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EMPIRICAL ASSET PRICING VIA MACHINE LEARNING: APPLIED TO THE MEXICAN STOCK MARKET

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II. Abstract

This thesis investigates the predictive power of twelve machine learning models, including Random Forest, Gradient Boosting, and five distinct Neural Network architectures to the challenging task of stock return prediction and portfolio construction in the Mexican equity market. Using a rolling window design (37 months: 36 for training and one for testing) and 27 predictors variables grouped into four categories: technical analysis, fundamental analysis, macroeconomics and market indicators, the study evaluates forecast accuracy, portfolio performance, and variable importance.

A key innovation is the introduction of a directional loss function for neural network architectures, which focuses on correctly capturing the direction of the stock returns. Despite modest out-of-sample R^2, most machine learning-based portfolios consistently outperformed the IPC benchmark. The analysis also identifies that certain predictors —such as sector index returns, country risk (EMBIG), enterprise value, short-term rate of price change, and liquidity— consistently play a significant role in how the models explain equity returns.

Overall, the findings validate the application of machine learning to empirical asset pricing in emerging markets and propose a practical framework for integrating prediction, interpretation, and investment strategies design.

Contents

1 Introduction

The prediction of asset returns remains one of the most challenging problems in finance, particularly in emerging markets where structural inefficiencies, lower liquidity, and limited data availability further complicate the research and evaluation of machine learning (ML) models in forecasting monthly stock returns. Although traditional empirical asset pricing models have made significant progress in explaining stock returns, challenges such as limited predictive power and recent proliferation of risk factors commonly referred to as the "factor zoo" persist. In response, machine learning methods have emerged as a powerful tool to enhance predictive accuracy, construct investment strategies, and identify relevant variables in asset pricing. However, these methodologies remain relatively underexplored in emerging markets such as the Mexican Stock Exchange.

Economic theory in asset pricing argues that prices reflect all available information; therefore, it is not possible to predict future prices or consistently earn extraordinary returns by outperforming the market (Fama, 1970). However, empirical evidence on asset prices has shown the existence of market inefficiencies and anomalies. This has led to extensive literature on stock price forecasting, exploring models and strategies seeking to identify patterns to generate arbitrage opportunities and profitable returns. Thus, asset pricing models have evolved by incorporating a growing number of risk factors to improve their accuracy leading to the "factor zoo" problem (Neuhierl et al., 2023). Despite this expanded research, the predictive accuracy and the explanation of asset pricing behavior remains modest.

Recent studies such as Gu et al. (2019) have demonstrated the ability of ML models — particularly tree-based algorithms and neural networks — to outperform the U.S. market benchmark by the construction of investment strategies based on return predictions, while also offering new tools to identify variable relevance. Most empirical research on the application of machine learning techniques in finance has focused on the U.S. stock market and the Asian region (Kumbure et al., 2022). In contrast to the extensive use of ML in developed markets, its application in the Mexican Stock Market has been relatively limited.

To fill this gap, this research contributes to the growing literature on empirical asset pricing by evaluating the effectiveness of machine learning methods in forecasting asset returns and constructing profitable investment strategies in emerging markets, particularly the Mexican Stock Exchange. Moreover, it proposes an approach for identifying the most relevant predictors of stock returns, providing insights into the economic, financial, and technical variables that influence asset pricing in developing economies. In addition to its academic contribution, the study tests the potential practical applicability of these models as a key tool for portfolio managers, financial institutions and corporate decision-makers to enhance investment strategies and risk management processes.

The methodology incorporates twelve machine learning models, including random forest, gradient boosting, and five distinct neural network architectures (Personal, NN2, NN3, NN4, and NN5), with the neural networks evaluated under two different loss functions to assess their performance in financial applications. The first loss function aims to minimize the mean squared prediction (MSE) between predicted and observed values, as is standard in the specialized literature. The second, a key innovation of this study, introduces a directional penalty to the MSE and focuses on correctly capturing the direction of the stock returns rather than their exact value. This approach leads to the alignment of model objectives with real-world contexts, where the direction of returns is often more important than precisely estimating their magnitude.

These models were evaluated across multiple rolling time windows of 37 months (36 for training and one for testing) from January 2019 to January 2025, using a set of 27 variables divided into four categories: technical analysis, fundamental analysis, macroeconomics, and market indicators. This variable set was designed to capture a comprehensive outlook of firm-specific conditions, price dynamics, and macroeconomic trends in the Mexican economy, allowing the identification of patterns and improving forecast accuracy.

The empirical analysis was conducted on the most actively traded Mexican stocks, focusing on monthly return prediction, the performance of investment strategies constructed from those predictions, and the variable importance derived from random forest and gradient boosting models. The performance analysis was conducted at two levels: aggregate model performance and individual stock-level performance, using two complementary out-of-sample R^2 measures to evaluate predictive accuracy.

For the investment strategies, portfolios were designed to directly exploit the forecasts generated by machine learning models. Following the approach presented by Gu et al. (2019), the one-month-ahead stock return predictions obtained in each rolling window were used to sort stocks into deciles based on their predicted returns. A zero-net-investment portfolio was then constructed by buying the highest expected return stocks (decile 10) and selling the lowest (decile 1), thus splitting the positions into long and short positions. Within each position, stocks were equally weighted, and the portfolio was rebalanced monthly. This approach does not include transaction cost or trading fees.

Regarding the variable importance analysis, the interpretation of variables in machine learning models is a fundamental challenge, since these models do not provide a detailed explanation of how input variables influence their predictions. However, random forest and gradient boosting models assign a relative importance score to each input variable, ranging from 0 to 1 and summing to 1 in total. Therefore, variable importance was calculated as the average relative importance of each input variable across all stocks and rolling windows.

The results are organized into three primary objectives: out-of-sample prediction performance, cumulative returns of machine learning-based portfolios, and the analysis of relative variable importance.

With respect to prediction accuracy, most out-of-sample R^2 values at the aggregate model level were negative, suggesting a limited predictive power across models, consistent with the existing literature (Díaz et al., 2023). Nonetheless, random forest, gradient boosting, and the NN5 neural network showed relatively better performance. It is important to highlight that these results were derived from 1,369 individual models (37 stocks x 37 rolling windows), since each model was independently trained for each stock and time window. For this reason, a disaggregated stock-level performance analysis was conducted. Although the overall results were negative, the random forest and gradient boosting models produced positive R^2 values for certain stocks.

These findings do not indicate a modeling failure, instead they highlight the fundamental unpredictability of monthly equity returns. These assets are characterized by high volatility, market sentiment, macroeconomic shocks, and unpredictable dynamics (e.g. investor behavior). These features severely limit model performance and provide a plausible explanation for the negative out-of-sample R^2 values.

In terms of portfolio performance, most of the machine learning portfolios outperformed the market benchmark (IPC[1]), with several achieving returns more than 25 percentage points above the index during the evaluation period. Despite exhibiting a lower R^2 than other models, the NN4 architecture produced the highest cumulative returns under both loss functions.

Furthermore, the results suggest that neural networks trained with the loss function, which explicitly penalizes directional errors, enhance the practical applicability of the machine learning models for financial portfolio construction, enabling portfolio managers to develop strategies that more effectively capture profitable trends. This underscores the importance of aligning model objectives with decision-making goals in financial applications, particularly when predicting the direction of returns is more relevant than estimating their exact value.

The final objective of this research is to examine variable importance as derived from random forest and gradient boosting models, contributing to a novel characterization of the Mexican equity market. The analysis reveals that certain predictors — such as sector index returns, country risk (EMBIG), enterprise value, short-term rate of price change, and liquidity — consistently play a significant role in how the models explain equity returns, the presence of variables from all four categories among the top ranked predictors validates the initial variable selection and highlights their relevance in explaining stock return behavior.

These findings improve the interpretability of both machine learning models, provide empirical support for addressing the "factor zoo" problem by identifying variables with significant relevance

[1] The IPC refers to S\&P/BMV IPC.

in return forecasting, and enhances our comprehension of the economic and financial signals that are most influential in return forecasting, particularly for the Mexican stock market.

The three main aspects of this study have practical relevance for multiple stakeholders in the Mexican financial sector. For institutional investors and portfolio managers, the evidence that trading strategies based on machine learning models can generate substantial excess returns suggests that incorporating these models into asset allocation frameworks may enhance the performance of these frameworks, particularly when they focus on correctly capturing the direction of the stock returns. For market analysts, the identification of relevant variables such as sector index returns, country risk (EMBIG), and liquidity provides valuable insights into the factors that influence stock pricing in Mexico, highlighting priority areas for deeper analysis.

Further extensions of this work would explore longer training windows, an expanded set of predictive variables to assess whether model performance improves, and other machine learning techniques such as Long-Short-Term Memory (LSTM) networks which may offer better adaptability by capturing temporal dynamics across features and potentially enhancing forecast accuracy.

Overall, the findings demonstrate the promise of machine learning techniques in emerging financial markets and provide evidence that these methods can serve as powerful tools for return prediction, investment strategy design, and variable relevance analysis, offering a valuable foundation for both academic research and practical implementations in data-driven asset management and portfolio optimization.

In summary, this study explores the intersection of machine learning and empirical asset pricing in emerging markets. It aims to evaluate the predictive performance of multiple ML models, assess the effectiveness of model-based predictions to generate excess returns through the proposed investment strategy, and examine the relevance of various financial and macroeconomic indicators in predicting stock returns in Mexico. Using multiple models, an extensive set of predictors, and a systematic evaluation approach, this study sheds light on the practical and methodological implications of using machine learning techniques for forecasting returns in an emerging market context that remains understudied in the literature.

This research makes a valuable contribution to the application of machine learning in financial economics, offering empirical support and conceptual clarity for its role in asset pricing within developing economies.

2 Literature Review

Economic theory suggests that the price of a good or service is determined by the laws of supply and demand, however, asset pricing in the stock market is a highly complex and challenging task due to its dynamic, volatile, sentiment-influenced and often chaotic nature, determined by the behavior of investors (Rafiuddin et al., 2023). Among the theories developed by the academic community to explain the stock price behavior, one of the most influential is the Efficient Market Hypothesis (EMH) (Tsai & Hsiao, 2010).

This theory, developed by Fama (1970), argues that stock prices fully reflect all available information according to different levels of efficiency. Under the weak form, asset prices incorporate all the historical prices or return sequences, implying that prices follow a random walk and cannot be predicted through technical analysis. The semi-strong form assumes that prices reflect all publicly available information, including historical data, news, financial statements and economic indicators. In this case, neither technical nor fundamental analysis can consistently outperform the market. Finally, the strong form suggests that the asset price reflects all existing information, both public and private (including insider information). Therefore, even access to privileged information will not allow investors to earn extraordinary returns.

While EMH has served as a fundamental theory in financial economics, subsequent empirical evidence on asset prices has suggested the presence of inefficiencies or anomalies in the market (Schwert, 2003). Although such inefficiencies are quickly corrected and are essentially temporary (Marwala & Hurwitz, 2017). Notably, these empirical challenges had already been reviewed and discussed by Fama (1991), who acknowledged the growing empirical evidence and documented anomalies inconsistent with market efficiency. He also discussed some developments in asset return predictability, including the explanatory power of certain variables such as size, leverage E/P and book-to-market equity on expected stock returns. In particular, Fama and French (1992) demonstrated that size and book-to-market equity effectively explain the cross-section of the average stock returns, while the relationship between market betas and average return appears weak. Consequently, Fama and French (1993) proposed the three-factor model, which incorporated market risk, size (SMB), and value factors (HML). Together, these studies marked an important shift in asset pricing research, resulting in extensive literature on stock price forecasting, exploring models and strategies seeking to identify patterns to generate arbitrage opportunities and profitable returns.

Thus, asset pricing models have evolved by incorporating a growing number of risk factors to improve their accuracy leading to an excess of proposed factors commonly referred to as the "factor zoo" (Neuhierl et al., 2023). Technical indicators, financial ratios and macroeconomic variables have been identified in the literature as key factors influencing stock price behavior (Tsai & Hsiao, 2010). However, in the review of 138 articles published between 2000 to 2019, Kumbure et al. (2022) examined the variables used in stock price prediction models. Their findings show that studies incorporate different sets of input variables, reflecting the lack of consensus on which variables are most relevant for predicting stocks prices.

To address this proliferation, various approaches have been developed to impose more discipline in selecting relevant factors. For example, Feng et al. (2019) proposed a systematic method to evaluate a wide range of factors that had been introduced over the last 30 years in the literature with the aim of assessing their individual contribution to asset pricing. Specifically, their research focuses on evaluating the marginal contribution of new factors relative to the existing one, showing that while many new factors are redundant, a few exhibit statistically significant explanatory power. In addition to this complexity, Bagnara (2024) highlights that the latest development in asset pricing research is the application of machine learning (ML) techniques to address the "factor zoo" problem, because of its flexibility and measurement accuracy.

More broadly, the application of machine learning in finance has been classified into four main research streams of study. The first focuses on asset price prediction. The second centers on the prediction of hard or soft financial events including earnings surprises, corporate defaults, and mergers and acquisitions. The third focuses on estimating values not directly related to the price of an asset such as volatility, firm valuation and credit ratings. Lastly, the fourth stream is oriented to solving optimization problems such as position sizing and portfolio optimization (Snow, 2020b). Regarding to the first stream, it can be subdivided into two main approaches: return prediction, and the estimation of factor models with associated Stochastic Discount Factor (SDF) (Bagnara, 2024).

Within the return prediction approach, Gu et al. (2019) conduct a comparative analysis of different ML techniques to forecast cross-sectional returns of US stocks. Their study includes methods such as neural networks and regression trees including boosted trees and random forest. The authors demonstrate that techniques such as decision trees and neural networks can significantly improve the estimation of market risk premia. Additionally, they identify the most relevant predictor variables used by each technique and classify them into three categories: price trend (e. g. stock momentum, industry momentum and short-term reversal), liquidity (e. g. market value, bid-ask spread and dollar volume) and return volatility (e. g. idiosyncratic volatility, market beta and beta squared). These results show that ML approaches can enhance our empirical understanding of asset pricing.

Chen et al. (2019) follow the second approach within the asset pricing literature by estimating the SDF using deep neural networks. One of their main innovations is the integration of the no-arbitrage condition directly into the learning algorithm, ensuring that the estimated SDF satisfies the fundamental asset pricing equation. Their model not only allows for a flexible, nonparametric estimation of the SDF from a rich set of firm characteristics and macroeconomic variables, but also captures the underlying structure and key factors that drive asset prices.

Although their approaches differ, both studies share the use of macroeconomic variables, stock returns and firm-specific characteristics as input variables in their respective models. These variables not only enhance the accuracy of investment strategies but also support portfolio optimization, which can be considered part of an integrated system. While an investment strategy consists of the use of perceived signals to execute transactions, portfolio weight optimization seeks to optimally allocate assets within active and passive strategies (Snow, 2020a).

According to Kumbure et al. (2022), their literature review, which examined 138 journal articles published between 2000 and 2019, revealed that the U.S. stock market, particularly the S&P 500 index is the most frequently analyzed stock index for machine learning applications in stock market forecasting. This popularity may be attributed to the size, liquidity and availability of high-quality data in the U.S. Additionally, at the regional level, Asia emerged as the most extensively studied region, with the TAIEX (Taiwan) ranking as the second most analyzed stock index, just behind the S&P 500.

In contrast to the extensive use of ML in developed markets, its application in the Mexican Stock Market has been relatively limited. However, some studies have emerged. For instance, Rafiuddin et al. (2023) used support vector machines, artificial neural networks and deep neural networks to predict the movement (up or down) of stock prices, obtaining high levels of accuracy similar to those reported in works conducted in developed financial markets. Their model relied exclusively on historical stock price data, specifically data from the Mexican stock index (IPC) and seven individual stocks over the period from September 2013 to December 2019.

Similarly, Parra (2023) explored the use of ML techniques to define investment strategies and build optimal portfolios in the Mexican Stock Market. The study employed three different time windows: One-Month lag (OML), Three-Month lag (TML), Cumulative Month training (CM), as well as a rolling window of 800 training days. In this analysis, two ML models were employed: Tiny Reinforcement Learning (Tiny RL) used to design the optimal trading strategy, and Least Absolute Shrinkage and Selection Operator (LASSO) to determine portfolio weights. Like Rafiuddin et al. (2023), Parra's research also relied on historical stock price data, using information from 96 stocks listed on the Mexican stock market for the period from January 2019 to December 2022. The results showed returns above the Mexican stock index (IPC), highlighting that the OML outperformed other configurations.

