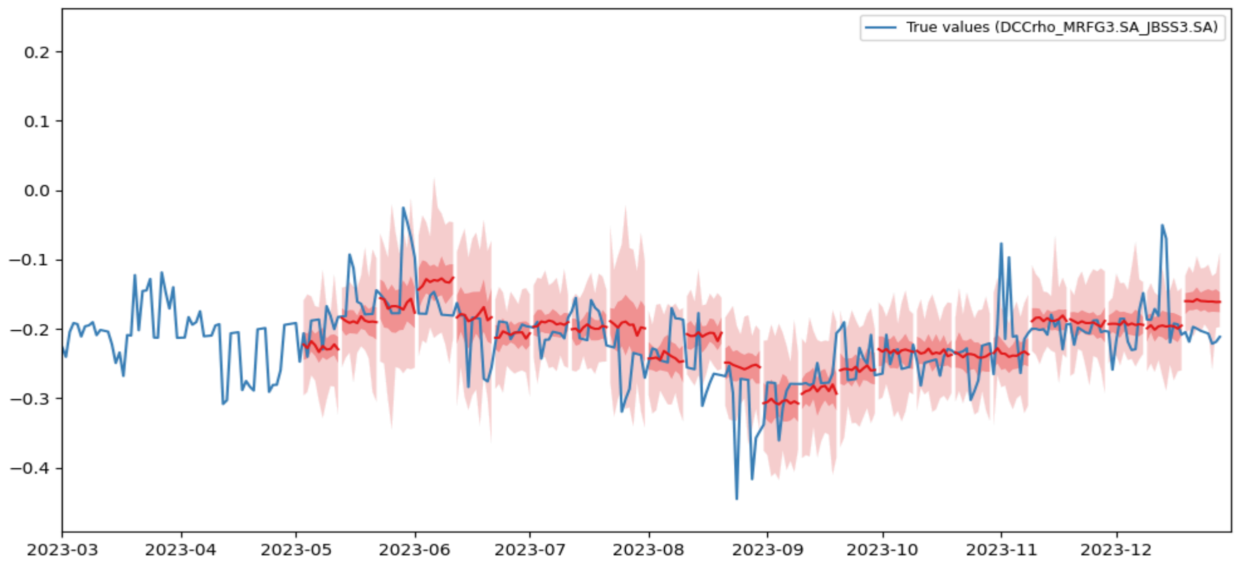
Country Correlation coefficient: Below is a graph depicting the forecasted correlations between Banco Bradesco (Brazil) and Tesla (Brazil). The model was trained on multiple time series data of companies in Brazil from 2018-01 to 2023-05 and is able to forecast correlations from 2023-05 to 2024-01.



Financial sector correlation coefficient: Below is a graph depicting the forecasted correlations between Banco de Brasil (Brazil) vs Inter Titulos Imobiliarios Fundo De Investimento (Brazil). The model was trained on multiple time series data of companies in the financial industry of Brazil from 2018-01 to 2023-05 and is able to forecast correlations from 2023-05 to 2024-01.



Non Financial sector correlation coefficient: Below is a graph depicting the forecasted correlations between Marfrig Global Foods (Brazil) vs JBS (Brazil). The model was trained on multiple time series data of companies in the non-financial industry of Brazil from 2018-01 to 2023-05 and is able to forecast correlations from 2023-05 to 2024-01.



Limitations

While the DCC-GJR-GARCH model combined with DeepAR forecasting presents a novel approach to understanding and predicting default correlations in the Latin American and Caribbean region, several limitations must be acknowledged:

I. Market Coverage

The reliance on publicly traded companies listed on US or South American exchanges may exclude significant segments of the regional economy, particularly smaller firms or those not publicly traded. This limitation could potentially bias our understanding of the broader default correlation dynamics within the region.

II. Data Quality and Availability

The quality of data sourced from Yahoo Finance, while generally reliable, may vary, especially for less liquid assets or those with less market visibility. Moreover, macroeconomic variables, crucial for enhancing our model, might suffer from reporting lags or revisions, impacting the timeliness and accuracy of our forecasts.

III. Model Assumptions

The DCC-GJR-GARCH model, despite its flexibility, relies on assumptions that may not fully capture the complex realities of financial markets, such as linear correlations and t-distribution of returns. These assumptions might oversimplify the nuanced behaviors observed in times of financial distress or market bubbles.

IV. DeepAR Specification

While DeepAR allows for the incorporation of multiple covariates and probabilistic forecasting, its performance depends on the representativeness of the training data. The model's effectiveness in capturing sudden, systemic financial shocks or predicting default correlations far into the future may be limited by these factors.

Conclusion

Our study represents a significant step forward in modeling and forecasting credit default correlations in the Latin American and Caribbean region. By leveraging the DCC-GJR-GARCH model to account for volatility clustering and leverage effects, and employing DeepAR for extensive forecasting, we offer a comprehensive methodology that addresses both the mean and variance aspects of financial time series.

The application of this methodology reveals dynamic correlation patterns among firms within the region, underscoring the importance of considering both global and sector-specific factors in credit risk analysis. Our findings highlight the potential for improved risk management strategies and more informed investment decisions through the understanding of default correlations.

Furthermore, our approach demonstrates the utility of combining traditional econometric models with advanced machine learning techniques to tackle complex financial forecasting problems. The flexibility to incorporate multiple covariates and the ability to produce probabilistic forecasts make this methodology particularly suited to the uncertain and fast-evolving financial landscapes of emerging markets.

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