Do the Stock Markets Have a Memory ? **(Overview lecture)**

Dr. Thomas Guhr

University of Duisburg-Essen, Germany

Courses -

1. Workshop (3 hours)

Commercial Mexican Banks 2018-2023: Risk and Capital Structural Changes.
Dr. José Juan Chávez Gudiño
Scotiabank and Universidad Anahuac

2. Workshop (2 hours)
CVA and DVA models
Dr. Raúl Álvarez del Castillo
Banco de México

3. Workshop (4 hours)

"Modelos de Teoría de Juegos para explicar el Comportamiento de Redes"

Dr. Adolfo Guzmán-Arenas

IPN

4. Workshop (6 horas)

Statistical methods in finance for discriminating randomness from true structure

Dr. Roberto Mota

Universidad de Palermo, Italy

5. Workshop (4 horas)

Concept of market states and its applications

Dra. Parisa Majari

ICF-UNAM

6. Workshop (4 horas)

Information theory

Dr. Jorge Ramos Mercado

EGADE - Uni. of Minnesota

7. Basic time series forecasting and visualization (4 horas)

Mijail Martinez

ICF-UNAM

Keynote Speakers -

1. Humberto Valencia-Herrera y Roberto R. Barrera-Rivera

Does US interest rate sentiment impact Latin American ETFs?

ITESM

2. Luis A. Martínez-Chigo

“The income gradient in COVID-19 mortality and hospitalisation: An observational study with social security administrative records in Mexico”

BBVA

3. Examples of statistical analysis for financial time series

Dr. Francois Leyvraz

ICF-UNAM, Mexico

4. Simplifying complex financial markets using data science

Dr. Anirban Chakraborti

JNU, New Delhi, India

5. Some comments on non-linear time series analysis and the usage of surrogate data

Dr. Markus Mueller

Centro de Investigación en Ciencias, Universidad Autónoma del Estado de Morelos, Mexico

Talks -

1. A Forecasting Model Approach: Investigating Calendar Anomalies and Volatility Patterns in the Cryptocurrency Market

Sonal Sahu,

EGADE Business School, Tecnológico de Monterrey

2. A Credit Rating Forecasting Model Using SVM for Imbalanced Datasets

Jesús Gopar,

EGADE Business School, Tecnológico de Monterrey

3. LSTM for price prediction, applications in the Mexican Stock Market

Samuel García,

EGADE Business School, Tecnológico de Monterrey

4. Efficiency of Green and Sustainable Markets

Kathia Ramos Garza,

EGADE Business School, Tecnológico de Monterrey

5. Inclusión financiera para la supervivencia de la crisis COVID-19 en México

Miguel Ángel Rendón,

EGADE Business School, Tecnológico de Monterrey

6. Correlations beyond the trend: a financial market analysis

Manuel Mijail Martinez Ramos,

ICF-UNAM, Mexico

7. Unveiling Novel Parameters to Understand Market's Critical Behavior

Dr. Hirdesh K. Pharasi

BML Munjal University, India

8. Stylized facts on the income distribution in Mexico

Dr. Raul Hernandez

Universidad Veracruzana, Xalapa, Mexico

9. ”Random matrix and clustering analysis of Hopfield networks as associative memories”

Dr. Thomas Gorin

UdG, Mexico

10. Social Gas

Dr. Luz Marina Reyes Barrera

UdeG, Mexico

11. Nonlinear correlation analysis in financial market data

Dr. Manan Vyas

ICF, UNAM

12. Some comments about brain connectivity

Dr. Jorge Israel Castro Alatorre
ICF, UNAM

A Forecasting Model Approach: Investigating Calendar Anomalies and Volatility Patterns in the Cryptocurrency Market

Sonal Sahu

Abstract

This paper investigates calendar anomalies, volatility patterns, and the best forecasting model for predicting volatility in the cryptocurrency market, focusing on ten prominent cryptocurrencies: Binance USD, Bitcoin, Binance Coin, Cardano, Dogecoin, Ethereum, Solana, Tether, USD Coin, and Ripple. Spanning from January 2016 to December 2023, the study utilizes sophisticated statistical models such as GARCH (p,q), EGARCH (p,q), and GJR-GARCH (p,q) to analyze precise changes in market dynamics and the impact of day-of-week fluctuations on cryptocurrency returns. Empirical evidence reveals significant findings regarding the persistence of volatility, positive and negative news effects on volatility, and day-of-week effects on cryptocurrency returns. Post-COVID-19, Sunday emerges as the least volatile day for cryptocurrencies, while Thursdays and Tuesdays exhibit greater volatility. Binance, Ethereum, Dogecoin, and Tether show anomalies where returns on Tuesday and Thursday significantly differed from those on other days of the week. Many other currencies, like the USD coin, Cardano, and Ripple, show anomalies only in the pre-COVID-19 period. The findings highlight the best forecast model for volatility for each top cryptocurrency, offering practical implications for investors, traders, regulators, and policymakers. These insights emphasize the importance of understanding and addressing calendar anomalies in the cryptocurrency market for informed decision-making, trading strategies, regulatory frameworks, and market stability.

1. Introduction

Calendar anomalies in financial time series datasets have been the subject of research for more than a century. Calendar anomalies, which are patterns or effects beyond the explanation of conventional asset pricing models, are subject to the influence of psychological and seasonal factors [1]. Kumar [2] presents a counterargument to the Efficient Market Hypothesis (EMH) by asserting that investors can capitalize on predictable patterns in asset prices to generate anomalous returns, thereby facilitating the development of efficient trading strategies.

Cryptocurrencies have posed new challenges in the analysis of calendar anomalies. With over 22,235 cryptocurrencies listed on CoinMarketCap, the emergence of digital assets has upended traditional monetary systems and called into question established standards [3,4]. As cryptocurrencies gain popularity, retail investors are increasingly including them in their portfolios [5]. This emerging phenomenon entails incorporating the rapidly expanding cryptocurrency sector, which represents a new and distinct financial domain, into the investigation of calendar anomalies.

In contrast to conventional financial theories, the Adaptive Market Hypothesis (AMH) posits that market inefficiency and efficiency can coexist, enabling market participants and investors to adapt to fluctuating market conditions [6]. The hypothesis proposes that as market participants' knowledge and market dynamics evolve, they adapt their strategies, leading to the development of trading strategies and pricing models that are more precise [7]. Miralles-Quirós & Miralles-Quirós [8] found evidence of calendar anomalies in cryptocurrencies, including the day-of-the-week effect, which shows predictable patterns in returns based on specific days. The AMH's emphasis on market adaptability is consistent with reported anomalies in cryptocurrency markets, where investors may modify their trading methods based on calendar impacts [9]. Understanding these anomalies is crucial for developing effective investment strategies and regulatory frameworks.