Despite the significant potential for the application of machine learning techniques in finance, particularly in asset return prediction, it is important to emphasize that the improved predictions of these models are only measurements, and do not explain economic mechanisms or market equilibria. In other words, machine learning methods focus on statistical associations rather than on identifying fundamental relationships between asset prices and their conditioning variables (Gu et al., 2019).

3 Methodology

This section provides a detailed description of the tools and procedures used in this research, including the machine learning techniques, the variables considered, the performance evaluation, and the trading strategy. Each subsection offers an in-depth explanation of the corresponding aspect.

The methodological process is illustrated in the following flowchart (see Figure **1**). Before applying the machine learning techniques, a dataset was constructed for each selected stock. Next, the input variables within each rolling window were standardized to ensure comparability across features. After training the models, the expected returns were subsequently estimated. Finally, these predicted values were used to implement a trading strategy to construct investment portfolios. This approach enabled the evaluation of both the predictive accuracy of individual stock returns and the comparative forecasting performance of machine learning methods at the aggregate portfolio level.

This methodology is based on the hypothesis that machine learning can serve as a key tool developing and evaluating investment strategies in the Mexican Stock Market. By testing its predictive capacity and practical applicability under local market conditions.

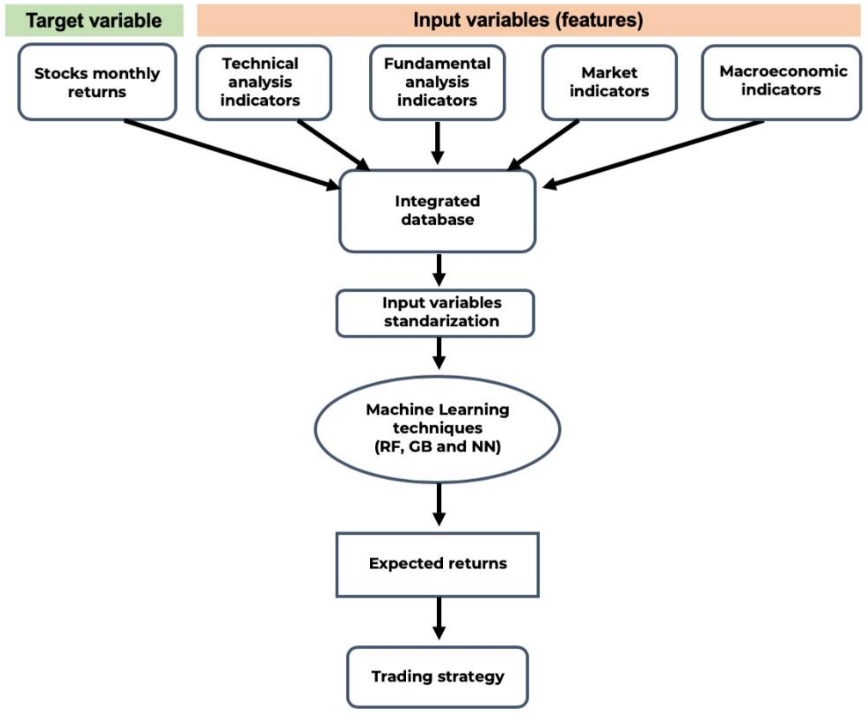

Figure 1. Methodological Flowchart.

3.1 Machine Learning

Machine learning is the branch of artificial intelligence mainly focused on statistical prediction, positioning itself at the intersection between statistics, computer science, and artificial intelligence (Cerulli, 2023). As a result of this multidisciplinary foundation, it has become one of the fastest growing areas in computer science, with far-reaching applications across industries and disciplines (Shalev-Shwartz & Ben-David, 2014).

Fundamentally, machine learning is defined as the process of programming computers to optimize a performance criterion using example data or past experience (Alpaydin, 2020). For the purpose of this research, it also refers to the automated detection of meaningful patterns in data (Shalev-Shwartz & Ben-David, 2014). Based on how learning is guided and evaluated, machine learning techniques are generally classified into three main categories: supervised, unsupervised and reinforcement learning (Jung, 2022).

- **Supervised Learning:** This approach relies on a training dataset that consists of labeled data points, with the objective of learning a hypothesis function that accurately maps inputs to outputs by minimizing the discrepancy between the predicted and the true labels in the training set. To implement this process, a loss function is required to quantify the fitting error and guide the optimization of the model (Jung, 2022).
- **Unsupervised Learning:** In this approach, the algorithm does not require knowledge of the label values for any data point; instead, it relies solely on the intrinsic structure of data points (Jung, 2022). The objective is to discover the regularities or patterns in the input features (Alpaydin, 2020). Unsupervised learning is commonly applied to find hidden structures within unclassified datasets (Sutton & Barto, 2018).
- **Reinforcement Learning:** This is a computational approach to understand and automating goal-directed learning and decision making. Basically, it consists of an agent that must learn to maximize a numerical reward signal through interaction with an environment. The goal is for the agent to discover the actions that produce the highest reward through trial and error, this method does not learn from a training set provided by an external supervisor. Instead, learning is driven by feedback from the environment in the form of rewards or penalties (Sutton & Barto, 2018).

3.1.1 Random Forest and Gradient Boosting

Before introducing Random Forest and Gradient Boosting, it is important to first explain decision trees. This technique can be described as a flowchart-like structure representing a function $h: X \rightarrow Y$, which maps the features $x \in X$ of a data point to a predicted label $h(x) \in Y$ (Jung, 2022). Figure **2** presents an example of a decision tree, illustrating the general framework. The process begins at the root node of a tree and proceeds to a leaf node, based on a majority vote among the labels in the training set (Shalev-Shwartz & Ben-David, 2014). The tree "grows" in a sequence of steps, where each new branch divides the remaining data according to one of the predictor variables (Gu et al., 2019).

The following model presented by Gu et al. (2019) provides a formal description of the prediction function in a decision tree (T):

$$g(z_{i,t};\theta,K,L) = \sum_{k=1}^{K} \theta_k \mathbb{I}_{z_{i,t}\in C_k(L)}$$

where K represents the number of leaves (terminal nodes), L is the depth of the tree, and $C_k(L)$ is one of the K partitions of the data. The constant associated with each partition, denoted θ_k, corresponds to the sample average of outcomes within that partition.

However, Decision Trees tend to be one of the prediction methods most prone to overfitting (Gu et al., 2019). To mitigate this issue, a general approach is to construct an ensemble of trees (Shalev-Shwartz & Ben-David, 2014), which acts as a form of regularization. The general idea behind ensemble models is that although shallow trees have limited predictive power, when combined into an ensemble, they can produce a stronger learner with greater stability than a single complex tree (Gu et al., 2019). Specifically, this research focuses on two types of ensemble regularized methods: Random Forest and Gradient Boosting.

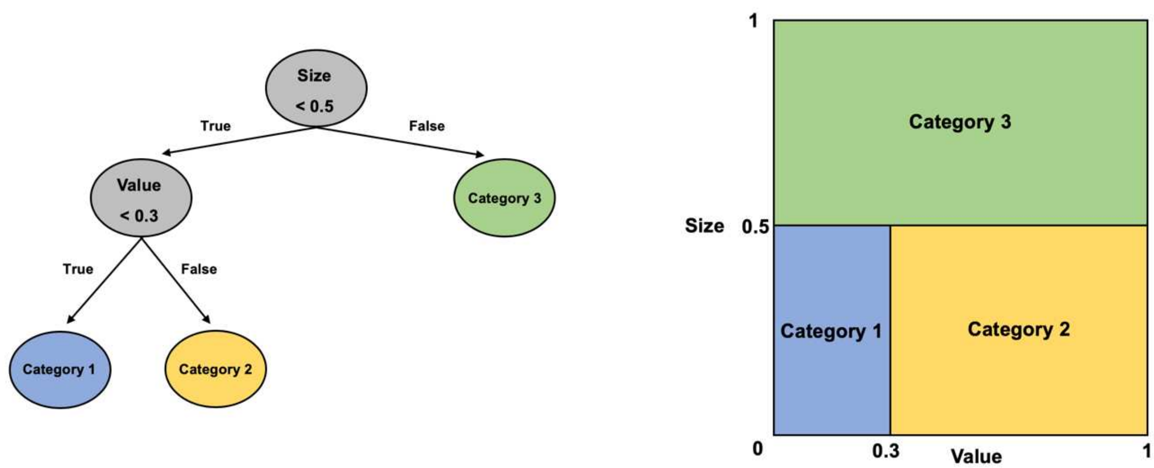

Figure 2. Regression Tree Example[2]. Own elaboration based on the conceptual example presented in Gu et al. (2019).

[2] **Note:** The figure presents the diagrams of a regression tree (left) and an equivalent representation (right) in the space defined by two stock characteristics: size and value. Based on these values, individual stocks are classified into three categories. The prediction equation is: $g(z_{i,t};\theta,3,2) = \theta_1\mathbb{I}(size_{i,t} < 0.5)\mathbb{I}(value_{i,t} < 0.3) + \theta_2\mathbb{I}(size_{i,t} < 0.5)\mathbb{I}(value_{i,t} > 0.3) + \theta_3\mathbb{I}(size_{i,t} \geq 0.5)$.

3.1.1.1 Random Forest

The general principle of this approach is based on a collection of Decision Trees, where the final result is obtained by aggregating predictions from multiple random decision trees. Each tree is constructed by applying an algorithm A to the training set S and an additional random vector θ, where θ is sampled i.i.d. from some distribution (Shalev-Shwartz & Ben-David, 2014). Because individual trees are randomly perturbed, the forest benefits from a more extensive exploration of the space of possible tree predictors, often resulting in improved predictive performance (Genuer & Poggi, 2020).

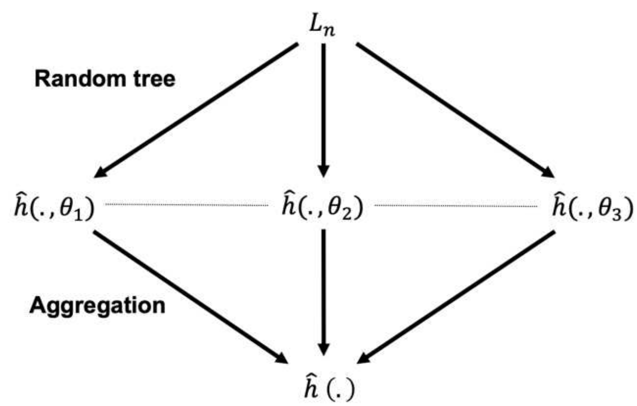

Figure 3. General scheme of random forests. Own elaboration based on the conceptual example presented in Genuer & Poggi (2020).

3.1.1.2 Gradient Boosting

A simple decision tree is typically a weak predictive model with limited performance and high bias on the training sample. Therefore, Gradient Boosting learns from the mistakes (residuals) of individual trees, by using an iterative process that adds additional shallow trees, where each new tree is trained to fit the residuals of the previous one. A key feature of this method is the inclusion of a shrinkage factor $\upsilon \in (0,1)$, which reduces the contribution of each new tree to prevent the model from overfitting the residuals. As a result, the final output is obtained by summing the predictions of all trees in the ensemble (Gu et al., 2019).

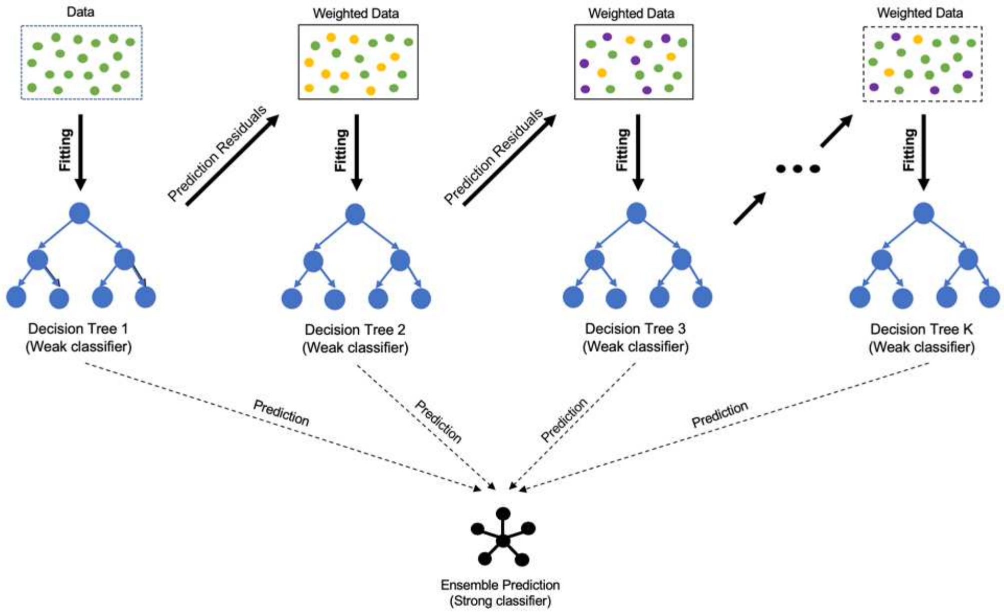

Figure 4. Gradient Boosting Tree Ensemble: Model Structure. Own elaboration based on the conceptual example presented in Deng et al. (2021).

3.1.2 Neural Networks

Neural Networks are a nonlinear method which simulate the mechanism of learning in biological organism (Aggarwal, 2018). It consists of a large number of basic computing devices (neurons) that are connected to each other in a complex communication network. Each neuron receives as input a weighted sum of the outputs of the neurons connected to tits incoming edges, whose correspond to the links between them (Shalev-Shwartz & Ben-David, 2014). Figure 5 illustrates a single-layer (left) and multi-layer (right) neural networks. A single-layer network maps inputs directly to outputs using a generalized linear function. In contrast, multi-layer networks, include hidden layers between the input and output (Aggarwal, 2018).

In general, selecting an optimal network architecture is a difficult task because of the uncountably set of options (Gu et al., 2019). For this research, the architectures are described as:

- **NN2:** Two hidden layers with 32 and 16 neurons, respectively.
- **NN3:** Three hidden layers with 32, 16 and 8 neurons, respectively.
- **NN4:** Four hidden layers with 32, 16, 8 and 4 neurons, respectively.

- **NN5:** Five hidden layers with 32, 16, 8, 4 and 2 neurons, respectively.
- **Personal:** Four hidden layers with 100, 50, 30 and 5 neurons, respectively.

The architectures NN2, NN3, NN4 and NN5 were selected following the methodology proposed by Gu et al. (2019). On the other hand, personal architecture refers to a personal selection of the number of neurons and hidden layers.

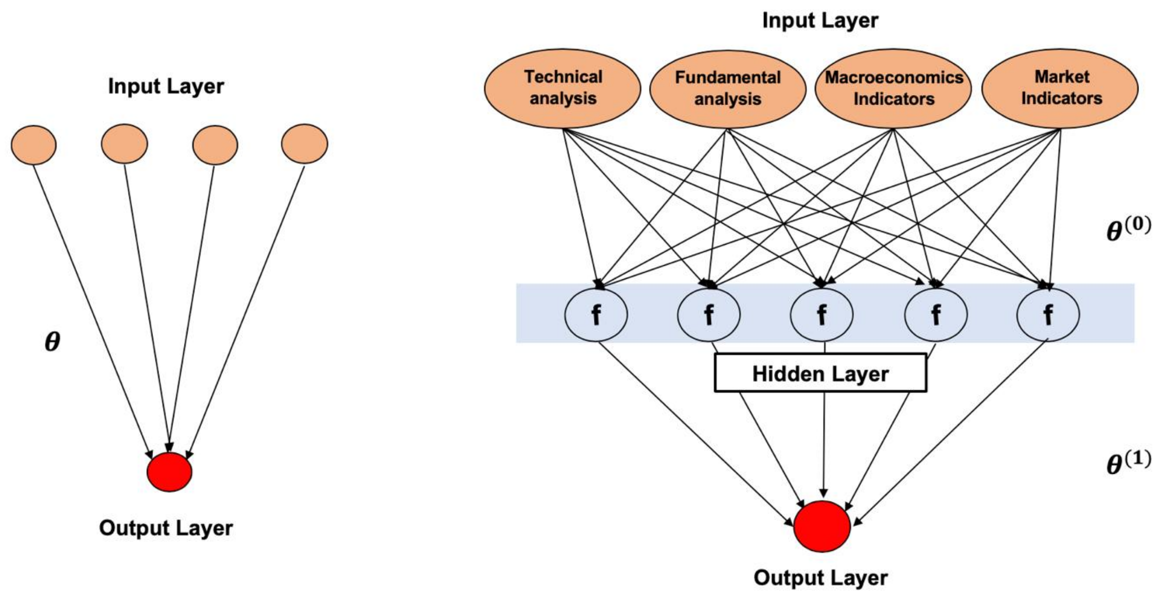

Figure 5. Neural Networks. Own elaboration adapted from the example presented in Gu et al. (2019).

The model presented by Gu et al. (2019) provides a generalized for a multi-layer networks. Let $K^{(l)}$ denote the number of neurons in hidden layer $l = 1, \dots, L$. The output of the k neuron in the layer l is denoted $x_k^{(l)}$. The vector of outputs for this layer (augmented to include a constant, $x_0^{(l)}$) as $x^{(l)} = (1, x_1^{(l)}, \dots, x_{K^{(l)}}^{(l)})'$. To initialize the network, similarly, define the input layer using the raw predictors, $x^{(0)} = (1, z_1, \dots, z_N)'$.

For any hidden layer $l > 0$, the output of neuron k is computed via a nonlinear transformation (ReLU activation) of a linear combination of the outputs from the previous layer then:

$$x_k^{(l)} = ReLU\left(\left(x^{(l-1)}\right)'\theta_k^{(l-1)}\right)$$

Where $\theta_k^{(l-1)}$ is the vector of weights connecting layer $l-1$ to neuron k in layer l. The ReLU function is defined as:

$$ReLU(x) = \begin{cases} 0, & if\ x < 0 \\ x, & otherwise \end{cases}$$

The final output of the neural network is given by linear combination of the last hidden layer's outputs:

$$g(z;\theta) = \left(x^{(L-1)}\right)'\theta^{(L-1)}$$

Where $\theta^{(L-1)}$ is a vector of weights for the output layer. The number of weight parameters in each hidden layer l is $K^{(l)}(1 + K^{(l-1)})$, plus another $1 + K^{(L-1)})$, weights for the output layer.

The objective during this process is to minimize prediction error, even though a formal optimization formulation was not presented. This is achieved through the use of an objective function, usually referred to in the literature as a loss function (Aggarwal, 2018). In this research, two approaches were tested to evaluate their performance in the application of neural networks to finance, specifically for predicting expected returns.

The first loss function aims to minimize mean squared prediction error (MSE) between predicted and observed values. The second loss function introduces a directional penalty to the MSE[3]. The procedure is as follows:

- If the predicted and actual returns have the same sign, the model uses the standard MSE:

$$Loss\ function = \sum (y - \hat{y})^2$$

- However, if they have opposite signs, a penalization factor is applied to increase the loss. The value of this factor depends on the severity of the penalty, in this case, it is set to 10.

[3] Based on the DataCamp course "Machine Learning for Finance in Python" (George, 2025).

$$Loss\ function = \sum (y - \hat{y})^2 \times 10$$

In the second function, predicting the correct movement (up or down) of stock returns is prioritized over predicting their exact value.

3.2 Training Window

In machine learning methods, the selection of training and test samples is a key aspect of model evaluation. In this research, following a similar approach to Gu et al. (2019) and Parra (2023), a rolling window method was implemented, using 37-month window: 36 months for the training set and 1 month for testing. This window moves dynamically across the evaluation period from January 2019 to January 2025, resulting in a total of 37 windows, as shown in Figure 6.

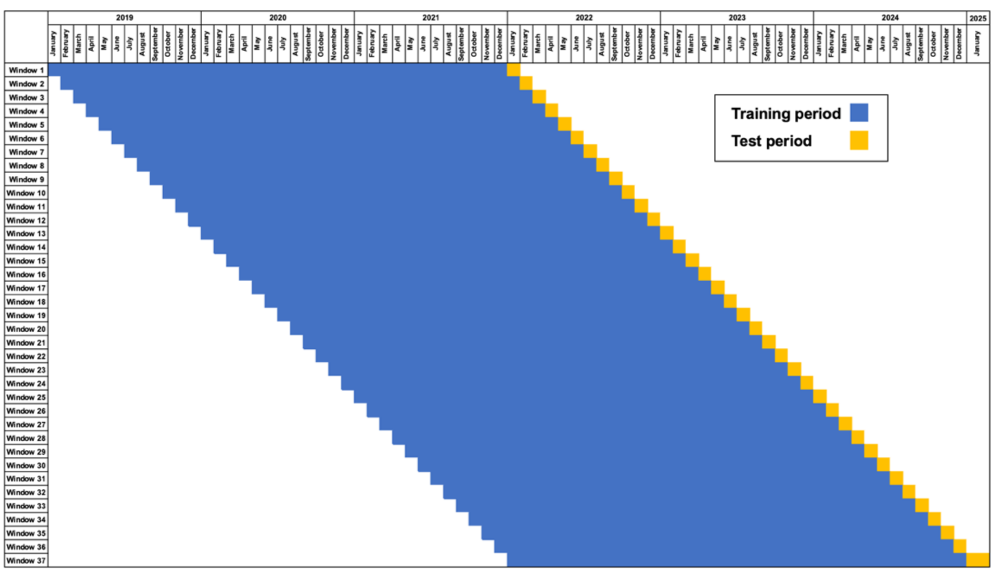

Figure 6. Rolling Window Scheme.

3.3 Performance Evaluation

The evaluation criterion is a crucial aspect of this research as each model is designed to predict individual stock returns across firms and overtime. To address this problem, the performance of each model was evaluated according to the following the methodology proposed by Gu et al. (2019), in which the out-of-sample R^2 is calculated as:

$$R^2_{(oos,0)} = 1 - \frac{\sum_{(i,t) \in T_3} \left(r_{i,t+1} - \hat{r}_{i,t+1}\right)^2}{\sum_{(i,t) \in T_3} r^2_{i,t+1}}$$

Where T_3 denotes the testing subsample, $r_{i,t+1}$ represents the real return of asset i at time $t+1$, and $\hat{r}_{i,t+1}$ is the corresponding model prediction.

It is important to highlight that the denominator is the sum of squared returns without demeaning, in contrast to many out-of-sample forecasting studies. The reason behind this decision is that using historical average returns is substantial noise, which artificially lowers the threshold for "good" forecasting performance (Gu et al., 2019). Instead, this evaluation approach benchmarks against a zero-return forecast. Nonetheless, it is important to verify whether the standard $R^2_{(oos,\bar{r})}$ is appropriate for this type of research. Therefore, the prediction performance was evaluated considering also the standard $R^2_{(oos,\bar{r})}$, defined as follows:

$$R^2_{(oos,\bar{r})} = 1 - \frac{\sum_{(i,t) \in T_3} \left(r_{i,t+1} - \hat{r}_{i,t+1}\right)^2}{\sum_{(i,t) \in T_3} \left(r_{i,t+1} - \bar{r}\right)^2}$$

Where $\bar{r}$ represents the average return.

3.4 Trading Strategy

The construction of the optimal investment strategy is a key component of this research, as it provides an additional approach to evaluate the performance of the models. For this purpose, portfolios were designed to directly exploit the forecasts generated by machine learning models. Following the approach presented by Gu et al. (2019), using the one-month-ahead stock return predictions obtained in each rolling window, stocks were sorted into deciles based on their predicted returns. A zero-net-investment portfolio was then constructed by buying the highest expected return stocks (decile 10) and selling the lowest (decile 1), thus splitting the positions into long and short positions. Within each position, stocks were equally weighted, and the portfolio was rebalanced monthly.

Formally, the return of the long portfolio at time t is computed as the average realized return of the assets that were selected for the long position at time t, based on their actual returns observed in $t+1$:

$$R_t^{long} = \frac{1}{N_L} \sum_{i \in L_t} r_{i,t+1}$$

Similarly, the return of the short portfolio corresponds to the average realized return in $t+1$ of the assets selected for the short position at time t:

$$R_t^{short} = \frac{1}{N_S} \sum_{i \in S_t} r_{i,t+1}$$

Where:

- R_t^{long} is the average realized return in $t+1$ of the stocks selected for the long position at time t.
- L_t and S_t denote the sets of stocks assigned to the long and short portfolios at time t, respectively.
- $r_{i,t+1}$ is the realized return of stock i in month $t+1$.
- R_t^{short} is the average realized return in $t+1$ of the stocks selected for the short position at time t.
- N_L and N_S represent the number of stocks in the long and short portfolios, respectively.

Given the zero-net-investment nature of the strategy, the long-short return is computed by assigning equal but opposite weights to both sides of the portfolio:

$$R_t^{LS} = \frac{1}{2} R_t^{long} + \frac{1}{2} R_t^{short}$$

Where:

- R_t^{LS} denotes the return of the long-short strategy constructed at time t.

It is important to specify that the portfolio is rebalanced monthly, in accordance with the rolling window predictions. This approach does not include transaction cost or trading fees. The objective of the trading strategy is to evaluate the model's ability to generate profitable returns and to compare its performance against the returns offered by the Mexican stock market index.

4 Data

In this study, the data were obtained from Economatica, Banco de México (Banxico), the National Institute of Statistics and Geography (INEGI), S&P Global, and the Central Bank of Chile. The details of the data are presented in Table 1. Based on these data, the variables (both input and output) for the models were derived and classified following the procedure described below.

Table 1. Details of the data.

No.	Variable	Frequency	Data Source
1	Stock closing price	Daily	Economatica
2	Price to Earnings Ratio	Daily	Economatica
3	Price to Book Ratio	Daily	Economatica
4	Price to Free Cash Flow	Daily	Economatica
5	Enterprise Value	Daily	Economatica
6	EV / EBITDA company	Daily	Economatica
7	EV / EBIT company	Daily	Economatica
8	EV / Sales	Daily	Economatica
9	Earnings Yield	Daily	Economatica
10	Liquidity	Daily	Economatica
11	Unemployment	Monthly	INEGI
12	Core inflation	Monthly	Banxico
13	Monthly Indicator of Private Consumption in the Internal Market (IMCPMI)	Monthly	INEGI
14	Emerging Markets Bond Index Global (EMBIG)	Monthly	The Central Bank of Chile
15	Global Indicator of Economic Activity (IGAE)	Monthly	INEGI
16	S&P/BMV IPC	Daily	S&P Global
17	S&P/BMV IPC CompMX Materials	Daily	S&P Global
18	S&P/BMV IPC CompMX Industrials	Daily	S&P Global
19	S&P/BMV IPC CompMX Consumer Discretionary	Daily	S&P Global
20	S&P/BMV IPC CompMX Consumer Staples	Daily	S&P Global
21	S&P/BMV IPC CompMX Communication Services	Daily	S&P Global
22	S&P/BMV IPC CompMX Financials	Daily	S&P Global

4.1 Output Variables

It is important to note that the monthly returns serve as the output variable, that is, the target prediction for the models tested in this research. Monthly log-returns were calculated as the natural logarithm of the ratio between the stock price at the end of the month t and the stock price at the end of month $t+1$, as follows:

$$monthly\_return_{t+1} = \ln\left(\frac{P_{t+1}}{P_t}\right)$$

Where:

- P_t refers to the last stock closing price of the month t.
- P_{t+1} refers to the last stock closing price of the month $t+1$.

4.2 Input Variables

The input variables, or features, were divided into four categories: technical analysis indicators, fundamental analysis indicators, market indicators, and macroeconomic indicators. This variable set was designed to capture a comprehensive outlook of firm-specific conditions, price dynamics, and macroeconomic trends in the Mexican economy, allowing the identification of patterns and improving forecast accuracy.

4.2.1 Technical Analysis Indicators

As defined by Murphy (1999), technical analysis is the study of market action for the purpose of forecasting future price trends, based on three principal sources of information: price, volume, and open interest. In this context, the purpose of this category is to provide machine learning models with variables that capture potential future price trends to support the prediction of stock returns. Consequently, this category the Rate of Change (RoC) over horizons ranging from 1 to 12 months. The RoC is the percentage change in price between the current price and the price a certain number of periods ago, and It is calculated as:

$$RoC_i = \frac{P_t - P_{t-i}}{P_{t-i}}$$

Where:

- P_t refers to the last stock closing price of the month t.
- i is the number of months lagged, with $i \in [1,12]$.

4.2.2 Fundamental Analysis Indicators

The fundamental approach analyzes all relevant factors affecting a market to determine the intrinsic value of that market, which indicates the real worth. According to Murphy (1999), fundamental analysis studies the cause of market movement (i.e. if an intrinsic value is under the current market price, then the market is overpriced and the stock should be sold). The primary purpose of these variables is to provide the models with information about intrinsic value of stocks, thereby enabling more accurate forecasts of their future performance.

For this category, the selected variables were: Price to Earnings Ratio, Price to Book Ratio, Earnings Yield, Price to Free Cash Flow, Enterprise Value, EV / EBITDA company, EV / EBIT company, EV / Sales, Earnings Yield and Liquidity. These variables were obtained from Economatica at a daily frequency, so to derive monthly values, the arithmetic mean was calculated for each variable over the corresponding month.

4.2.3 Macroeconomics Indicators

The influence of macroeconomic variables has been examined in previous studies, such as those conducted by Tsai & Hsiao (2010) and González et al. (2018). In this study, macroeconomic indicators are incorporating to capture the broader economic environment, which can influence investor behavior causing movements in stock returns that may not be directly related to the individual characteristics of the stocks.

Thus, the variables selected for this category were: Global Indicator of Economic Activity (IGAE), Emerging Markets Bond Index Global (EMBIG), Monthly Indicator of Private Consumption in the Internal Market (IMCPMI), Core Inflation, and Unemployment Rate. Since all the variables were available at a monthly frequency, no additional processing was applied to the data.

4.2.4 Market Indicators

The purpose of these variables is to incorporate information about the aggregate sector performance as input features for the machine learning models. Specifically, this is achieved through the use of monthly log-returns from the following sector indexes:

- S&P/BMV IPC CompMX Materials
- S&P/BMV IPC CompMX Industrials
- S&P/BMV IPC CompMX Consumer Discretionary
- S&P/BMV IPC CompMX Consumer Staples
- S&P/BMV IPC CompMX Communication Services
- S&P/BMV IPC CompMX Financials

For each stock analyzed, the corresponding sector index log-return is included as an input variable, based on the stock's sector classification.

$$Sector\_return_i = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where:

- P_t refers to the last sector index closing price of the month t.
- P_{t+1} refers to the last sector index closing price of the month $t-1$.

4.3 Mexican Stock Exchange

The Mexican Stock Exchange is composed by 133 domestic stocks[4], classified into eight sectors: Energy, Industrials, Materials, Health Care, Consumer Staples, Telecommunication Services, Financial Services and Consumer Discretionary & Services, as shown Figure 7 and Figure 8. The

[4] Information obtained from https://www.bmv.com.mx/es/emisoras/informacion-de-emisoras, accessed on February 26, 2025.

annual evolution of key indicators of the Mexican equity market from 2010 to 2024 is summarized in Table 2.

Table 2. Evolution of Domestic Stocks Listed on the Mexican Stock Exchange (2010–2024)[5].

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Domestic Stock	130	128	131	131	131	136	137	141	140	139	140	137	133	136	133
Share Series	161	155	156	151	152	187	186	190	194	187	187	183	179	178	181
Market Capitalization*	5.6	5.7	6.8	6.9	7.1	7.0	7.6	8.2	7.6	7.8	7.9	9.4	8.8	9.8	8.5

* In trillions of Mexican pesos (MXN).

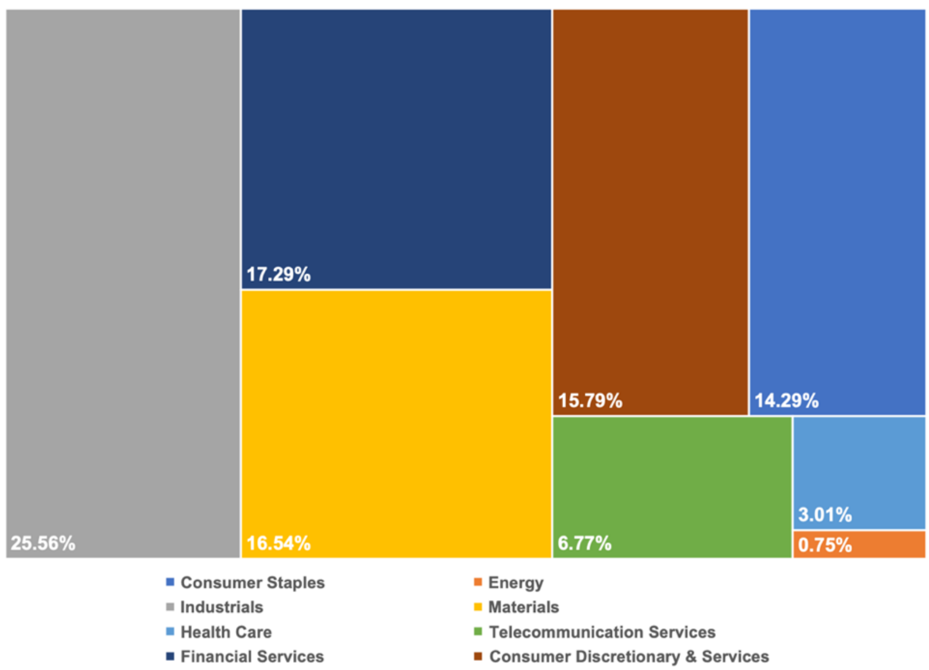

Figure 7. Sectorial Composition of the Mexican Stock Exchange.