To enhance risk management, regulatory compliance, and forecasting precision, it is imperative to employ sophisticated statistical models to simulate the volatility and day-to-day fluctuations of cryptocurrencies. Generalized autoregressive conditional heteroscedasticity (GARCH) models, whether symmetrical or asymmetric, are appropriate for this objective. They influence crypto regulatory policies [10] aid regulators in analyzing crypto risk and volatility [11], facilitate market surveillance [12], and provide insights into market risks [13].

This study aims to investigate the volatility patterns of the cryptocurrency market both before and after the COVID-19 epidemic. We utilized sophisticated statistical models such as GARCH (p,q), EGARCH (p,q), and GJR-GARCH (p,q) to detect subtle changes in market dynamics. Furthermore, we shall examine the impact of day-of-week fluctuations on cryptocurrency returns to shed light on possible irregularities and their repercussions on market efficiency. To ensure extensive market coverage and representativeness, we used data on the ten most prominent cryptocurrencies in terms of market share. Moreover, our research ascertains the most effective GARCH model for forecasting the volatility of cryptocurrencies. This provides valuable insights that can assist policymakers, regulators, investors, and traders in effectively traversing the intricate dynamics of this rapidly growing financial domain.

The subsequent sections of this paper have the following structure: The following sections elaborate on our study: Section 3 provides an overview of the relevant literature; Section 4 analyzes and discusses empirical data; and, finally, Section 5 concludes our research.

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Efficiency of Green and Sustainable Markets

Kathia Ramos[1]

and

Jesús Cuauhtémoc Téllez Gaytán[2]

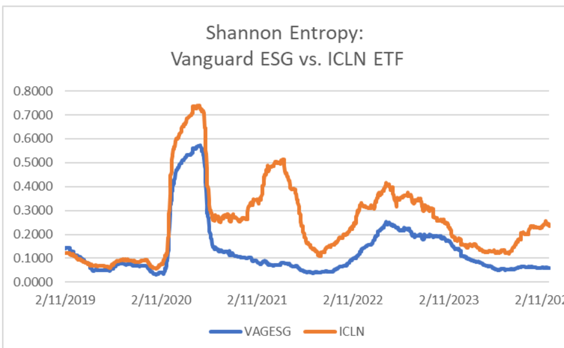
Abstract

The aim of this research is to measure the efficiency degree of Green and Sustainable markets based on the Shannon Entropy (SE) and the Hurst Exponent (HE). The study considers daily prices from September 2018 to February 2024, which depends on the available historical data. The variables considered in the study are the Vanguard ESG US Stock ETF (VAGESG), the iShares Global Clean Energy ETF (ICLN), the iShares MSCI Global Sustainable Development Goals (MSCIGSDG), the S&P 500 ESG Index (SPESG), the S&P Green Bond Index, and S&P Global Clean Energy Index (SPGCEI). On one hand, the research seeks to identify which variables have shown a high and low degree of efficiency in its weak form. On the other hand, the study compares the efficiency degree among different monetary policy stances before, during and after Covid-19 pandemic. For those purposes it is applied the Shannon Entropy and the Hurst Exponent on the full data and by rolling windows of 100, 150, 200 and 300-days. Based on the SE measure, as the index value increases then the less efficient the market is. In that sense, it is observed that at any window frame the ICLN

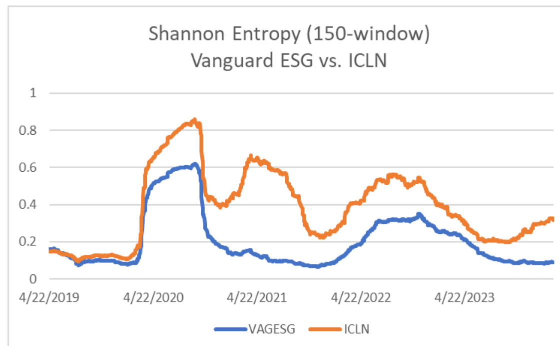
[1] Tecnologico de Monterrey, Business School, kramos@tec.mx

[2] Tecnologico de Monterrey, Business School, cuauhtemoc.tellez@tec.mx

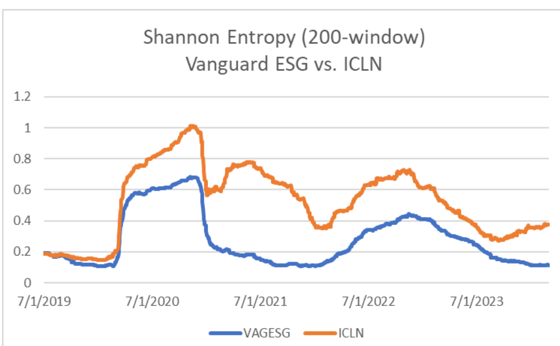
ETF is the least efficient among the other sustainable variables. As the rolling window widens the Shannon Entropy index increases which signals greater uncertainty to predict the event of a negative (down) or positive (up) movement. Fig 1 shows the SE between ICLN and VAGESG, where it is observed that as the windows opens to 300 days, the SE increases. The most remarkable result is that during the Covid-19 Pandemic, the Russian-Ukraine war, and the beginning of a "hawkish" monetary policy, the ICLN becomes more inefficient than VAGESG. So, ICLN would be considered as the less likelihood to predict.



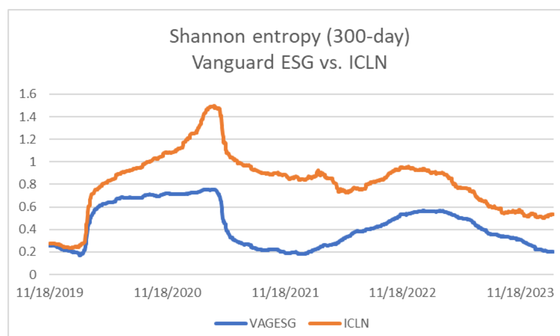
(a) 100-days



(b) 150-days



(c) 200-days



(d) 300-days

Fig. 1. Shannon Entropy measure of ICLN and VAGESG under 100, 150, 200, and 300-days rolling windows.

On the other side, as the Hurst Exponent (HE) moves around 0.5 and 1.0 it means that the time series (log returns) are persistent, where at a HE of 0.5 it is considered that log-returns are totally random and when the HI oscillates between 0.0 and 0.5 it means that the time series are mean reverting. In that case, Fig. 2 shows that ICLN and VAGESG move around an HE less than 0.5 even at a 300-days rolling window, where the greatest HE value was observed during Covid-19 Pandemic. So, it could be stated that both sustainable ETFs are mean reverting time series and the likelihood to predict negative (down) or positive (up) movements increases. However, careful should be taken since the HE considers that time series behave as a geometric Brownian motion, where the probability of extreme values occurrence is almost zero.