[5] This table was constructed using data from annual reports published by the Mexican Stock Exchange (BMV) for the period 2012-2024 (Mexican Stock Exchange (BMV), 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024, 2025).

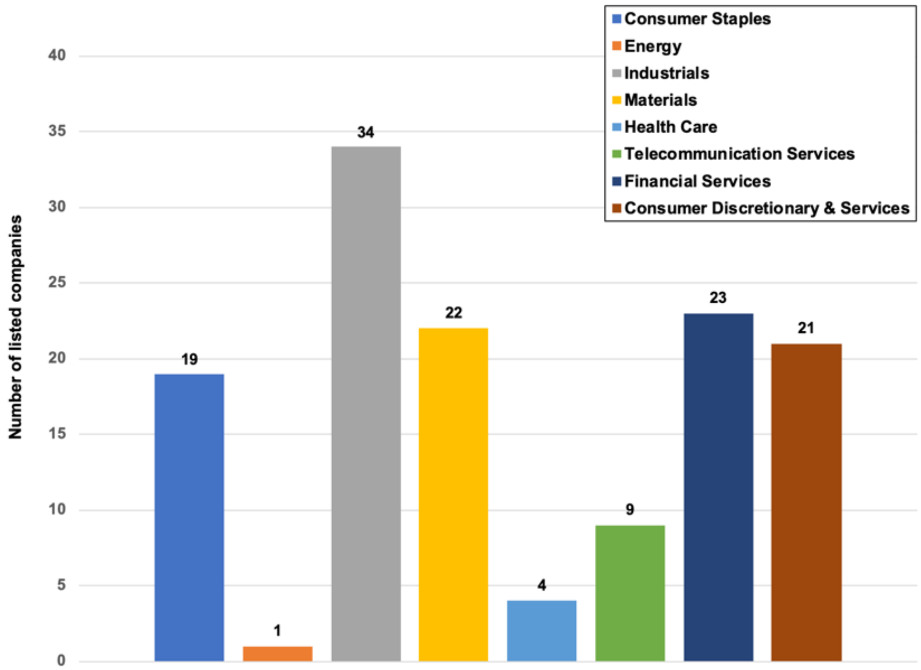

Figure 8. Number of Listed Companies by Sector on the Mexican Stock Exchange.

4.3.1 Selected Stocks for Empirical Analysis

For this research, historical prices data and financial variables for 75 domestic stocks were obtained for the period from January 01, 2018 to March 28, 2025. However, many stocks did not trade regularly, as shown in Table 3, so they were excluded from this analysis. Table 4 presents the 37 final selected stocks, corresponding to those stocks that only have 69 non-trading days, which correspond to official holidays[6].

Table 3. Stock Trading Activity.

No.	Stock	Non-Trading Days	Trading Days
1	lacomerubc	69	1821
2	ara	69	1821
3	gcarsoa1	69	1821
4	traxiona	69	1821
5	livepolc-1	69	1821
6	pe&oles	69	1821

[6] Genoma Lab international, S.A.B. de C.V. (labb) was excluded from the selected stocks due to the unavailability of a corresponding index for the health care sector. Instead, GMéxico Transportes, S.A.B. de C.V. (gmxt) was included as a substitute.

No.	Stock	Non-Trading Days	Trading Days
7	axtelcpo	69	1821
8	femsaubd	69	1821
9	volara	69	1821
10	herdez	69	1821
11	omab	69	1821
12	megacpo	69	1821
13	gapb	69	1821
14	walmex	69	1821
15	hcity	69	1821
16	gmexicob	69	1821
17	amxb	69	1821
18	tlevisacpo	69	1821
19	alfaa	69	1821
20	agua	69	1821
21	nemaka	69	1821
22	alpeka	69	1821
23	pinfra	69	1821
24	gcc	69	1821
25	grumab	69	1821
26	asurb	69	1821
27	bolsaa	69	1821
28	cemexcpo	69	1821
29	orbia	69	1821
30	cuervo	69	1821
31	ac	69	1821
32	bimboa	69	1821
33	kimbera	69	1821
34	alsea	69	1821
35	chdraui	69	1821
36	vesta	69	1821
37	labb	69	1821
38	gmxt	74	1816
39	sites1	83	1807
40	autlanb	88	1802
41	homex	104	1786
42	sorianab	154	1736
43	elektra	156	1734
44	mfriscoa-1	160	1730
45	gicsab	171	1719
46	kofubl	175	1715

No.	Stock	Non-Trading Days	Trading Days
47	ichb	187	1703
48	simecb	214	1676
49	vinte	223	1667
50	hotel	244	1646
51	gissaa	301	1589
52	cadua	370	1520
53	vitroa	430	1460
54	sports	444	1446
55	cultibab	586	1304
56	vistaa	601	1289
57	tmma	625	1265
58	fraguab	636	1254
59	teakcpo	672	1218
60	medicab	694	1196
61	cydsasaa	747	1143
62	cmrb	837	1053
63	pochtecb	877	1013
64	unifina	913	977
65	cmoctez	935	955
66	vasconi	1077	813
67	cieb	1107	783
68	gigante	1353	537
69	posadasa	1414	476
70	rlha	1591	299
71	gmd	1600	290
72	minsab	1631	259
73	kuoa	1632	258
74	cidmega	1744	146
75	javer	1782	108

Table 4. Selected Stocks for Empirical Analysis.

No.	Stock	Company	Sector
1	livepolc	El Puerto de Liverpool, S.A.B. de C.V.	Consumer Discretionary & Services
2	alsea	Alsea, S.A.B. de C.V.	Consumer Discretionary & Services
3	hcity	Promotora de Hoteles Norte 19, S.A.B. de C.V.	Consumer Discretionary & Services

No.	Stock	Company	Sector
4	kimbera	Kimberly-Clark de México, S.A.B. de C.V.	Consumer Staples
5	cuervo	Becle, S.A.B. de C.V.	Consumer Staples
6	bimboa	Grupo Bimbo, S.A.B. de C.V.	Consumer Staples
7	herdez	Grupo Herdez, S.A.B. de C.V.	Consumer Staples
8	ac	Arca Continental, S.A.B. de C.V.	Consumer Staples
9	grumab	Gruma, S.A.B. de C.V.	Consumer Staples
10	walmex	Wal-Mart de México, S.A.B. de C.V.	Consumer Staples
11	chdraui	Grupo Comercial Chedraui, S.A.B. de C.V.	Consumer Staples
12	lacomerubc	La Comer, S.A.B. de C.V.	Consumer Staples
13	femsaubd	Fomento Económico Mexicano, S.A.B. de C.V.	Consumer Staples
14	bolsaa	Bolsa Mexicana de Valores, S.A.B. de C.V.	Financial Services
15	pinfra	Promotora y Operadora de Infraestructura, S.A.B. de C.V.	Industrials
16	agua	Grupo Rotoplas, S.A.B. de C.V.	Industrials
17	omab	Grupo Aeroportuario del Centro Norte, S.A.B. de C.V.	Industrials
18	gapb	Grupo Aeroportuario del Pacífico, S.A.B. de C.V.	Industrials
19	vesta	Corporación Inmobiliaria Vesta, S.A.B. de C.V.	Industrials
20	gmxt	Gméxico Transportes, S.A.B. de C.V.	Industrials
21	orbia	Orbia Advance Corporation, S.A.B. de C.V.	Industrials
22	volara	Controladora Vuela Compañía de Aviación, S.A.B. de C.V.	Industrials
23	ara	Consorcio Ara, S.A.B. de C.V.	Industrials
24	asurb	Grupo Aeroportuario del Sureste, S.A.B. de C.V.	Industrials
25	traxiona	Grupo Traxión, S.A.B. de C.V.	Industrials
26	alfaa	Alfa, S.A.B. de C.V.	Industrials
27	gcarsoa1	Grupo Carso, S.A.B. de C.V.	Industrials
28	cemexcpo	Cemex, S.A.B. de C.V.	Materials
29	alpeka	Alpek, S.A.B. de C.V.	Materials
30	gcc	GCC, S.A.B. de C.V.	Materials
31	autlanb	Compañía Minera Autlán, S.A.B. de C.V.	Materials
32	pe&oles	Industrias Peñoles, S.A.B. de C.V.	Materials
33	gmexicob	Grupo México, S.A.B. de C.V.	Materials
34	amxb	América Móvil, S.A.B. de C.V.	Telecommunication Services
35	tlevisacpo	Grupo Televisa, S.A.B.	Telecommunication Services
36	axtelcpo	Axtel, S.A.B. de C.V.	Telecommunication Services
37	megacpo	Megacable Holdings, S.A.B. de C.V.	Telecommunication Services

5 Results

This section is divided into three parts. The first part discusses the model's performance in terms of their out-of-sample predictions. The second part presents the results of the investment strategie performance using the methodology proposed in Section 3.4. Finally, the third part provides an analysis of variable importance, aiming to identify the most influential predictors and offer insights into the key factors driving stock returns.

5.1 Out-of-sample Prediction Performance

At the end, twelve different machine learning models were compared: Random Forest, Gradient Boosting, and five distinct neural networks architectures, each trained with two different loss functions, as described in Section 3.1.2. The performance analysis was conducted at two levels: aggregate model performance and individual stock-level performance.

Table 5 reports the aggregated stock return predictive performance, where $R^2_{(oos,0)}$ and $R^2_{(oos,\bar{r})}$ are negative, each with distinct statistical implications. The first implies that the model´s predictions are less accurate than a simple prediction of zero. In the second case, it means that the model´s predictions perform worse than simply using the historical mean as a prediction. Notably, Random Forest (-0.1274) and Gradient Boosting (-0.1321) out-perform most neural networks architectures, except for NN5 (-0.8005) and NN5* (-0.6091). Moreover, as neural networks architectures increase in complexity, their R^2 values tend to converge toward zero in both metrics. These results are consistent with existing literature, such as Díaz et al. (2023), who assess the predictive accuracy of machine learning models for estimating the gold risk premium and report negative out-of-sample R^2, highlighting the challenge of outperforming the historical average.

It is important to highlight that these results are derived from the predictions of 1,369 different trained models (37 stocks x 37 rolling windows) for each machine learning composition model showed in Table 5, since each model was fitted individually for each stock and rolling window. Consequently, an individual stock-level performance analysis was conducted to evaluate the models at a less aggregated level, the results are shown in Tables **Table 7** and **Table 8** in Appendix

A. Although the overall results were negative, Random Forest and Gradient Boosting models produced positive values of $R^2_{(oos,0)}$ and $R^2_{(oos,\bar{r})}$ for certain stocks.

Table 5. Training and Out-of-Sample Performance by Model.

Model	**Average $R^2_{training}$**	$R^2_{(oos,0)}$	$R^2_{(oos,\bar{r})}$
Random Forest	0.8225	-0.1274	-0.1277
Gradient Boosting	0.8103	-0.1321	-0.1324
Personal	0.7893	-1.9065	-1.9072
NN2	0.8936	-10.1545	-10.1573
NN3	0.6371	-3.6319	-3.633
NN4	0.861	-2.6913	-2.6922
NN5	0.629	-0.8005	-0.8009
Personal*	0.6301	-1.4449	-1.4455
NN2*	0.2364	-11.0927	-11.0957
NN3*	0.4619	-3.7533	-3.7545
NN4*	0.7009	-2.599	-2.5999
NN5*	0.3026	-0.6091	-0.6095

The overall negative values of out-of-sample R^2 suggest a lack of predictive power across models. Rather than reflecting a modeling failure, these results highlight the inherent unpredictability of monthly equity returns. Nonetheless, several technical factors may contribute to the low predictable power, including overfitting, short training windows, inadequate variable selection, and others.

Variable selection is a crucial component of predictive accuracy, as is the amount of information provided. For instance, Gu et al. (2019) in a similar approach, they employed an extensive data set information from 920 covariates which generate a huge contrast with the 27 variables using in this research. Additionally, the richer information set in their study allowed for the use of longer training windows (18 years), increasing model stability and improving the potential for capturing consistent patterns. Despite this, they only obtained positive but near-zero values and negative values for their ordinary least squares (OLS) model with all covariates and partial least squares (PLS).

In order to evaluate the potential impact of overfitting on the model outcomes, Table 5 also reports the aggregate average $R^2_{training}$ values for each model. The NN2 architecture trained using MSE achieved the highest value (0.8936), while the same architecture trained penalizing directional errors exhibited the lowest value (0.2364), indicating limited adaptation to the training data. Additionally, Table 9 in Appendix A presents the average $R^2_{training}$ values for each stock across models. Taking together, the results suggest that overfitting does not appear to be a major concern.

Finally, it is important to emphasize the intrinsic challenge of forecasting monthly stocks returns. These assets are characterized by high volatility, market sentiment, macroeconomic shocks and unpredictable dynamics (e.g. investor behavior). These features severely limit model performance and provide a plausible explanation for the negative out-of-sample R^2 values.

5.2 Machine Learning Portfolios

Following the methodology proposed in Section 3.4, twelve investment strategies were constructed to evaluate their performance against the Mexican stock index (IPC). The results of these strategies are shown in **Figure 9**, **Figure 10**, and **Figure 11**. To facilitate a direct comparison across different models, cumulative returns are normalized to start in 1. This rescaling allows us to interpret the relative performance of each strategy as a percentage change from the portfolio initial value.

Figure 9 illustrates the performance of the trading strategies based on random forest and gradient boosting predictions, highlighting several key aspects. First, both methods exhibit similar performance suggesting that models capture similar patterns in the data, which is expected due to their shared conceptual foundation. Second, throughout most of the evaluation period, both strategies outperformed the IPC exhibiting an upward trend. Third, by the end of three-year evaluation period, these investment strategies achieved returns more than 25 percent points above the market index (final value: 0.9191), Table 10 reports the monthly returns of these strategies and their the cumulative returns evolution.

Finally, to illustrate the construction and evolution of these strategies, Table 13 displays the selected stock compositions for random forest strategy over time, as well as a comparison between predicted and realized returns for every stock selected in the strategy.

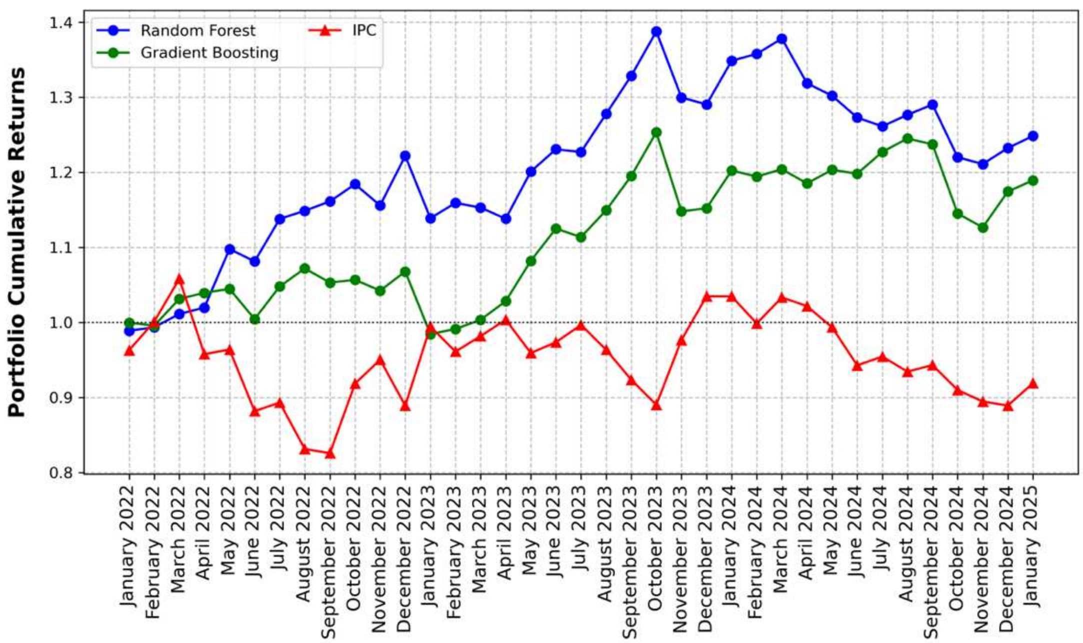

Figure 9. Portfolio Cumulative Returns Constructed Using Random Forest and Gradient Boosting Against the IPC.

Figure 10 and **Figure 11** display the performance of investment strategies based on neural networks predictions. While, Figure 10 presents the results of neural network models trained with a directional error penalty, Figure 11 shows the performance of models trained using the Mean Squared Error (MSE) loss function.

These charts exhibit a notable difference between the same architectures. The models trained with directional error penalty show less volatile behavior in their cumulative returns and generally outperform those trained with MSE, the clearest exception is the NN4 architecture. Despite exhibiting a lower R^2 than other models, NN4 generated the most successful investment strategy under both loss functions (NN4: 1.6022 and NN4*: 1.3864[7]). For both configurations, these results suggest that neural networks were able to correctly capture the directional movement of the stocks in deciles 1 and 10, even if its predictions were not highly accurate. It is important to note that the only model which failed to outperform the market index by the end of the evaluation period is the NN3 architecture trained with MSE. For further insight into the performance of neural-network-based portfolios, Tables **Table 11** and **Table 12** present the evolution of cumulative returns under both loss functions.

Table 6. Final Returns.

Model	Final Return
Random Forest	1.2484
Gradient Boosting	1.1892
Personal	1.1608
NN2	1.0025
NN3	0.8687
NN4	1.6022
NN5	1.1302
Personal*	1.127
NN2*	0.9771
NN3*	1.0746
NN4*	1.3864
NN5*	1.3338
IPC	0.9191

Furthermore, the results suggest that neural networks trained with the loss function, which explicitly penalizes directional errors enhance the practical applicability of the machine learning models for financial portfolio construction, enabling portfolio managers to develop strategies that more effectively capture profitable trends. This underscores the importance of aligning model objectives with decision-making goals in financial applications, particularly when predicting the direction of returns is more relevant than estimating their exact value.

[7] Models trained by penalizing directional errors.

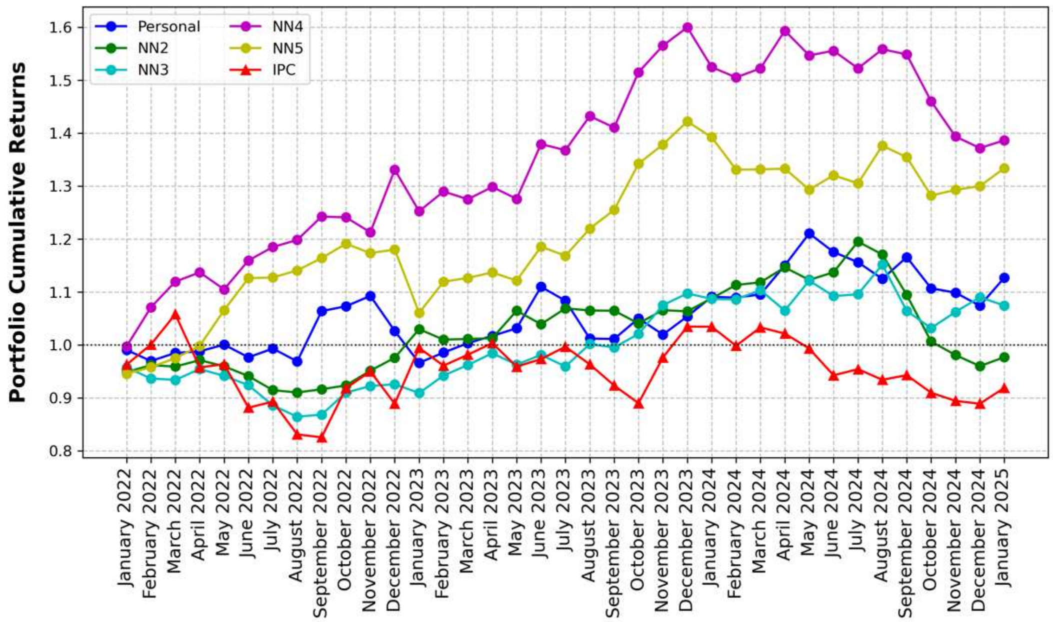

Figure 10. Portfolio Cumulative Returns Constructed Using Neural Networks Predictions Trained by Penalizing Directional Errors Against the IPC.

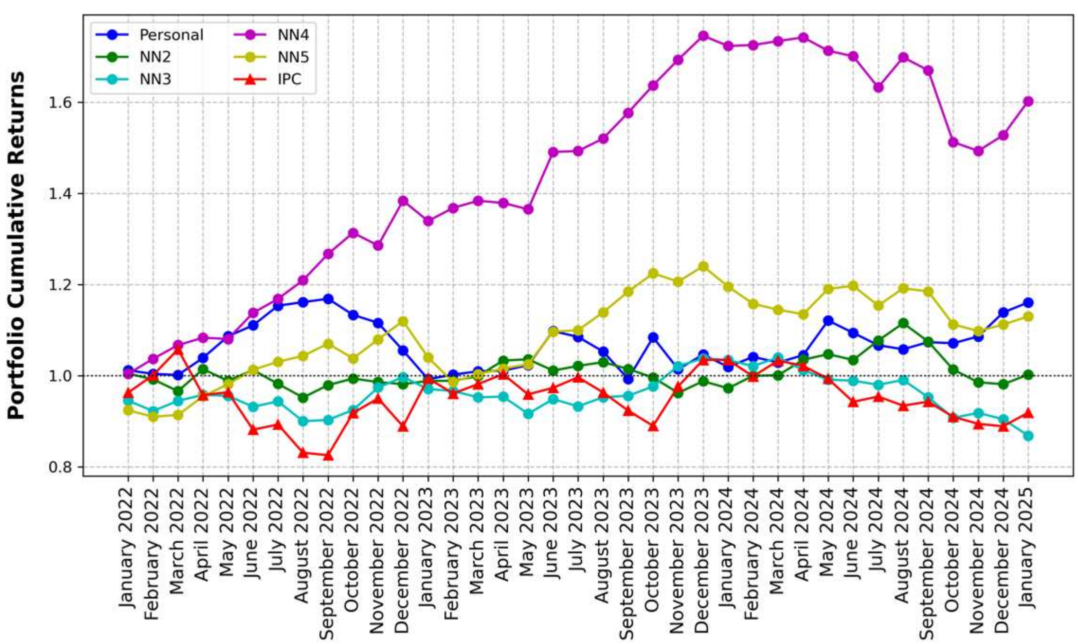

Figure 11. Portfolio Cumulative Returns Constructed Using Neural Networks Predictions Trained by MSE Against the IPC.

Lastly, it is important to highlight the overall superior performance of the neural networks trained with the loss function adopted in this study, which explicitly penalizes directional errors. These results suggest that incorporating directional accuracy into the training process enhances the practical applicability of the machine learning models such as financial portfolio construction.

5.3 Variable Importance

This section is a key component of this research, as it presents a relative variable importance analysis for random forest and gradient boosting models, which assign an importance score to each input variable, ranging from 0 to 1 and summing to 1 in total. The interpretation of variables in machine learning methods is a fundamental challenge, since these models do not provide a detailed explanation of how input variables influence their predictions. Therefore, identifying which variables are highly valued by the models is essential for gaining insight into their internal decision-making processes. This type of analysis also contributes to addressing the so-called "factor zoo" problem by providing an alternative perspective on variable importance for financial analysis.

The results were derived from the average of each input variable relative importance value across all stocks and rolling windows. Figure 12 illustrates the relative importance average for the random forest model, showing that the three most highly valued variables were the sector index, EMBIG and enterprise value. In contrast, gradient boosting assigned the highest importance to the sector index, one-month rate of change, and EMBIG, as shown in Figure 13. Both models demonstrate strong consistency in their top five most important variables, suggesting that these features play a significant role in their interpretation of equity return modelling. The presence of variables from all four categories among the top ranked predictors validates the initial variable selection and highlights their relevance in explaining stock return behavior.

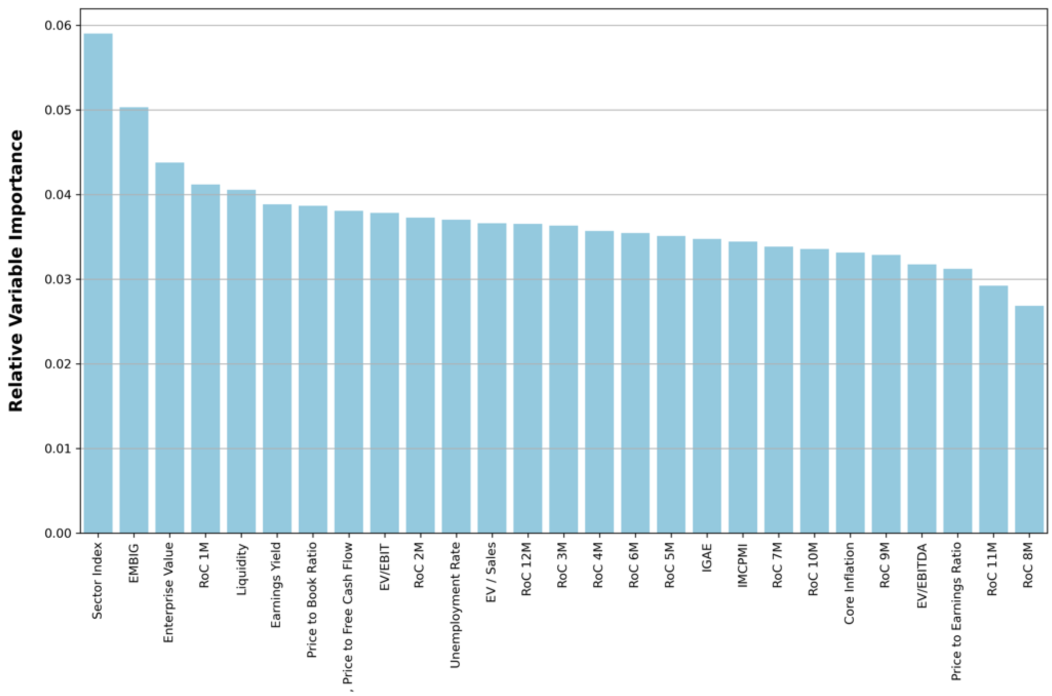

Figure 12. Variable Importance Random Forest Model.

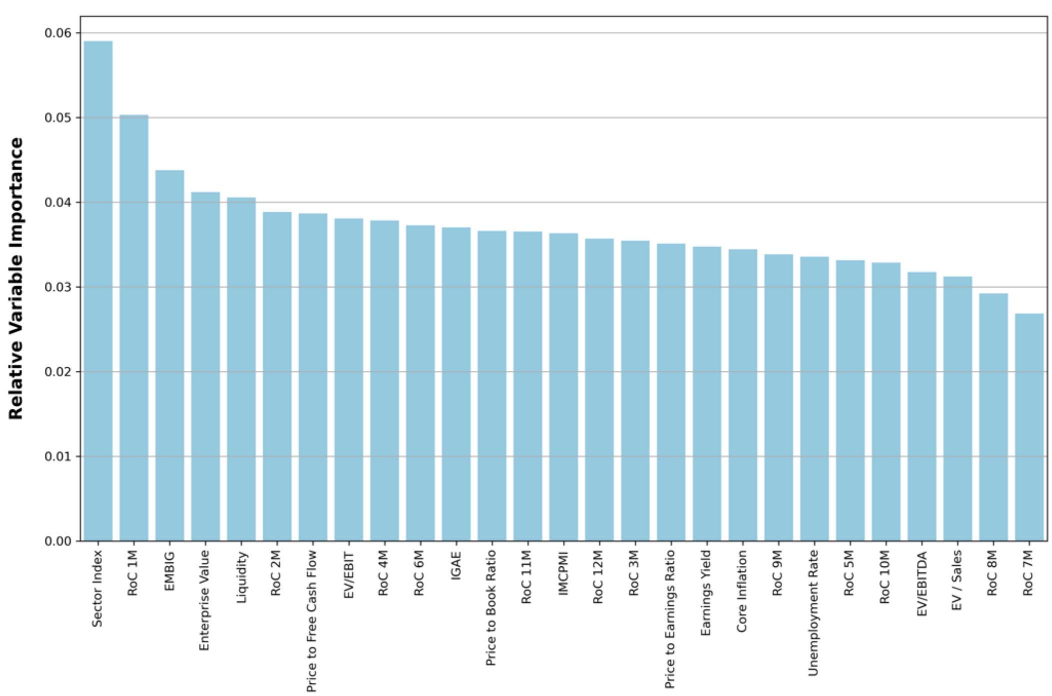

Figure 13. Variable Importance Gradient Boosting Model.

Although the importance of the most influential variables may appear intuitive, an explanatory analysis can help clarify the reasons for their relevance. In the context of a developing economy, country risk (as measured by the EMBIG) appears to be a key indicator for understanding market movements, as increases in this indicator are associated with reductions in firm-level investment and employment, leading to a decline in the aggregate stock market value (Hassan et al., 2021). Furthermore, Montes & Tiberto (2012) found a significant negative correlation between country risk and stock market index in Brazil, another developing country.

Another important variable is the one-month rate of change, which captures the most recent shifts in asset prices and may reflect the short-term market sentiment and investor reactions at the stock level. Additionally, liquidity represents the ease with which stocks can be traded without significantly impacting on their prices, as lower liquidity can increase transaction costs and price volatility, making return prediction more difficult. These findings are consistent with those reported by Gu et al. (2019), where recent price trends and liquidity variables are among the most influential stock-level predictors.

Lastly, the relevance of the sector index may be attributed to its ability to capture the aggregate dynamics and reflect broader trends, offering insights into sector-wide conditions and movements that influence firm-level returns.

In summary, this section not only provides a deeper understanding of the internal logic of two machine learning models but also enhances our comprehension of the economic and financial signals that are most influential in return forecasting, particularly for the Mexican Stock Market. These insights can support market analysts by providing key factors that influence stock pricing in Mexico, highlighting priority areas for deeper analysis.

6 Conclusion

This research contributes to the growing literature on empirical asset pricing by evaluating the effectiveness of machine learning methods in forecasting asset returns and constructing profitable investment strategies in emerging markets, particularly, the Mexican stock exchange. Moreover, it proposes an approach for identifying the most relevant predictors of stock returns, providing insights into the economic, financial, and technical variables that influence asset pricing in developing economies. In addition to its academic contribution, the study demonstrates the potential applicability of these models for portfolio managers, financial institutions and corporate decision-makers to enhance investment strategies and risk management processes.

Despite the well-documented challenges associated with forecasting equity returns, the results offer meaningful insights. Although most out-of-sample R^2 values were negative, reflecting a limited predictive power, the study identified models with relatively better performance, particularly random forest, gradient boosting and the NN5 neural network. The high volatility, market sentiment, macroeconomic shocks, and unpredictable dynamics of these assets severely limit model performance, explaining the negative out-of-sample R^2 values.

Based on the model's predictions, a zero-investment strategy with equal-weighted portfolios was constructed for each model. Most of these machine learning portfolios outperformed the market benchmark (IPC), with several achieving returns over 25 percentage points above the index over the evaluation period. Another important result is that portfolios generated using neural networks trained with a loss function designed to penalize directional errors generally outperformed those trained by minimizing the squared errors.

This result highlights the importance of aligning model objectives with decision-making goals in financial applications, especially when predicting the direction of returns is more relevant than estimating their exact value. For portfolio managers, this approach enables the development of strategies that more effectively capture profitable trends.

Additionally, this research incorporates a detailed analysis of variable importance, offering a novel characterization of the Mexican equity market. The results show that variables such as sector index returns, country risk (EMBIG), enterprise value, short-term rate of price change, and liquidity are consistently among the most influential predictors. These insights not only enhance interpretability but also contribute to addressing the "factor zoo" problem by providing empirical evidence of variable relevance in asset pricing and enhances our comprehension of the economic and financial signals that are most influential in return forecasting, particularly for the Mexican stock market.