Up to here, it can be concluded that the sustainable finance market is not as efficient (weak form) market as it would be supposed to be. Based on Fama's (1970) premise of "informationally efficient market", the sustainable finance market is not incorporating all available information even that ETFs are considered as passive funds, which makes it less certain to predict its movements. Although the Hurst Exponent showed values less than 0.5 (mean reverting time series), it is not capturing at all extreme movements. So, the next step in this research is to estimate the alpha-stable Levy distribution which captures leptokurtic returns. Implications of this research are for investment fund purposes who are seeking to invest in the sustainable finance market.

Commercial Mexican Banks 2018-2023: Risk and Capital Structural Changes

Jose J Chavez

1. Introduction

During the period 2018 – 2023 it is possible to identify important changes in the risk and capital structure of Mexican Banks measured through the information of the capital ratio and its components.

The key indicator of bank's financial health is the capital adequacy ratio (CAR) and is computed as the quotient of the regulatory capital divided by the risk weighted assets. Regulatory capital is determined as the one that is enough to support the risk that the bank has taken (In terms of potential unexpected losses), including credit, market, and operational risks, on the other hand, the regulatory capital differs from accounting capital, sometimes importantly.

So, in one side we have total assets and risk weighted assets, the size of the difference between original assets and weighted assets depends on the risks taken by banks, the risk amplifies or reduces the size. The higher the risk the higher the multiplier (weight) of risk d the other side we have accounting capital and regulatory capital the difference between the is attributed to:

- Capital deductions, that reduce the capital for regulatory purposes. Are the capital concepts that, from regulatory point of view, are not valid for facing the bank financial risks. We will address this issue later.

- Subordinated debt placements that regulation permits to include as capital to face losses (They can be both, Tier 1 or Tier 2). In some cases, this component will result important to face losses due to taken risks.
- Additional global (No specific) provisions, that regulation allows to be classified as complementary capital.

In general capital deductions reduce the capital, and Subordinated debt placements and additional provisions increases the capital for regulatory purposes.

As we can easily identify, keeping track on the difference of both pair of variables (Assets - Risk Weighted Assets, Accounting Capital – Regulatory capital), and the resulting capital ratio, is worthy to identify the risks the banks are taking and the capital that is paying such risks. Is a natural view of the banking system, groups of banks and individual entities. Even more, a complete view would show a complete landscape of the risk and solvency of the banking system, and how this has evolved.

Implicitly we will identify the general risk weight and possible rational of its size. Mexican regulator (CNBV) discloses regularly very detailed information of the banking system at different levels that allows to do this analysis, available information very huge.

Changes in size and structure of risks and capital impacted profitability measures adjusted by risk.

So, we can use metrics based on risk to assess profitability, one example is the Return on Risk Weighted Assets (RORWA) that was proposed some time ago versus the traditional ROA and the return on regulatory capital (RORC) versus the ROE. Our view of the institutions may change importantly through this lens in terms of competitivity and profitability.

Topics to be developed:

- Capital ratio and its components.
    - Capital components.

    - Risk components:
        - Credit
        - Market
        - Operational
- Mexican Commercial banks and its composition by type of bank.
- Events that impacted the commercial banks capital and risk structure during 2018-2023.
    - Accounting changes.
    - Regulatory changes.
    - Pandemic and its impact.
    - Defaults and rating downgrades.
    - Banks bankruptcies,
    - Corporate changes.
- Initial risk and capital structure and track of changes.
- Findings.

Temario del curso "Modelos de Teoría de Juegos para explicar el Comportamiento de Redes”

Dr. Adolfo Guzmán-Arenas

El curso abarca el uso de la teoría de juegos para estudiar la formación de redes, incluyendo el cálculo del costo social ideal, el costo con agentes egoístas, y los equilibrios Nash que resultan. También explora comportamientos estratégicos para compartir costos en redes. Por su duración, los temas "teoría para redes comprador-vendedor" (la relación entre los intereses individuales de los agentes y los intereses colectivos) y "mercado de búsquedas con patrocinio" solo se esbozan, pero se proporcionan sus presentaciones

Un modelo de calificación crediticia para neobancos utilizando Modified Boosted Support Vector Machines

Jesús Gopar. EGADE Business School

El sistema de calificaciones crediticias ha probado ser útil para monitorear la solvencia de los bancos. Sin embargo, el análisis de crédito es un proceso lento y costoso. Los bancos centrales y los reguladores necesitan un mecanismo para identificar cambios en el perfil crediticio de un banco de manera oportuna para mantener la estabilidad del sistema financiero.

En este sentido, diversos articulos científicos han analizado el uso de técnicas estadísticas tradicionales como análisis discriminante y regresión logística así como técnicas de machine learning para pronosticar la calificación crediticia de los bancos. Se ha demostrado que los modelos de pronóstico basados en machine learning tienen un desempeño superior porque captan relaciones no lineales presentes en los datos financieros. Dentro de esta categoría, los modelos basados en redes neuronales (Neural Networks o NN) y máquinas de vectores de soporte (Support Vector Machine o SVM) superan a otros algoritmos (Parisa, Ionuţ, Rupak, 2020). Originalmente, las SVM fueron diseñadas para resolver problemas de clasificación binarios, pero actualmente existen alternativas para resolver problemas de clasificación multiclase como en el caso de los modelos de pronóstico de calificaciones crediticias.

Los modelos de calificaciones crediticias utilizan bases de datos desbalanceadas. En la literatura científica existen dos alternativas para resolverlo: balancear la base de datos o mejorar el algoritmo clasificador (Sundar y Punniyamoorthy, 2019). Por ejemplo, Hari Hari et al. utilizaron el algoritmo modified boosted SVM (MBSVM) de Sundar y Punniyamoorthy para pronosticar la calificación crediticia de bancos utilizando una base de datos desbalanceada y concluyeron que su capacidad de clasificación supera a otros algoritmos. La evolución de nuevos paradigmas informáticos y tecnológicos así como los cambios en los hábitos de consumo han permitido el rápido crecimiento de los Neobancos en los últimos años. Algunos Neobancos operan con una licencia bancaria y otros no por lo que no están sujetos al mismo nivel de regulación y supervisión que los bancos tradicionales. Por su naturaleza, las bases de datos para resolver el problema de clasificación crediticia son altamente desbalanceadas.

En este artículo utilizaremos el algoritmo MBSVM para pronosticar la calificación crediticia de los Neobancos y lo compararemos con otros algoritmos de ML que han ganado popularidad tales como weighted support vector machine (WSVM) y redes neuronales (NN)

Comparing the Performance of Long Short-Term Memory Architectures (LSTM) in Equity Price Forecasting: A Research on the Mexican Stock Market

Comparación del desempeño de arquitecturas de memoria a corto y largo plazo (LSTM) en el pronóstico de precios de acciones: una investigación sobre el mercado bursátil mexicano

Samuel García

Tecnológico de Monterrey, Mexico

Abstract

This study compares the performance of univariate and multivariate Long Short-Term Memory (LSTM) to predict next-day closing prices on four stocks in the consumer retail sector of the Mexican Stock Exchange. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Median Absolute Percentage Error (MdAPE), and Root Mean Squared Error (RMSE) are used to test the networks' performance. Results show a better performance on multivariate price forecasts when using 20-day and 15-day length sequences, generating consistent results for the sample, including illiquid and liquid stocks. On the other hand, univariate LTSM discloses lower forecast performance when predicting the price of illiquid stocks.