Overall, the findings demonstrate the promise of machine learning techniques in emerging financial markets and provide evidence that these methods can serve as powerful tools for return prediction, investment strategy design, and variable relevance analysis, offering a valuable foundation for both academic research and practical implementations in data-driven asset management and portfolio optimization. Moreover, these results are consistent with those observed in developed markets (e.g., the U.S. stock market), although the lower prediction accuracy obtained in this research ($R^2_{(oos,0)}$ and $R^2_{(oos,\bar{r})}$) compared to that reported by Gu et al. (2019) may be attributed to factors such as the size, liquidity, and availability of high-quality data, which are more favorable in developed markets.

Regarding the insights obtained from the variable importance analysis, comparison with other studies is more complex due to the use of different sets of predictors. Nonetheless, it is still possible to identify points of convergence, particularly in how these results contribute to the characterization of stock markets in both developing and developed countries.

Further extensions of this work would explore longer training windows, an expanded set of predictive variables to assess whether model performance improves, and other machine learning techniques such as Long-Short-Term Memory (LSTM) networks which may offer better adaptability by capturing temporal dynamics across features and potentially enhancing forecast accuracy.

In conclusion, this study demonstrates the promise of machine learning techniques in emerging financial markets. It provides evidence that these methods can serve as powerful tools for return prediction, investment strategy design, and variable relevance analysis, offering a valuable foundation for both academic research and practical implementations in data-driven asset management.

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8 Appendix A

Table 7. Individual Stock Out-of-Sample Prediction Performance by Model ($\boldsymbol{R^2_{(oos,0)}}$).

Stock	Personal*	NN2*	NN3*	NN4*	NN5*	Personal	NN2	NN3	NN4	NN5	RF	GB
ac	-1.3403	-30.9617	-12.3650	-6.6539	-3.0896	-4.8605	-41.2418	-11.1277	-7.9412	-2.1770	0.0207	-0.0102
agua	-3.4320	-5.2601	-2.3718	-4.3921	-0.4873	-5.3879	-5.7490	-2.6020	-4.1926	-0.1483	-0.2093	-0.1593
alfaa	-0.6123	-22.6491	-9.0743	-3.3495	-1.4224	-2.3009	-23.9114	-10.0867	-3.5362	-2.4525	-0.0488	-0.0468
alpeka	-3.4320	-8.4990	-6.4071	-3.2787	-2.7394	-1.0672	-28.0452	-9.1173	-3.9697	-2.0635	-0.4138	-0.4043
alsea	-1.1809	-9.9579	-4.3732	-1.9685	-0.4360	-1.9205	-7.7997	-2.4955	-2.2267	-0.6296	-0.1982	-0.2669
amxb	-8.2399	-30.5247	-11.5601	-8.2187	-0.9982	-3.8503	-18.9409	-11.0666	-9.4807	-2.5245	-0.3747	-0.3101
ara	-1.5112	-18.8466	-4.6935	-3.7355	-0.3918	-2.9599	-10.8129	-4.1931	-3.5880	-0.5279	-0.3105	-0.2758
asurb	-0.2109	-13.3161	-1.9417	-2.0521	-0.0291	-2.7769	-10.2293	-3.2526	-1.6767	-0.2718	-0.1855	-0.1805
autlanb	-1.5142	-17.7044	-4.0998	-2.9028	-0.9613	-2.3857	-16.7266	-4.5549	-3.3473	-1.8523	-0.1915	-0.2145
axtelcpo	-1.0890	-2.5271	-2.0439	-0.8477	-0.0427	-1.6437	-2.8021	-2.0131	-2.1693	-0.8189	0.0176	0.0523
bimboa	-2.8261	-12.7768	-7.6959	-4.5264	-2.0218	-2.7178	-22.9520	-6.4861	-4.1449	-1.8609	-0.2517	-0.2609
bolsaa	-0.5066	-17.6058	-3.5539	-4.1992	-0.9585	-3.5476	-7.7162	-3.9156	-6.5284	-0.3051	0.0029	-0.0104
cemexcpo	-0.8683	-6.8674	-3.5321	-1.5266	-0.3613	-1.2939	-7.9667	-3.0951	-1.6030	-0.4874	-0.2553	-0.2144
chdraui	-0.7360	-10.0093	-2.0412	-1.1942	-0.1401	-0.3582	-11.3946	-4.2778	-2.9604	-0.9267	0.0294	-0.0026
cuervo	-0.4389	-5.7457	-2.3358	-1.6601	-0.5066	-1.2219	-4.7406	-1.2887	-1.5793	-0.6763	0.0107	0.0100
femsaubd	-6.3065	-68.8267	-13.7138	-8.9101	-0.9932	-3.3477	-47.0234	-10.7702	-9.0355	-0.6618	-0.1373	-0.1572
gapb	-1.7489	-7.1907	-3.6603	-1.6387	-0.2327	-3.3272	-6.7038	-2.9661	-1.4732	-0.3421	-0.2943	-0.4189
gcarsoa1	-0.4696	-7.8691	-2.8291	-1.4492	-0.2099	-1.2486	-9.6283	-3.8967	-0.8744	-0.2625	-0.0685	-0.1007
gcc	-1.0719	-29.5757	-8.3980	-3.6058	-0.3321	-3.2166	-16.4508	-6.6098	-2.6314	-1.0941	-0.2612	-0.3020
gmexicob	-1.1554	-10.3739	-2.0947	-2.4403	-0.4885	-0.8281	-7.9692	-1.7140	-2.5404	-0.4273	-0.2811	-0.2393
gmxt	-1.5419	-20.3434	-6.6928	-6.4643	-1.4820	-4.7353	-14.6269	-6.3534	-8.3053	-1.3378	-0.1935	-0.2065
grumab	-0.7832	-23.4543	-11.7285	-4.3182	-1.1066	-2.1715	-17.4730	-10.7625	-2.7485	-1.4493	-0.1139	-0.0941
hcity	-1.4056	-13.1955	-3.1157	-4.3322	-0.9224	-2.0502	-10.5753	-1.2308	-2.2222	-0.2552	-0.0802	-0.1292
herdez	-1.6279	-10.5352	-3.2228	-2.4983	-0.5437	-3.0239	-13.1207	-3.0354	-3.2292	-0.5591	-0.0618	-0.0974
kimbera	-1.0107	-20.5965	-7.4916	-4.8287	-1.1785	-2.6638	-20.5016	-7.4331	-5.6450	-1.2925	-0.0420	-0.0734
lacomerubc	-2.3261	-36.2089	-10.2541	-6.9971	-2.1499	-2.0601	-13.2882	-13.2872	-6.7574	-4.1909	-0.1486	-0.1654
livepolc_1	-0.6662	-10.2828	-1.8582	-2.9585	-0.1075	-1.3457	-8.2823	-2.0169	-3.7965	-0.2149	-0.2732	-0.3040
megacpo	-1.0810	-14.7050	-2.9862	-2.9758	-0.8175	-2.6723	-10.1808	-2.2052	-3.8233	-1.6303	-0.2657	-0.2485
omab	-0.5429	-10.5271	-6.9463	-3.1913	-0.5563	-1.0368	-10.6791	-4.1240	-2.1984	-0.5810	-0.1571	-0.1213
orbia	-1.2362	-10.5753	-2.8739	-2.6751	-0.4757	-0.8895	-6.9111	-2.5907	-2.5577	-0.6193	-0.1914	-0.1902
pe&oles	-0.4839	-5.1873	-1.0076	-0.9868	0.0413	-0.6878	-5.4416	-1.2663	-0.8047	-0.2954	-0.0071	0.0121
pinfra	-0.5050	-20.1688	-2.4551	-3.8670	-0.1786	-0.5132	-11.3206	-1.8453	-4.9240	-0.3578	0.0716	0.0853
tlevisacpo	-2.8488	-5.3387	-1.1688	-1.6202	-0.1155	-1.8854	-2.6581	-0.9220	-1.1387	-0.1703	-0.0535	-0.0356
traxiona	-0.9395	-7.7649	-1.8517	-2.1370	-0.6344	-1.2115	-8.6517	-2.9203	-1.4640	-0.5469	-0.1549	-0.1558
vesta	-2.3647	-15.0181	-7.5028	-2.9444	-0.8503	-4.1407	-15.1018	-5.9021	-2.8160	-1.0107	-0.0975	-0.0672
volara	-1.0629	-1.7635	-0.8772	-0.7755	-0.0474	-1.0325	-1.9475	-0.9659	-1.0040	-0.3659	-0.0426	-0.0899
walmex	-1.3337	-25.6412	-9.5543	-5.1215	-2.5976	-3.1040	-21.2384	-10.5720	-6.3090	-2.1324	-0.1810	-0.2284

RF: Random Forest. GB: Gradient Boosting.

* Models trained by penalizing directional errors.

Table 8. Individual Stock Out-of-Sample Prediction Performance by Model ($\boldsymbol{R^2_{(oos,\bar{r})}}$).

Stock	Personal*	NN2*	NN3*	NN4*	NN5*	Personal	NN2	NN3	NN4	NN5	RF	GB
ac	-1.4943	-33.0641	-13.2442	-7.1574	-3.3586	-5.2460	-44.0204	-11.9254	-8.5294	-2.3860	-0.0437	-0.0766
agua	-3.5005	-5.3569	-2.4240	-4.4755	-0.5103	-5.4866	-5.8534	-2.6577	-4.2729	-0.1661	-0.2280	-0.1772
alfaa	-0.6203	-22.7667	-9.1244	-3.3711	-1.4344	-2.3173	-24.0353	-10.1418	-3.5587	-2.4696	-0.0540	-0.0520
alpeka	-3.4371	-8.5101	-6.4158	-3.2838	-2.7438	-1.0696	-28.0792	-9.1291	-3.9756	-2.0671	-0.4155	-0.4059
alsea	-1.1871	-9.9890	-4.3884	-1.9769	-0.4401	-1.9288	-7.8247	-2.5054	-2.2359	-0.6342	-0.2016	-0.2705
amxb	-8.4764	-31.3315	-11.8815	-8.4546	-1.0493	-3.9745	-19.4512	-11.3754	-9.7489	-2.6147	-0.4099	-0.3436
ara	-1.5305	-18.9994	-4.7373	-3.7720	-0.4025	-2.9904	-10.9039	-4.2331	-3.6233	-0.5397	-0.3206	-0.2857
asurb	-0.2433	-13.6990	-2.0203	-2.1338	-0.0566	-2.8779	-10.5297	-3.3664	-1.7483	-0.3058	-0.2172	-0.2120
autlanb	-1.5958	-18.3112	-4.2652	-3.0294	-1.0249	-2.4955	-17.3017	-4.7351	-3.4883	-1.9449	-0.2301	-0.2539
axtelcpo	-1.1916	-2.7004	-2.1935	-0.9385	-0.0940	-1.7736	-2.9889	-2.1612	-2.3251	-0.9083	-0.0306	0.0057
bimboa	-2.8321	-12.7986	-7.7096	-4.5351	-2.0266	-2.7236	-22.9898	-6.4979	-4.1531	-1.8654	-0.2537	-0.2629
bolsaa	-0.5067	-17.6068	-3.5542	-4.1995	-0.9587	-3.5479	-7.7166	-3.9158	-6.5288	-0.3052	0.0028	-0.0105
cemexcpo	-0.8699	-6.8742	-3.5360	-1.5287	-0.3624	-1.2958	-7.9744	-3.0986	-1.6052	-0.4887	-0.2564	-0.2155
chdraui	-0.9591	-11.4241	-2.4320	-1.4762	-0.2866	-0.5327	-12.9875	-4.9560	-3.4694	-1.1743	-0.0953	-0.1314
cuervo	-0.5413	-6.2258	-2.5733	-1.8495	-0.6139	-1.3801	-5.1492	-1.4516	-1.7629	-0.7956	-0.0597	-0.0605
femsaubd	-6.3793	-69.5229	-13.8605	-9.0089	-1.0131	-3.3910	-47.5022	-10.8875	-9.1355	-0.6783	-0.1486	-0.1687
gapb	-1.7894	-7.3113	-3.7290	-1.6776	-0.2509	-3.3909	-6.8172	-3.0245	-1.5096	-0.3619	-0.3134	-0.4398
gcarsoa1	-0.5054	-8.0848	-2.9222	-1.5088	-0.2393	-1.3032	-9.8868	-4.0158	-0.9199	-0.2932	-0.0945	-0.1274
gcc	-1.0863	-29.7891	-8.4636	-3.6379	-0.3414	-3.2461	-16.5725	-6.6629	-2.6567	-1.1087	-0.2700	-0.3111
gmexicob	-1.1679	-10.4395	-2.1125	-2.4601	-0.4971	-0.8386	-8.0210	-1.7297	-2.5609	-0.4356	-0.2885	-0.2465
gmxt	-1.5438	-20.3598	-6.6987	-6.4701	-1.4839	-4.7397	-14.6389	-6.3591	-8.3125	-1.3396	-0.1944	-0.2074
grumab	-0.8240	-24.0138	-12.0197	-4.4399	-1.1548	-2.2441	-17.8956	-11.0316	-2.8342	-1.5054	-0.1394	-0.1191
hcity	-1.4062	-13.1987	-3.1166	-4.3334	-0.9229	-2.0509	-10.5779	-1.2313	-2.2229	-0.2555	-0.0804	-0.1295
herdez	-1.6802	-10.7646	-3.3067	-2.5679	-0.5744	-3.1039	-13.4015	-3.1157	-3.3133	-0.5901	-0.0829	-0.1192
kimbera	-1.0184	-20.6792	-7.5241	-4.8510	-1.1868	-2.6778	-20.5839	-7.4654	-5.6704	-1.3013	-0.0459	-0.0775
lacomerubc	-2.3261	-36.2096	-10.2543	-6.9973	-2.1499	-2.0602	-13.2884	-13.2874	-6.7575	-4.1910	-0.1486	-0.1654
livepolc_1	-0.6785	-10.3662	-1.8793	-2.9877	-0.1156	-1.3630	-8.3508	-2.0392	-3.8319	-0.2239	-0.2826	-0.3136
megacpo	-1.0947	-14.8081	-3.0124	-3.0019	-0.8294	-2.6964	-10.2542	-2.2262	-3.8549	-1.6475	-0.2740	-0.2567
omab	-0.5823	-10.8216	-7.1493	-3.2984	-0.5960	-1.0888	-10.9775	-4.2549	-2.2801	-0.6214	-0.1867	-0.1500
orbia	-1.4884	-11.8811	-3.3109	-3.0897	-0.6421	-1.1027	-7.8036	-2.9958	-2.9590	-0.8020	-0.3258	-0.3245
pe&oles	-0.4874	-5.2018	-1.0122	-0.9914	0.0390	-0.6917	-5.4566	-1.2715	-0.8089	-0.2984	-0.0094	0.0098
pinfra	-0.5285	-20.4997	-2.5091	-3.9431	-0.1971	-0.5369	-11.5132	-1.8898	-5.0166	-0.3790	0.0571	0.0710
tlevisacpo	-3.1287	-5.7997	-1.3265	-1.8107	-0.1966	-2.0953	-2.9241	-1.0618	-1.2943	-0.2554	-0.1302	-0.1110
traxiona	-0.9989	-8.0333	-1.9390	-2.2331	-0.6845	-1.2792	-8.9473	-3.0404	-1.5394	-0.5943	-0.1903	-0.1912
vesta	-2.4472	-15.4108	-7.7113	-3.0412	-0.8957	-4.2668	-15.4966	-6.0714	-2.9096	-1.0600	-0.1245	-0.0933
volara	-1.0985	-1.8113	-0.9096	-0.8062	-0.0655	-1.0677	-1.9985	-0.9999	-1.0386	-0.3895	-0.0606	-0.1088
walmex	-1.3670	-26.0217	-9.7051	-5.2089	-2.6490	-3.1626	-21.5561	-10.7373	-6.4134	-2.1771	-0.1978	-0.2459

RF: Random Forest. GB: Gradient Boosting.

* Models trained by penalizing directional errors.

Table 9. Individual Stock $R^2_{training}$ by Model.