Keywords: *forecast, stocks, univariate, multivariate, LSTM.*

JEL Classification: *G1, G15, G20, C6.*

Resumen
Este trabajo compara el desempeño de la memoria de corto y largo plazo (LSTM, por sus siglas en inglés) univariada y multivariada en la predicción de los precios de cierre del día siguiente de cuatro acciones del sector de consumo minorista en la Bolsa Mexicana de Valores. El error absoluto medio (MAE, por sus siglas en inglés), el error porcentual absoluto medio (MAPE, por sus siglas en inglés), la mediana del error porcentual absoluto (MdAPE, por sus siglas en inglés) y la raíz del error cuadrático medio (RMSE, por sus siglas en inglés) se utilizan para probar el desempeño de las redes. Por un lado, los resultados muestran un mejor desempeño en el pronóstico multivariado de precios cuando se utilizan secuencias de 20 y 15 días de duración, generando resultados coherentes para la muestra, incluidas las acciones líquidas e ilíquidas. Por otro lado, la LSTM univariada revela un desempeño de pronóstico menor para la predicción del precio de acciones ilíquidas.

Palabras clave: *predicción, acciones, univariada, multivariada, LSTM*.

Clasificación JEL: *G1, G15, G20, C6.*

1. Introduction

Given the growing complexity of the global financial industry and the unstable nature of the financial markets, pricing analysis of financial assets— like stocks— and predicting future prices and returns in the financial market is a complex and challenging activity, highly valued in the financial sector. Since noise and non-parametric and non-linear dynamics are characteristic of the stock market, its traditional statistical tools to analyze historical data—where past events have great importance in predicting future states (e.g., price and returns) and trends—may struggle to model those dynamics on stock prices over time (Pramod & Mallikarjuna, 2020; Bhandari et al., 2022).

In recent years, developments in ML, AI, and Deep Learning (DL) have played a central role in enhancing stock price prediction. A case in point is that academics have noticed the advantages of DL models when capturing non-linear features of data sequences through Recurrent Neural Networks (RNN) and LSTM networks (Tianxiang & Zihan, 2020). ML is a sub-field of AI, which tries to emulate some human cognitive features like the learning process to identify patterns and/or classify specific sets of objects and is currently used in the financial sector because of its analytical capabilities to analyze and manage big data (Lu, 2017; Liebergen, 2017).

Artificial Neural Networks (ANN) are part of deep learning, which attempt to recreate the logic of the human brain to perform cognitive tasks. These models are mainly based on the interconnection of individual neurons, which creates a network (Nielsen, 2015; Krenker et al., 2011; Tirozzi et al, 2007); RNNs and LSTMs are a subset of Neural Networks, mainly designed to capture information on historical data.

According to the literature reviewed, there is no extensive research on the price forecasting capabilities of LSTM in Latin American markets. Given the importance of AI and DL techniques in the analysis and prediction of financial assets' prices, as well as the growing presence of Latin American financial markets on the global financial landscape, this research is focused on comparing the performance of univariate and multivariate LSTM when predicting next day closing price of four Mexican stocks from the consumer retail sector in the Mexican Stock Exchange (BMV), as well as analyzing the impact of the size of the sequence length used for prediction accuracy. As mentioned, the sample used for this work includes four stocks, two of them liquid when comparing the 3-month and 10-day average traded volume with the other two stocks in the sample. The contribution of this research is to test the performance of LSTM when predicting stock prices, using different historical timeframes, to predict the prices of four Mexican stocks from the consumer retail sector.

As part of the results, it can be observed that the size of the rolling window impacts the performance of the univariate model when predicting the price of illiquid stocks, assessed through four performance metrics to measure the magnitude of errors: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Median Absolute Percentage Error (MDAPE), and Root Mean Squared Error (RMSE), whereas the performance of the multivariate output shows consistency for both illiquid and liquid stocks.

This paper is ordered as follows: Section 2 discloses works related to LSTMs prediction capabilities for a stock process; Section 3 provides an overview of the tested architectures and their features; Section 4 contains methodology and model implementation; Section 5 includes performance metrics; Section 6 details preliminary results; and Section 7 contains conclusions.

2. Related Works

Pricing prediction of financial products is a significant issue in the financial sector and the academy. Currently, several ML and AI models are used to enhance price prediction accuracy; most are based on RNNs, LSTM, and other DL. As mentioned in the previous section, RNNs were mainly designed to capture information on historical data. Focusing on RNNs and LSTM DL models, academic research is centered on analyzing the prediction capabilities of the DL through plain and mixed deep learning models, testing different variables, architectures, and levels of model parameters to obtain a better analysis and prediction accuracy. For instance, Nourbakhsh and Habibi (2023) combined Convolutional Neural Network and LSTM as well as specific variables used in fundamental analysis, to enhance the model's accuracy measured through MAE and MAPE. Also, Zaheer et al. (2023) explored the capabilities of a hybrid deep-learning model based on single and mixed RNN, LSTM, and CNN architectures to predict closing and high prices on the next trading day of the Shanghai Composite Index, where they found that a single layer RNN outperforms the other tested models showing the lowest MAE and RMSE metrics.

Another interesting option to enhance prediction capabilities is found in Tianxiang and Zihan (2020), who proposed a method to predict the West Texas Intermediate oil price, from January 1986 to January 2020, with the LSTM and GM (1,1) model, based on a multi-step prediction method. The model showed significant prediction accuracy measured through MAPE and RMSE. The model effectively captured long-term effects with lower frequency and also price trends. The work performed by these authors can show how mixing different DL models enriches the existing literature on price prediction of financial assets.

The model proposed in this paper analyses how the length of historical data would contribute to better price forecasting, as mentioned by Bhandari et al (2022) who used 15 years of market and macroeconomic data, as well as technical indicators to predict the closing price for the S&P 500 index through a multivariable LSTM. They found the best performance results were based on RSME, MAPE, and a correlation coefficient obtained through a single-layer model.

Although this research evaluates price prediction for the next trading day, other studies examined the prediction accuracy for longer periods. For example, Ghosh et al. (2019) employed LSTM techniques on historical stock price data of five companies from some pre-decided sectors in the Indian market, to infer future trends. The authors proposed a framework based on LSTM models to calculate the best time length to forecast the future share price of a company from a particular sector, as well as predict the future growth of a company for periods of 3 and 6 months, and 1 or 3 years. They found a decrease in the error level when using test data for longer periods, dependencies, and the same growth rate in companies from a certain sector.