Stock	Personal	RF	NN2	GB	NN5*	NN4*	NN3*	NN3	NN2*	NN4	NN5	Personal*
ac	0.7992	0.8332	0.8759	0.8181	0.4213	0.8057	0.6375	0.6855	-1.1267	0.8348	0.6931	0.5867
agua	0.8231	0.8280	0.9814	0.8124	0.2994	0.7413	0.5704	0.7391	0.6353	0.9298	0.6847	0.7035
alfaa	0.8305	0.8142	0.9153	0.8226	0.3026	0.6355	0.4884	0.6015	0.1217	0.8195	0.5733	0.6143
alpeka	0.8005	0.8135	0.9115	0.8124	0.2699	0.5836	0.4071	0.5587	0.4764	0.8437	0.5444	0.6168
alsea	0.8612	0.8063	0.9439	0.8119	0.3872	0.7100	0.4662	0.5875	0.4975	0.7292	0.5994	0.7527
amxb	0.5552	0.8093	0.8955	0.7988	0.1672	0.6693	0.2940	0.6787	0.3502	0.9195	0.7264	0.5875
ara	0.8642	0.8115	0.8795	0.8087	0.1430	0.7885	0.5240	0.6890	0.3609	0.9407	0.5663	0.7662
asurb	0.7340	0.8118	0.8227	0.8068	0.2548	0.7007	0.4611	0.6345	0.2080	0.8153	0.6263	0.5874
autlanb	0.7851	0.8226	0.9252	0.8048	0.3148	0.7901	0.4916	0.6237	-0.1475	0.9336	0.5919	0.6224
axtelcpo	0.9406	0.8484	0.9563	0.8273	0.2275	0.7385	0.3405	0.5606	0.8323	0.9227	0.6061	0.8012
bimboa	0.7379	0.8113	0.8736	0.7931	0.4025	0.7298	0.4880	0.6886	0.1472	0.8844	0.8012	0.6000
bolsaa	0.7631	0.8179	0.8897	0.8052	0.4055	0.7400	0.4790	0.6705	-0.0014	0.8523	0.6541	0.5749
cemexcpo	0.8062	0.8439	0.8718	0.8150	0.3386	0.7723	0.4918	0.6483	0.2143	0.8909	0.6871	0.6492
chdraui	0.7394	0.8130	0.9471	0.7959	0.4382	0.6574	0.5767	0.6919	0.3377	0.8473	0.7772	0.6301
cuervo	0.7443	0.8435	0.9251	0.8309	0.3011	0.7543	0.5488	0.6280	0.5347	0.8794	0.6738	0.6172
femsaubd	0.8200	0.8127	0.8196	0.8000	0.1313	0.6516	0.3779	0.5745	-0.2535	0.8301	0.6542	0.6909
gapb	0.6861	0.8151	0.9012	0.8180	0.3166	0.6216	0.4730	0.5764	0.4335	0.7461	0.5731	0.4714
gcarsoa1	0.8992	0.8263	0.9753	0.8127	0.4392	0.8833	0.6148	0.7033	0.6175	0.8966	0.7346	0.7428
gcc	0.8540	0.8227	0.8784	0.8098	0.2975	0.8878	0.5667	0.6414	0.2190	0.9354	0.5703	0.5360
gmexicob	0.6894	0.7815	0.9438	0.7644	0.2918	0.7200	0.5478	0.6452	0.5364	0.9282	0.5854	0.5384
gmxt	0.7200	0.8496	0.8656	0.8418	0.3609	0.6102	0.3221	0.6851	0.2432	0.8407	0.6043	0.5899
grumab	0.8345	0.8335	0.7971	0.8183	0.3165	0.7003	0.5547	0.7386	-0.0063	0.8842	0.6732	0.6145
hcity	0.8696	0.8177	0.9042	0.8130	0.1958	0.6305	0.3783	0.5388	0.6115	0.8722	0.5273	0.6777
herdez	0.8844	0.8004	0.9374	0.7919	0.3820	0.7214	0.4898	0.6424	0.4774	0.8092	0.5787	0.7411
kimbera	0.7163	0.8175	0.6417	0.7990	0.3954	0.7396	0.4700	0.6212	-0.2286	0.8954	0.6503	0.4755
lacomerubc	0.7481	0.8280	0.8744	0.8073	0.3274	0.7277	0.5136	0.6610	-0.1607	0.8425	0.6681	0.7035
livepolc_1	0.7093	0.8165	0.8297	0.8101	0.2875	0.6883	0.3928	0.5620	0.3897	0.8572	0.5599	0.4704
megacpo	0.8708	0.8018	0.8890	0.7843	0.2045	0.7011	0.2800	0.6469	0.4178	0.8846	0.5635	0.6822
omab	0.8677	0.8276	0.8979	0.8234	0.2758	0.6044	0.3953	0.5822	0.2464	0.7487	0.5416	0.5424
orbia	0.7634	0.8130	0.9243	0.7950	0.2369	0.6078	0.3499	0.6039	0.3726	0.7964	0.5676	0.6713
pe&oles	0.8127	0.8428	0.9542	0.8210	0.3928	0.8013	0.5780	0.7194	0.5946	0.9286	0.7420	0.6493
pinfra	0.8146	0.8284	0.9447	0.8169	0.4664	0.6851	0.5185	0.7197	0.1728	0.7954	0.6566	0.6178
tlevisacpo	0.8557	0.8458	0.9631	0.8221	0.1091	0.6500	0.2934	0.6068	0.5766	0.8688	0.5479	0.8350
traxiona	0.9110	0.8323	0.8756	0.8124	0.2862	0.6279	0.4837	0.6151	0.5423	0.9166	0.6939	0.6703
vesta	0.6707	0.8305	0.8574	0.8151	0.3412	0.7617	0.5690	0.6937	-0.3424	0.8849	0.5462	0.5671
volara	0.7380	0.8362	0.9299	0.8290	0.2688	0.5617	0.3680	0.5649	0.1527	0.7968	0.5906	0.6148
walmex	0.6837	0.8243	0.8426	0.8110	0.1999	0.5330	0.2892	0.5436	-0.3082	0.8554	0.6387	0.5001

RF: Random Forest. GB: Gradient Boosting.

* Models trained by penalizing directional errors.

9 Appendix B

Table 10. Monthly and Cumulative Returns by Window (RF and GB).

Window	Date	Monthly Return (RF)	Monthly Return (GB)	Cumulative Return (RF)	Cumulative Return (GB)
window_001	jan-22	-0.0113	-0.0004	0.9887	0.9996
window_002	feb-22	0.0048	-0.0040	0.9935	0.9956
window_003	mar-22	0.0177	0.0358	1.0111	1.0313
window_004	apr-22	0.0085	0.0078	1.0197	1.0394
window_005	may-22	0.0765	0.0051	1.0977	1.0446
window_006	jun-22	-0.0151	-0.0385	1.0812	1.0044
window_007	jul-22	0.0525	0.0433	1.1379	1.0479
window_008	aug-22	0.0095	0.0228	1.1487	1.0718
window_009	sep-22	0.0108	-0.0175	1.1612	1.0530
window_010	oct-22	0.0197	0.0034	1.1841	1.0566
window_011	nov-22	-0.0239	-0.0135	1.1558	1.0423
window_012	dec-22	0.0572	0.0244	1.2219	1.0677
window_013	jan-23	-0.0680	-0.0780	1.1388	0.9845
window_014	feb-23	0.0179	0.0068	1.1591	0.9912
window_015	mar-23	-0.0054	0.0124	1.1529	1.0035
window_016	apr-23	-0.0129	0.0246	1.1381	1.0282
window_017	may-23	0.0553	0.0524	1.2010	1.0820
window_018	jun-23	0.0247	0.0397	1.2306	1.1250
window_019	jul-23	-0.0030	-0.0101	1.2270	1.1137
window_020	aug-23	0.0414	0.0320	1.2778	1.1493
window_021	sep-23	0.0397	0.0397	1.3286	1.1950
window_022	oct-23	0.0445	0.0488	1.3876	1.2533
window_023	nov-23	-0.0634	-0.0842	1.2997	1.1478
window_024	dec-23	-0.0072	0.0038	1.2903	1.1521
window_025	jan-24	0.0452	0.0436	1.3486	1.2024
window_026	feb-24	0.0068	-0.0067	1.3577	1.1943
window_027	mar-24	0.0150	0.0081	1.3781	1.2040
window_028	apr-24	-0.0432	-0.0156	1.3185	1.1852
window_029	may-24	-0.0125	0.0153	1.3020	1.2033
window_030	jun-24	-0.0224	-0.0044	1.2728	1.1980
window_031	jul-24	-0.0091	0.0243	1.2612	1.2272
window_032	aug-24	0.0121	0.0145	1.2765	1.2449
window_033	sep-24	0.0107	-0.0062	1.2902	1.2372
window_034	oct-24	-0.0544	-0.0745	1.2200	1.1451
window_035	nov-24	-0.0074	-0.0162	1.2110	1.1266
window_036	dec-24	0.0176	0.0424	1.2323	1.1743
window_037	jan-25	0.0130	0.0126	1.2484	1.1892

RF: Random Forest. GB: Gradient Boosting.

Table 11. Cumulative Returns from Neural Network Models Trained by Penalizing Directional Errors.

Window	Date	Cumulative Return (Personal*)	Cumulative Return (NN2*)	Cumulative Return (NN3*)	Cumulative Return (NN4*)	Cumulative Return (NN5*)
window_001	jan-22	0.9906	0.9489	0.9578	0.9974	0.9457
window_002	feb-22	0.9698	0.9620	0.9367	1.0712	0.9581
window_003	mar-22	0.9850	0.9593	0.9342	1.1196	0.9752
window_004	apr-22	0.9880	0.9714	0.9546	1.1372	0.9983
window_005	may-22	1.0007	0.9598	0.9418	1.1050	1.0658
window_006	jun-22	0.9768	0.9413	0.9242	1.1597	1.1262
window_007	jul-22	0.9933	0.9148	0.8860	1.1849	1.1275
window_008	aug-22	0.9691	0.9104	0.8645	1.1984	1.1408
window_009	sep-22	1.0640	0.9164	0.8686	1.2426	1.1641
window_010	oct-22	1.0732	0.9237	0.9102	1.2410	1.1912
window_011	nov-22	1.0928	0.9516	0.9226	1.2128	1.1735
window_012	dec-22	1.0265	0.9759	0.9260	1.3310	1.1803
window_013	jan-23	0.9664	1.0300	0.9094	1.2525	1.0607
window_014	feb-23	0.9856	1.0101	0.9423	1.2898	1.1194
window_015	mar-23	1.0035	1.0115	0.9623	1.2752	1.1268
window_016	apr-23	1.0172	1.0128	0.9845	1.2984	1.1371
window_017	may-23	1.0316	1.0648	0.9630	1.2759	1.1217
window_018	jun-23	1.1099	1.0393	0.9813	1.3794	1.1857
window_019	jul-23	1.0836	1.0692	0.9595	1.3678	1.1685
window_020	aug-23	1.0122	1.0653	1.0019	1.4322	1.2197
window_021	sep-23	1.0114	1.0647	0.9953	1.4105	1.2551
window_022	oct-23	1.0503	1.0408	1.0209	1.5149	1.3424
window_023	nov-23	1.0196	1.0659	1.0752	1.5653	1.3786
window_024	dec-23	1.0540	1.0635	1.0975	1.5997	1.4220
window_025	jan-24	1.0911	1.0881	1.0870	1.5246	1.3922
window_026	feb-24	1.0894	1.1134	1.0862	1.5052	1.3311
window_027	mar-24	1.0956	1.1184	1.1037	1.5223	1.3315
window_028	apr-24	1.1504	1.1466	1.0650	1.5934	1.3330
window_029	may-24	1.2107	1.1229	1.1216	1.5468	1.2934
window_030	jun-24	1.1755	1.1374	1.0924	1.5556	1.3205
window_031	jul-24	1.1563	1.1952	1.0958	1.5223	1.3052
window_032	aug-24	1.1249	1.1709	1.1518	1.5584	1.3764
window_033	sep-24	1.1659	1.0946	1.0644	1.5486	1.3545
window_034	oct-24	1.1071	1.0066	1.0319	1.4601	1.2822
window_035	nov-24	1.0988	0.9811	1.0625	1.3936	1.2929
window_036	dec-24	1.0741	0.9601	1.0902	1.3718	1.3001
window_037	jan-25	1.1270	0.9771	1.0746	1.3864	1.3338

* Models trained by penalizing directional errors.

Table 12. Cumulative Returns from Neural Network Models Trained by MSE.

Window	Date	Cumulative Return (Personal)	Cumulative Return (NN2)	Cumulative Return (NN3)	Cumulative Return (NN4)	Cumulative Return (NN5)
window_001	jan-22	1.0119	1.0046	0.9456	1.0039	0.9244
window_002	feb-22	1.0041	0.9921	0.9226	1.0371	0.9101
window_003	mar-22	1.0016	0.9662	0.9450	1.0671	0.9141
window_004	apr-22	1.0391	1.0145	0.9580	1.0834	0.9548
window_005	may-22	1.0865	0.9887	0.9561	1.0806	0.9814
window_006	jun-22	1.1105	1.0126	0.9320	1.1378	1.0131
window_007	jul-22	1.1536	0.9821	0.9437	1.1686	1.0306
window_008	aug-22	1.1614	0.9523	0.9002	1.2093	1.0436
window_009	sep-22	1.1688	0.9794	0.9032	1.2671	1.0703
window_010	oct-22	1.1335	0.9940	0.9249	1.3135	1.0381
window_011	nov-22	1.1160	0.9861	0.9741	1.2855	1.0795
window_012	dec-22	1.0554	0.9815	0.9971	1.3839	1.1200
window_013	jan-23	0.9925	0.9887	0.9709	1.3392	1.0400
window_014	feb-23	1.0024	0.9889	0.9665	1.3680	0.9862
window_015	mar-23	1.0097	0.9992	0.9527	1.3836	1.0036
window_016	apr-23	1.0114	1.0332	0.9542	1.3789	1.0155
window_017	may-23	1.0230	1.0361	0.9166	1.3649	1.0253
window_018	jun-23	1.0980	1.0113	0.9487	1.4906	1.0965
window_019	jul-23	1.0851	1.0216	0.9330	1.4928	1.0999
window_020	aug-23	1.0531	1.0298	0.9528	1.5202	1.1390
window_021	sep-23	0.9929	1.0149	0.9560	1.5767	1.1843
window_022	oct-23	1.0842	0.9960	0.9766	1.6368	1.2245
window_023	nov-23	1.0144	0.9625	1.0211	1.6929	1.2064
window_024	dec-23	1.0464	0.9880	1.0380	1.7455	1.2401
window_025	jan-24	1.0194	0.9725	1.0345	1.7229	1.1954
window_026	feb-24	1.0414	1.0000	1.0211	1.7251	1.1577
window_027	mar-24	1.0289	1.0010	1.0402	1.7338	1.1448
window_028	apr-24	1.0451	1.0350	1.0121	1.7418	1.1348
window_029	may-24	1.1210	1.0474	0.9915	1.7125	1.1904
window_030	jun-24	1.0941	1.0345	0.9892	1.7005	1.1972
window_031	jul-24	1.0669	1.0770	0.9801	1.6322	1.1538
window_032	aug-24	1.0580	1.1153	0.9908	1.6982	1.1918
window_033	sep-24	1.0737	1.0750	0.9528	1.6696	1.1849
window_034	oct-24	1.0712	1.0135	0.9076	1.5123	1.1127
window_035	nov-24	1.0862	0.9857	0.9186	1.4929	1.0979
window_036	dec-24	1.1387	0.9813	0.9047	1.5273	1.1121
window_037	jan-25	1.1608	1.0025	0.8687	1.6022	1.1302

10 Appendix C

Table 13. Random Forest Portfolio Construction.