Published studies on price prediction have also explored the impact of transformed variables, the number of layers in models, parameter levels, and the length of historical data used, for better model learning, and enhancing prediction capabilities on DL models when compared to other statistical tools. For instance, Andi (2021) normalized variables on a data set to compare the performance of LSTM with other prediction models, like linear regression and the Lasso algorithm, concluding that the first model obtained the most accurate forecast on the Bitcoin price based on accuracy, precision, recall, and sensitivity because using common variation ranges on the variables allow capturing trends.

Finally, Pramod and Mallikarjuna (2020) explored predicting Tata Motors Limited's stock price using LSTM. The output produced a low loss and low error rate. They also found that increases in layers and epoch batch rates had a positive impact on the performance.

Overall, there is an extensive body of research focused on measuring the accuracy of DL models to enhance forecasting capabilities. For example, LSTM architectures combined with other DL models have been used, as well as other techniques like transformed variables to improve model performance, all these evaluated under different financial markets in Asia, Europe, and North America. However, there is no extensive body of research assessing the performance of LSTM models in predicting stock prices in the Latin American financial markets. The contribution of this research is to test the performance of LSTM, using different timeframes to predict the prices of four stocks issued by Mexican firms, with different liquidity attributes, in the Mexican Stock Exchange.

3. A brief on LSTM

Recurring Neural Networks (RNNs) have loops to feedback other neurons in the architecture, hence the output of a neuron in the network impacts the input of another neuron, resulting in closed paths for the transmission of information in the network (Haykin, 2010). LSTMs are a type of RNN architecture, used to find patterns in data, where the occurrence of events of interest is uncommon in time and frequently mixed with other events (Bhandari et al., 2022; Pramod & Mallikarjuna, 2020).

LSTMs deal with the problem of “long-term dependencies”, present in RNNs, by retaining information from past inputs contained in a variable number of time steps, so they can manage to learn and allow facts of interest to persist over time while overcoming the vanishing and exploding gradient problem. As mentioned previously, this network can find relationships in historical data where the existence of the event of interest is scarce in the data set (Benchaji et al, 2021a; Yu et al, 2019; Benchaji et al., 2021b).

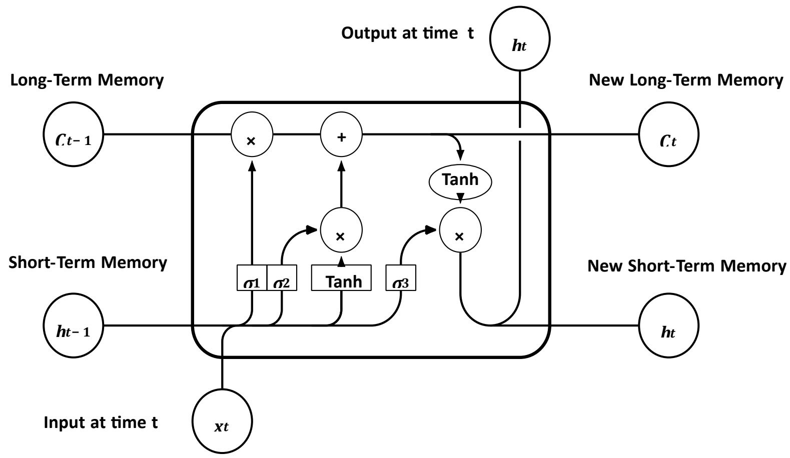
In general, a LSTM architecture (see Figure 1) has explicit memory blocks containing different states: a hidden state (h) and a cell state (C), which allow to store and manage both, short and long-term information through three gates (stages), each one performing an individual function:

1. Forget gate, which chooses, through a sigmoid function (σ_1), whether information coming from h_{t-1} and current input (x_t) needs to be remembered (values near to 1) or is irrelevant and can be forgotten (values near to 0).

2. Input (update) gate, this allows learning from the input x and h_{t-1} to update C, which contains the long-term information; the layer includes two parts: first, a sigmoid layer it will decide which new values will be stored in the cell state and second, a tangent layer creates a vector of new candidate data with values between -1 and 1 to rate relevant data. Then, the output of the input gate is obtained through multiplying the values of sigmoid layer and the tangent layer.

3. Output Layer determines the new hidden state (h_t), based on h_{t-1}, x_t and the tanh of the current cell state (C_t).

Figure 1. General Representation of a LSTM Cell



Source: Prepared by the author.

Where:
σ = Sigmoid Function
Tanh = Hyperbolic Tangent Function

4. Methodology and Model Implementation

4.1 Coding & Data Overview

The analysis for the Research was done using Scikit-learn, a Python-related library to create and implement ML models and perform statistical analysis and modelling; TensorFlow, a high-level open-sourced end-to-end platform to create DL and AI models, and Keras is a high-level open-sourced library which takes the underlying operations provided by other platforms like TensorFlow.

For this research, I used daily market data obtained from Yahoo Finance. The dataset contains stock transactions executed in the Mexican stock market, in the consumer retail sector from January 1, 2020, to February 9, 2024 (1036 workdays). This sector is important not only because it includes companies selling several retail products related to the basic needs of the Mexican population, distributed across Mexico, but the sector was resilient during the pandemic, presenting the smallest drop in value in the Mexican financial market. This sector had the speediest recovery in comparison to other sectors (Landazuri Aguilera & Ruíz Pérez, 2021).

The analyzed stocks were the following:

- Grupo Comercial Chedraui, S.A.B. de C.V. (ticker: CHDRAUIB.MX)
- La Comer, S.A.B. de C.V. (ticker: LACOMERUBC.MX)
- Organización Soriana, S. A. B. de C. V. (ticker: SORIANAB.MX)
- Wal-Mart de México, S.A.B. de C.V. (ticker: WALMEX.MX)

The four stocks were selected, since all of them are nationwide supermarkets, selling comparable retail products with similar target markets, making them comparable in terms of business models.

Table 1 shows some market data for the four stocks used for the research (see Table 1). WALMEX and LACOMERUBC would be considered the most liquid stocks in the sample because both have the greater number of shares outstanding and average traded volume on a three-month and ten-day timeframes, which allow the stocks to be easily traded in the stock market at the current fair market price (Armitage et al., 2014).

Table 1. Market Statistics for the Analyzed Stocks

Statistics	WALMEX	SORIANA	CHEDRAUI	LA COMER
Average Volume on a 3-month timeframe.	15.08 M	65.88 k	311.35 k	645.09 k
Average Volume on a 10-Day timeframe.	15.27 M	2.56 k	295.92 k	224.8 k
Shares Outstanding	17.46 B	1.8 B	959.82 M	1.09 B
Implied Shares Outstanding	17.46 B	1.85 B	959.82 M	N/A
Intraday Market Cap	1.19 T	62.76 B	120.30 B	N/A
Enterprise Value	1.21 T	81.19 B	163.16 B	N/A

Source: Prepared by the author with data from Yahoo Finance as of February 20, 2024.

The research was based on six variables extracted from the data set, including open, high, low, closing, and adjusted closing prices, as well as volume. During a trading day, open and close are prices at which the stock began and ended trading in the stock market, high and low prices are the highest and lowest traded prices for that stock, during a trading day. Adjusted (Adj) close price is the closing price after considering any splits and dividend distributions. Finally, volume indicates the total quantity of stocks traded during a day.

All variables in the dataset were normalized considering a 0 to 1 range to maintain a common scale and to contribute to the model's accuracy.

4.2 Model Implementation and Training

As mentioned in Section 1, this research aims to compare the prediction accuracy of univariate *vs*. multivariate LSTMs on stocks related to the consumer retail sector in Mexico. The research was performed through the following LSTM core architectures:

- Two hidden layers with 50 units each. For every network, the output h_t (see Figure 1), is an input for X_t, at time t, as shown before in Figure 1.
- A Dense layer with five neurons, to convert the output of the final layer into a vector.
- Finally, the vector flows to a linear activation, used to predict the next day's closing price.

Comparison between univariate and multivariate LSTM networks is performed using sequence lengths of 20, 15, and 10 historical stock prices and volume (described in Section 4.1). For example, Figure 2 discloses an architecture with a sequence length of 20 daily data (see Figure 2).

Figure 2. Architecture of a LSTM with a Sequence Length of 20 and 50 units

Layer (type)	Output Shape
lstm_2 (LSTM)	(None, 20, 50)
dropout_2 (Dropout)	(None, 20, 50)
lstm_3 (LSTM)	(None, 50)
dropout_3 (Dropout)	(None, 50)
dense_2 (Dense)	(None, 5)
dense_3 (Dense)	(None, 1)

Source: Prepared by the author.

Both LSTMs predicted the close price for the next trading day. Multivariate, forecasting was based on the six features mentioned in section 4.1. Univariate forecasting was run using the close price.

4.3 Hyperparameters

Following Wiese and Omlin (2009), several test runs were executed to find the best combination of hyperparameters before executing the runs of the research. The model was compiled using the following hyperparameters:

- Dropout technique of 30% to avoid overfitting and to allow the network to get a better generalization.
- Learning rate to adjust the weights in response to changes in the gradient. For this research, the learning rate is 0.0018.

- The m square error (MSE) Loss Function is commonly used on regression tasks. It calculates the magnitude of the average error between the model's prediction ($\hat{y}_i$) and the target value (y_i) by taking the average of the squared difference between these two values. Squaring differences results in a higher penalty for material deviations from the target value.

$$MSE = \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{n} \quad (1)$$

Where:

- n is the total sample size.
- $\hat{y}_i$ is model's prediction.
- y_i $is\ the$ target value.

5. Performance Metrics

To compare both architectures, the prediction accuracy was evaluated through four different metrics:

- MAE shows the arithmetic mean over the absolute difference between $\hat{y}_t$ and y_t (residuals) at time t in the analyzed timeframe.

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| y_t - \hat{y}_t \right| \quad (2)$$

Where “n" is the total sample size.

- MAPE. This indicator measures prediction accuracy as a percentage based on the average of the ratios of individual absolute errors, at each point in time. Defining the error between $\hat{y}_t$ and y_t at time t as a ratio, as follows:

$$e_t = \frac{y_t - \hat{y}_t}{y_t} \quad (3)$$

MAPE is represented as:

$$MAPE = \frac{\sum_{t=1}^{n} \lfloor e_t \rfloor}{n} * 100 \quad (4)$$

- MDAPE. It is a performance metric used to evaluate the accuracy of forecasts in time series analysis. Unlike MAPE, MDAPE uses the median of the absolute percentage errors. This property enables MDAPE to be less sensitive to outliers than MAPE. Mathematically, MDAPE is represented as follows:

$$\text{MDAPE} = median\left(\frac{|e_t|}{y_t}\right)*100 \tag{5}$$

- RMSE measures the difference between $\hat{y}_t$ and targets y_t at time t, through squaring the errors, taking the mean, and finally calculating the square root. RMSE is used to quantify the error on $\hat{y}_t$, when y_t is a continuous number and gives a friendly view of the model's performance, since it shows data on the same scale/units as the Target variable. RMSE is calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2} \tag{6}$$

6. Preliminary Results

Both architectures described in Section 4.2 were tested using the hyperparameters described in Section 4.3; early stopping was used to prevent overfitting. All tests were run considering a dataset from January 1st, 2020, to February 9th, 2024, encompassing 1036 trading days.

6.1. First Test

The test was run using a historical timeframe (sequence length) of 20 days. Table 2 shows the results for both architectures, after replicating 10 times the test over the same stock to provide model reliability (see Table 2).

Results suggest that the multivariate architecture has more consistent performance results (i.e., MAE, MAPE, MDAPE, and RMSE) on the four stocks than the univariate, where results for WALMEX and LA COMER differ significantly from those for SORIANA and CHEDRAHUI.

When comparing performance results between univariate and multivariate models, it can be observed that the multivariate model outperforms when forecasting prices of less liquid stocks: the univariate MAPE for SORIANA and CHEDRAUI is 357% and 1021% higher than the same multivariate metric (see Table 2). Additionally, the univariate MDAPE for the two cases is 457% and 1319% higher than the same metric obtained through the multivariate model. Similar differences are observed for RMSE where the univariate results are 92% and 1252% higher.

When comparing MAPE and MDAPE metrics obtained from the two models for WALMEX and LA COMER, the univariate results outperform the multivariate in almost all indicators (see Table 2). By way of illustration, the univariate MAE for WALMEX is 0.8500 and the multivariate is 1.1400. The results may imply that stock liquidity impacts the forecast capability of the univariate LSTM. Finally, the multivariable average MAE (1.0325) is -80.77% compared to the univariate (5.3700), MAPE -77.42%, MDAPE -81.14 %, and RSME -76.67% respectively.

Table 2. Long Short-Term Memory (LSTM), 20 days

Long Short Term Memory (LSTM)

Timesteps	20	Architecture	2 HL / 50 HU
Batch size	16	Data	From Jan 1, 2020 to Feb 9, 2024
Early stopping	yes	# Days	1036
Learning rate	0.0018	Frequency	Daily

		Univariate				Multivariate			
Issuer	Ticker	Median Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE) %	Median Absolute Percentage Error (MDAPE) %	Difference between actual and predicted values (RMSE)	MAE	MAPE (%)	MDAPE (%)	RMSE
WALMEX	WALMEX	0.8500	1.2600	0.8900	1.1796	1.1400	1.6800	1.4000	1.4259
SORIANA	SORIANA	2.1700	6.8600	6.3500	2.5707	1.0100	1.5000	1.1400	1.3365
CHEDRAUI	CHDRAUI	17.8800	17.4900	17.3100	18.2680	1.0500	1.5600	1.2200	1.3514
LA COMER	LACOMER	0.5800	1.4900	1.0600	0.7953	0.9300	1.3800	1.0700	1.2085
Average		**5.3700**	**6.7750**	**6.4025**	**5.7034**	**1.0325**	**1.5300**	**1.2075**	**1.3306**
Δ Univariate vs multivariate						-80.77%	-77.42%	-81.14%	-76.67%

Source: Prepared by the author.

6.2. Second Test

The sequence length was changed from 20 to 15 days. Table 3 shows the performance results (see Table 3).

Observing performance metrics, a shortened sequence length shows a positive impact on the univariate architecture when compared with the first test, lowering differences in performance metrics: as Table 3 shows, the average MAE is 1.7650, MAPE 3.0450%, MDAPE 2.5375% and RMSE 2.5305 among the four stocks, however the results are higher than those obtained with the multivariate.

Multivariate LSTM discloses more consistent and accurate results, showing small differences in the four indicators, on average MAE is 1.64, MAPE 2.42%, MDAPE 2.24%, and RMSE 1.93. Additionally, when comparing performance metrics between both architectures for the analyzed stocks, the multivariable average results are more accurate than the univariate: MAE is -6.94%, MAPE -20.36 %, MDAPE -11.53 %, and RSME -23.61% respectively.

Table 3. Long Short-Term Memory (LTSM), 15 days

Long Short Term Memory (LSTM)

Timesteps	15	Architecture	2 HL / 50 HU
Batch size	16	Data	From Jan 1, 2010 to Feb 9, 2024
Early stopping	yes	# Days	1036
Learning rate	0.0018	Frequency	Daily

		Univariate				Multivariate			
Issuer	Ticker	Median Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE) %	Median Absolute Percentage Error (MDAPE) %	Difference between actual and predicted values (RMSE)	MAE	MAPE (%)	MDAPE (%)	RMSE
WALMEX	WALMEX	2.6000	4.0500	3.1900	3.4742	1.6000	2.3600	2.1400	1.9060
SORIANA	SORIANA	1.4600	4.5500	4.8600	1.7166	1.5400	2.2800	2.0900	1.8417
CHEDRAUI	CHDRAUI	2.4700	2.2400	1.1200	4.1867	1.7600	2.6000	2.5300	2.0231
LA COMER	LACOMER	0.5300	1.3400	0.9800	0.7444	1.6700	2.4600	2.2200	1.9611
Average		**1.7650**	**3.0450**	**2.5375**	**2.5305**	**1.6425**	**2.4250**	**2.2450**	**1.9330**
Δ Univariate vs multivariate						-6.94%	-20.36%	-11.53%	-23.61%

Source: Prepared by the author.

6.3. Third Test

The third test was performed using the same database used for the first and second tests, the sequence length was changed to 10 trading days.

Table 4 shows the performance test results for both architectures (see Table 4). The average performance metrics for the univariate deteriorated when compared with the results in the second test (see Table 3), mainly for less liquid stocks (SORIANA and CHEDRAUI, In particular, SORIANA MAE varied from 1.45 in the second test to 7.8; MAPE from 4.55% to 8.11%, RMSE from 1.7166 to 2.9482, and MDAPE from 4.86% to 7.62%. Additionally, the performance metrics for the multivariate show the worst results when compared with tests one and two.

Although the multivariable performance results deteriorate when compared to those obtained for the same model in the first and second tests, these numbers are better than those in the univariate model. On average, multivariate (4.1450) MAE is -46.86% than univariate (7.8000), MAPE -42.38 %, MDAPE -45.40 % and RSME -44.42% respectively.

Table 4. Long Short-Term Memory (LTSM), 10 days

Long Short Term Memory (LSTM)

Timesteps	10	**Architecture**	2 HL / 50 HU
Batch size	16	**Data**	From Jan 1, 2010 to Feb 9, 2024
Early stopping	yes	**# Days**	1036
Learning rate	0.0018	**Frequency**	Daily

		Univariate				Multivariate			
Issuer	Ticker	Median Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE) %	Median Absolute Percentage Error (MDAPE) %	Difference between actual and predicted values (RMSE)	MAE	MAPE (%)	MDAPE (%)	RMSE
WALMEX	WALMEX	0.8700	1.2800	0.9400	1.1899	1.2900	1.8800	1.5500	1.6678
SORIANA	SORIANA	2.5600	8.1100	7.6200	2.9482	1.5700	5.0200	4.4100	1.8782
CHEDRAUI	CHDRAUI	27.2200	26.6300	26.8500	27.7901	13.0100	12.8700	12.5600	13.6385
LA COMER	LACOMER	0.5500	1.4000	1.0200	0.7522	0.7100	1.7900	1.3700	0.9799
Average		**7.8000**	**9.3550**	**9.1075**	**8.1701**	**4.1450**	**5.3900**	**4.9725**	**4.5411**
Δ Univariate vs multivariate						-46.86%	-42.38%	-45.40%	-44.42%

Source: Prepared by the author.

7. Conclusions

Stock price prediction is a very researched and complex area because all variables involved in trading activities have a nonlinear behavior. Thus, there is an interest in developing models that will allow more accurate and consistent forecasts. This study focuses on comparing the performance of univariate and multivariate LSTM in predicting prices for stocks in the consumer retail sector in Mexico, as well as the impact of the size of the sequence length on the models. The performance results under different sequence lengths were analyzed in Section 6.

In general, results show that the univariate LSTM works better when predicting prices over liquid stocks, although the performance in this model was less consistent among the four stocks in the sample than the multivariate. Multivariate LSTM shows accurate and consistent performance metrics when predicting prices for liquid and illiquid stocks, producing minor errors, measured through the performance metrics.

Sequence length impacts the accuracy of price prediction on both tested models. For instance, the univariate model disclosed a better performance with a sequence length of 15 trading days, whereas the multivariate shows a better performance with a sequence length of 20 days and 15 days.

Finally, it is worthwhile to continue exploring in future works the impact of price volatility and trends on predicting prices of illiquid stocks traded in developing economies.

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About the author

Samuel García is Mexican and has earned two Master's degrees: the first in Economics and Technological Change and the second in Finance, and a Bachelor's in Business Administration. He has 25 years of experience in national and international financial institutions. He is a senior executive with knowledge of market surveillance, compliance, risk management, structured finance, financial products, and strategic management. Samuel worked at Citi for 16 years, where he was responsible for building and providing strategic direction for the ICRM

Surveillance program, covering sales and trading as well as banking businesses across the Latin American Region—with more than 20 countries, including Mexico.

A1018966@tec.mx
https://orcid.org/0000-0001-7366-1406

The sensitivity of bond ETFs to changes in the United States interest rates sentiment.

(La sensibilidad de los ETF de bonos a los cambios del sentimiento de las tasas de interés en los Estados Unidos)

Valencia-Herrera, H.[1] & Barrera R. R.[3]

Abstract

We analyze the daily returns of eleven emerging market bonds ETFs and twelve international and US bonds ETFs exchanged in US markets for the years 2022 and 2023. The returns from the emerging market bond ETFs show more sensitivity to the changes to the US interest rate sentiment than the considered US Bonds ETFs exchanged in the Unites States. More ETFs show dependencies to changes in US interest rate sentiment with more lags than less in the sentiment variables. All the emerging market bond ETFs considered show sensitivity to changes in US sentiment when including up to two lags in changes in the sentiment except the emerging market high yield bond ETF. Of the considered US bond ETFs, only four ETFs show statistically significant sensitivity changes in US interest rate sentiment when including up to two lags in the sentiment.

Keywords: ETF, sentiment, bonds, interest rates.

Resumen:

Analizamos los rendimientos diarios de once ETF de bonos de mercados emergentes y doce ETF de bonos internacionales y estadounidenses intercambiados en los mercados estadounidenses durante los años 2022 y 2023. Los rendimientos de los ETF de bonos de mercados emergentes muestran más sensibilidad a los cambios en el sentimiento de las tasas de interés de EE. UU. que los considerados ETF de bonos estadounidenses intercambiados en Estados Unidos. Más ETF muestran dependencia de los cambios en el sentimiento de las tasas de interés de EE. UU. con más retrasos que menos en las variables de sentimiento. Todos los ETF de bonos de mercados emergentes considerados muestran sensibilidad a los cambios en el sentimiento estadounidense al incluir hasta dos rezagos en los cambios en el sentimiento, excepto el ETF de bonos de alto rendimiento de mercados emergentes. De los ETF de bonos estadounidenses considerados, sólo cuatro ETF muestran cambios de sensibilidad estadísticamente significativos en el sentimiento de las tasas de interés de EE. UU. al incluir hasta dos rezagos en el sentimiento.

[3] EGADE Business School, Tecnológico de Monterrey

Introduction:

The study of how sentiment in the news and social media can help predict the profitability of financial instruments is of great interest both in academia and in the professional field of fund managers and investors. This relationship has been primarily studied in the stock market, both considering the impact of market sentiment on stock prices and the market, as well as the impact of prevailing sentiment on particular assets and their prices. Studies analyzing the dynamic effect of sentiment captured by news regarding economic policy instruments on financial assets have been more limited. This study analyzes the dynamic impact of sentiment captured by news regarding monetary policy on the future returns of bond ETFs that replicate different segments of the bond market in the United States and emerging countries.
The dynamic effects of sentiment captured by news on asset returns is an effect that indicates a violation of weak stock market efficiency, and could potentially result in windfall profits for investors. In this article we show that the mainly emerging bond markets in the analyzed period were able to obtain extraordinary profits using dynamic information derived from the analysis of the sentiment shown in the news available on the network regarding monetary policy in the United States.

The article is divided as follows. After this introduction, the next part is the bibliographic review and theoretical framework. The next section discusses the methodology used. This is followed by the discussion of the main results. The article ends with a discussion of the conclusions and recommendations.

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Stylized facts on the income distribution in Mexico

Alejandro Raul Hernandez Montoya

We present an analysis of the distribution of individual and household income data in Mexico using a sample from INEGI data from the late 1980s to 2018.

We observe that the shape of the income distribution in Mexico is consistent with the empirical form considered universal and observed in other societies and countries.

Hirdesh K. Pharasi

Talk title: Unveiling Novel Parameters to Understand Market's Critical Behaviour

Abstract: This talk will delve into the diversity within market crashes, aiming to identify and characterize distinct crash types using advanced clustering techniques. Our research has revealed subtle distinctions among various crash types based on market correlation characteristics and underlying mechanisms. We have analyzed four financial markets: S&P 500, Nikkei 225, FTSE 350, and HSCI, based on the clustering analysis of cross-correlation structure patterns of short-time epochs over the last 24 years (21st century). This approach sheds light on the diverse nature of market crashes and provides a quantitative measure to assess their impact and predict potential market movements.

Luis A. Martínez-Chigo

The income gradient in COVID-19 mortality and hospitalisation: An observational study with socialsecurity administrative records in Mexico

Summary

Background The COVID-19 pandemic revealed large structural inequalities that led to disparities in health outcomes related to socioeconomic status. So far, most of the evidence is based on aggregated data or simulations with individual data, which point to various possible mechanisms behind the association. To date, there have been no studies regarding an income gradient in COVID-19 mortality based on individual-level data and adjusting for comorbidities or access to healthcare.

Methods

In this paper, we use linked employee-patient data for patients tested for COVID-19 at the Mexican Institute of Social Security. We estimate the association of the probability of dying with income centiles, using a probit estimation and adjusting for COVID-19 diagnosis, sociodemographic variables, and comorbidities. Findings

After controlling for all these variables, we find that persons in the lowest income decile still had a probability of dying from COVID-19 five times greater than those at the top decile.

Interpretation: Our results imply that the association between income and COVID

outcomes is not explained by the prevalence of comorbidities or by a lack of access to healthcare among the low-income population.

Does US interest rate sentiment impact Latin American ETFs?

Humberto Valencia-Herrera y Roberto R. Barrera-Rivera

Abstract

We analyze the dependence of the returns of Exchange Traded Funds (ETFs) from six Latin American countries on interest rates and the Federal Reserve (FED)´s sentiment in the United States (US) news during the period 2022 to 2023. We use for each country robust regressions with zero to two lags for positive and negative sentiments, and the previous returns. We found that the sentiment is statistically significant for some lags for returns of ETFs from Brazil, Chile, and Peru, in both the local currency and the US dollar. The Latin American 40 ETF also depends on the sentiment in US currency. There is also a moment effect on returns in the US currency and a mean reverting effect in local currency. A panel data model for the considered countries'ETFs with random effects and zero to two lags in the change of sentiment shows that all considered changes in sentiment are statistically significant for the returns, except the one for the change in positive sentiment without lags.

Statistical methods in finance for discriminating randomness from true structure Abstract

Roberto Mota, ICF-UNAM

In this workshop we will study tools for the development of hypothesis tests designed to differentiate statistical properties in a given set of data that could be easily obtained by a simple random process from properties that are more likely to be the result of complex stochastic processes or even deterministic ones.

Along the way we will learn the difference between estimating a statistic from a finite sample of observations and deriving theoretical results in the asymptotic regime. This is a crucial aspect to have in mind if one wants to have better chances of avoiding the multiple fallacies than can come up in statistics.

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Epilogue

- Why most published research is wrong
- Take home message: do not be dishonest, try to destroy your assumptions

Title: Simplifying complex financial markets using data science

Anirban Chakraborti, JNU

Abstract: Financial markets, being spectacular examples of complex systems, display rich correlation structures among price returns of different assets. The correlation structures change drastically, akin to critical phenomena in physics, as do the influential stocks (leaders) and sectors (communities), during market events like crashes. Using the approaches of data science, we present the results for a few generic indicators that monitor the dynamics and internal structures of the market—important for managing risk and foreseeing tipping points of complex financial systems.