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_001	amxb	long	0.0340	-0.1113
window_001	gmxt	long	0.0251	0.0794
window_001	traxiona	long	0.0275	-0.0863
window_001	walmex	long	0.0421	-0.0814
window_001	axtelcpo	short	-0.0422	-0.1295
window_001	pe&oles	short	-0.0381	-0.0638
window_001	tlevisacpo	short	-0.0320	0.0867
window_001	volara	short	-0.0432	-0.0027
window_002	amxb	long	0.0715	-0.0476
window_002	kimbera	long	0.0260	-0.0362
window_002	vesta	long	0.0364	-0.0574
window_002	walmex	long	0.0232	0.1049
window_002	alsea	short	-0.0703	0.0473
window_002	axtelcpo	short	-0.0806	-0.0859
window_002	hcity	short	-0.0551	0.1284
window_002	herdez	short	-0.0578	-0.1648
window_003	ac	long	0.0279	0.0010
window_003	alpeka	long	0.0288	0.0929
window_003	alsea	long	0.0310	0.1169
window_003	volara	long	0.0315	-0.0706
window_003	axtelcpo	short	-0.0593	-0.1046
window_003	cemexcpo	short	-0.0495	0.0160
window_003	herdez	short	-0.0491	0.0807
window_003	omab	short	-0.0562	0.0061
window_004	alpeka	long	0.0405	0.0168
window_004	autlanb	long	0.0458	-0.0762
window_004	gmexicob	long	0.0679	-0.2198
window_004	volara	long	0.0447	-0.1046
window_004	agua	short	-0.0347	-0.0362
window_004	axtelcpo	short	-0.0594	-0.2493
window_004	hcity	short	-0.0322	-0.0546
window_004	pe&oles	short	-0.0620	-0.1118
window_005	ac	long	0.0370	0.0327
window_005	amxb	long	0.0283	0.0468
window_005	chdraui	long	0.0459	0.0587
window_005	grumab	long	0.0270	-0.0358
window_005	alsea	short	-0.0793	-0.0594
window_005	axtelcpo	short	-0.0890	-0.3265
window_005	hcity	short	-0.0439	-0.1940
window_005	tlevisacpo	short	-0.0451	0.0705
window_006	gcarsoa1	long	0.0396	-0.0720
window_006	gmexicob	long	0.0440	-0.1548
window_006	grumab	long	0.0421	-0.0496
window_006	walmex	long	0.0379	-0.0484
window_006	alsea	short	-0.0610	-0.1015

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_006	axtelcpo	short	-0.1059	-0.0322
window_006	gapb	short	-0.0288	-0.0534
window_006	hcity	short	-0.0638	-0.0172
window_007	chdraui	long	0.0405	0.1301
window_007	gmexicob	long	0.0569	-0.0326
window_007	grumab	long	0.0381	0.1361
window_007	pe&oles	long	0.1085	0.0966
window_007	alsea	short	-0.1471	0.0407
window_007	axtelcpo	short	-0.1034	-0.0606
window_007	hcity	short	-0.1042	-0.0430
window_007	tlevisacpo	short	-0.0607	-0.0267
window_008	chdraui	long	0.0535	-0.0768
window_008	gmxt	long	0.0403	-0.0462
window_008	megacpo	long	0.0613	-0.1152
window_008	volara	long	0.0548	-0.1050
window_008	agua	short	-0.0371	-0.1216
window_008	axtelcpo	short	-0.0361	-0.1023
window_008	hcity	short	-0.0683	-0.0503
window_008	traxiona	short	-0.0537	-0.1449
window_009	autlanb	long	0.0436	0.0642
window_009	chdraui	long	0.0504	0.0361
window_009	gmexicob	long	0.0468	-0.1131
window_009	grumab	long	0.0476	-0.1293
window_009	axtelcpo	short	-0.0976	0.0953
window_009	cemexcpo	short	-0.0540	-0.0736
window_009	orbia	short	-0.0431	-0.0982
window_009	tlevisacpo	short	-0.0755	-0.1524
window_010	cuervo	long	0.0292	0.1612
window_010	gmxt	long	0.0361	0.0962
window_010	grumab	long	0.0317	0.1820
window_010	herdez	long	0.0753	0.0838
window_010	gapb	short	-0.0698	0.1870
window_010	orbia	short	-0.0554	-0.0098
window_010	tlevisacpo	short	-0.1221	-0.0364
window_010	traxiona	short	-0.0679	0.2247
window_011	agua	long	0.0538	0.0904
window_011	autlanb	long	0.0500	-0.0031
window_011	gmxt	long	0.0488	0.0675
window_011	herdez	long	0.1055	-0.0116
window_011	axtelcpo	short	-0.0372	0.0627
window_011	orbia	short	-0.0428	0.1204
window_011	pe&oles	short	-0.0357	0.1433
window_011	tlevisacpo	short	-0.0786	0.0081
window_012	agua	long	0.0654	-0.0420
window_012	alpeka	long	0.0305	0.0164
window_012	autlanb	long	0.0483	0.0031
window_012	hcity	long	0.0389	0.2119
window_012	axtelcpo	short	-0.0413	-0.0772
window_012	livepolc_1	short	-0.0409	0.0219
window_012	pinfra	short	-0.0570	-0.0337
window_012	tlevisacpo	short	-0.0486	-0.1788
window_013	agua	long	0.0820	-0.1082

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_013	amxb	long	0.0342	0.1072
window_013	chdraui	long	0.0403	0.1076
window_013	hcity	long	0.0849	-0.0828
window_013	gcc	short	-0.0471	0.1471
window_013	livepolc_1	short	-0.0551	0.0328
window_013	pinfra	short	-0.0460	0.1342
window_013	volara	short	-0.0483	0.2537
window_014	agua	long	0.0473	0.0547
window_014	ara	long	0.0575	-0.0593
window_014	autlanb	long	0.0421	-0.0852
window_014	traxiona	long	0.0722	-0.0224
window_014	axtelcpo	short	-0.0469	-0.1374
window_014	hcity	short	-0.0435	0.0792
window_014	tlevisacpo	short	-0.0734	-0.2294
window_014	volara	short	-0.0467	0.0323
window_015	agua	long	0.0332	-0.0791
window_015	bimboa	long	0.0448	0.0432
window_015	chdraui	long	0.0263	0.0990
window_015	vesta	long	0.0263	0.0642
window_015	axtelcpo	short	-0.0873	0.0305
window_015	cemexcpo	short	-0.0783	0.0767
window_015	tlevisacpo	short	-0.1071	0.0407
window_015	volara	short	-0.0407	0.0223
window_016	alpeka	long	0.0272	-0.0512
window_016	chdraui	long	0.0340	0.0353
window_016	traxiona	long	0.0354	-0.0621
window_016	vesta	long	0.0400	0.0102
window_016	cemexcpo	short	-0.0338	0.0880
window_016	pe&oles	short	-0.0488	0.0387
window_016	tlevisacpo	short	-0.0789	-0.0445
window_016	volara	short	-0.0311	-0.0470
window_017	cemexcpo	long	0.0599	-0.0149
window_017	gapb	long	0.0656	-0.0104
window_017	gcarsoa1	long	0.0473	0.0362
window_017	volara	long	0.0564	0.1415
window_017	amxb	short	-0.0029	-0.0267
window_017	axtelcpo	short	-0.0304	-0.2451
window_017	cuervo	short	-0.0037	0.0022
window_017	pe&oles	short	-0.0183	-0.0205
window_018	bimboa	long	0.0500	-0.0313
window_018	chdraui	long	0.0756	0.0641
window_018	pe&oles	long	0.0420	-0.1185
window_018	volara	long	0.0685	-0.0178
window_018	alsea	short	-0.0255	0.0787
window_018	amxb	short	-0.0220	-0.0149
window_018	axtelcpo	short	-0.0989	-0.3835
window_018	orbia	short	-0.0238	0.0191
window_019	alsea	long	0.0295	0.0458
window_019	bimboa	long	0.0304	-0.0543
window_019	cemexcpo	long	0.0599	0.0500
window_019	chdraui	long	0.0693	0.0036
window_019	alpeka	short	-0.0345	0.0180

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_019	axtelcpo	short	-0.2191	-0.0388
window_019	grumab	short	-0.0304	0.0939
window_019	pe&oles	short	-0.0404	-0.0042
window_020	cemexcpo	long	0.0339	0.0558
window_020	chdraui	long	0.0412	-0.0269
window_020	hcity	long	0.0909	-0.0192
window_020	traxiona	long	0.0300	-0.1433
window_020	axtelcpo	short	-0.0933	-0.1199
window_020	lacomerubc	short	-0.0037	-0.1179
window_020	pinfra	short	-0.0154	-0.0576
window_020	volara	short	-0.0701	-0.1695
window_021	amxb	long	0.0628	-0.0617
window_021	asurb	long	0.0476	-0.0854
window_021	cemexcpo	long	0.0524	-0.1680
window_021	chdraui	long	0.0523	0.0695
window_021	autlanb	short	-0.1149	0.0078
window_021	axtelcpo	short	-0.0951	0.1464
window_021	tlevisacpo	short	-0.0469	-0.3568
window_021	volara	short	-0.0942	-0.3609
window_022	asurb	long	0.0673	-0.0933
window_022	chdraui	long	0.0480	0.0226
window_022	gapb	long	0.0456	-0.2934
window_022	pe&oles	long	0.0678	-0.0206
window_022	alpeka	short	-0.0414	-0.3597
window_022	autlanb	short	-0.0341	0.0087
window_022	tlevisacpo	short	-0.1461	-0.2473
window_022	volara	short	-0.1337	-0.1421
window_023	asurb	long	0.0600	0.0790
window_023	hcity	long	0.0515	0.0290
window_023	omab	long	0.0695	0.1361
window_023	pe&oles	long	0.0578	0.2356
window_023	alpeka	short	-0.1996	0.2277
window_023	gapb	short	-0.0819	0.2295
window_023	orbia	short	-0.0867	0.2388
window_023	tlevisacpo	short	-0.1357	0.2907
window_024	chdraui	long	0.0367	0.0046
window_024	megacpo	long	0.0472	-0.0778
window_024	omab	long	0.1013	0.1309
window_024	orbia	long	0.0322	0.0285
window_024	autlanb	short	-0.0231	0.1373
window_024	axtelcpo	short	-0.0278	0.0075
window_024	pe&oles	short	-0.0605	-0.0259
window_024	tlevisacpo	short	-0.1169	0.0250
window_025	alsea	long	0.0264	0.0472
window_025	gcc	long	0.0349	-0.0066
window_025	gmxt	long	0.0324	0.0289
window_025	omab	long	0.0725	-0.1318
window_025	gcarsoa1	short	-0.0361	-0.1612
window_025	pe&oles	short	-0.0546	-0.0924
window_025	pinfra	short	-0.0313	-0.0814
window_025	tlevisacpo	short	-0.0440	-0.0885
window_026	alsea	long	0.0407	-0.0293

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_026	asurb	long	0.0783	-0.0033
window_026	omab	long	0.1046	-0.0645
window_026	pinfra	long	0.0486	0.0450
window_026	alpeka	short	-0.0357	-0.0593
window_026	autlanb	short	-0.0419	-0.0217
window_026	pe&oles	short	-0.0274	-0.0580
window_026	tlevisacpo	short	-0.0631	0.0328
window_027	omab	long	0.0460	0.1009
window_027	pe&oles	long	0.0782	0.0954
window_027	traxiona	long	0.0483	0.0003
window_027	vesta	long	0.0456	0.0822
window_027	alpeka	short	-0.0811	0.1136
window_027	bolsaa	short	-0.0336	0.0070
window_027	gapb	short	-0.0540	0.0592
window_027	volara	short	-0.0432	-0.0212
window_028	alsea	long	0.0300	-0.1331
window_028	gapb	long	0.0554	0.1558
window_028	gcarsoa1	long	0.0348	-0.0947
window_028	omab	long	0.0623	0.1490
window_028	autlanb	short	-0.0482	0.1416
window_028	gmexicob	short	-0.0471	0.0757
window_028	pe&oles	short	-0.0616	0.0564
window_028	volara	short	-0.0839	0.1490
window_029	chdraui	long	0.0347	-0.0081
window_029	gcarsoa1	long	0.0318	-0.0276
window_029	lacomerubc	long	0.0447	0.0340
window_029	walmex	long	0.0317	-0.0020
window_029	autlanb	short	-0.0332	0.0000
window_029	cuervo	short	-0.0552	-0.1054
window_029	pe&oles	short	-0.0573	0.0770
window_029	tlevisacpo	short	-0.0409	0.1249
window_030	alpeka	long	0.0696	-0.0983
window_030	axtelcpo	long	0.1968	-0.1087
window_030	gcarsoa1	long	0.0423	-0.0355
window_030	megacpo	long	0.0405	-0.1522
window_030	cemexcpo	short	-0.0290	-0.0834
window_030	hcity	short	-0.0305	0.0024
window_030	livepolc_1	short	-0.0319	0.0235
window_030	volara	short	-0.0293	-0.1578
window_031	axtelcpo	long	0.0374	-0.1069
window_031	gcarsoa1	long	0.0303	-0.0486
window_031	pinfra	long	0.0433	0.0332
window_031	traxiona	long	0.0330	-0.1962
window_031	alpeka	short	-0.0190	-0.0686
window_031	cemexcpo	short	-0.0226	0.0278
window_031	tlevisacpo	short	-0.0192	-0.1948
window_031	volara	short	-0.0785	-0.0095
window_032	grumab	long	0.0363	0.0369
window_032	omab	long	0.0412	-0.0143
window_032	pinfra	long	0.0392	0.0447
window_032	traxiona	long	0.0257	-0.0975
window_032	alpeka	short	-0.0708	0.0247

Window	Stock	Portfolio Position	Predicted Return	Actual Return
window_032	autlanb	short	-0.0221	0.0326
window_032	pe&oles	short	-0.0219	-0.1412
window_032	tlevisacpo	short	-0.0849	-0.0435
window_033	chdraui	long	0.0251	-0.0087
window_033	gmxt	long	0.0463	0.0319
window_033	omab	long	0.0362	0.0537
window_033	pinfra	long	0.0235	0.0127
window_033	alpeka	short	-0.0480	0.0824
window_033	bimboa	short	-0.0345	-0.0392
window_033	hcity	short	-0.0460	-0.0045
window_033	orbia	short	-0.0351	-0.0350
window_034	axtelcpo	long	0.0273	0.0793
window_034	gmxt	long	0.0459	-0.1213
window_034	livepolc_1	long	0.0560	-0.0988
window_034	tlevisacpo	long	0.0237	-0.0010
window_034	bimboa	short	-0.0260	-0.0863
window_034	gapb	short	-0.0397	0.0147
window_034	pe&oles	short	-0.0435	0.1846
window_034	volara	short	-0.0505	0.1806
window_035	agua	long	0.0280	-0.1316
window_035	axtelcpo	long	0.0729	-0.0522
window_035	cuervo	long	0.0391	-0.0042
window_035	grumab	long	0.0344	-0.0020
window_035	cemexcpo	short	-0.0536	0.0554
window_035	orbia	short	-0.0363	-0.0038
window_035	tlevisacpo	short	-0.0339	-0.2254
window_035	volara	short	-0.0425	0.0434
window_036	ac	long	0.0368	0.0041
window_036	chdraui	long	0.0415	-0.0531
window_036	grumab	long	0.0335	-0.0568
window_036	lacomerubc	long	0.0286	-0.0009
window_036	alsea	short	-0.0387	-0.0355
window_036	cemexcpo	short	-0.0291	0.0579
window_036	orbia	short	-0.0421	-0.1740
window_036	pe&oles	short	-0.0444	-0.0963
window_037	cuervo	long	0.0608	-0.2433
window_037	lacomerubc	long	0.0484	0.0321
window_037	livepolc_1	long	0.0338	0.0459
window_037	pinfra	long	0.0398	0.1171
window_037	agua	short	-0.0725	0.1030
window_037	femsaubd	short	-0.0358	0.0022
window_037	orbia	short	-0.0259	-0.1257
window_037	traxiona	short	-0.0337	-0.1318

11 Glossary

Core inflation: Refers to the underlying trend obtained from the series of monthly percentage changes in the Consumer Price Index (INPC) (Mateos & Gaytán, 1998).

Earnings Yield: In simple terms, it is the inverse of the price-to-earnings ratio. It is often useful to avoid the problem of zero earnings in the denominator of the price-to-earnings ratio (Nasdaq, 2025a).

Emerging Markets Bond Index Global (EMBIG): This refers to the J.P. Morgan Emerging Markets Bond Index Global for México. The index measures the interest rate spread between Mexican sovereign bonds and U.S. Treasury bonds. It includes dollar-denominated bonds issued by government entities or institutions for which Mexican government holds joint liability (Banco de México, 2022). The EMBIG is commonly used as a proxy for sovereign risk, reflecting a country's ability to meet external debt obligations, as well as its economic and institutional strength, capacity to absorb adverse shocks, and overall fiscal stability (Heath, 2012).

Enterprise Value: The market capitalization of a firm's equity plus the market value of the firm's debt, in simple words it measures the company's total value (Nasdaq, 2025c).

EV / EBIT company: It compares Enterprise Value (EV) with Earnings Before Interest and Taxes (EBIT), defined as revenues less cost of goods sold and selling, general, and administrative expenses
(Nasdaq, 2025b).

EV / EBITDA company: This ratio compares Enterprise Value (EV) with Earnings Before Interest, Taxes, Depreciation, and Amortization (EBITDA), also known as the enterprise multiple (Nasdaq, 2025d). It is used to compare a company's value with the market, analyze the company's operational efficiency and estimate its potential for future growth (Investment Banking Council, 2025).

$$\text{Enterprise Multiple} = \frac{EV}{EBITDA}$$

EV / Sales: This refers to the ratio of Enterprise Value (EV) to annual sales.

Global Indicator of Economic Activity (IGAE): This indicator tracks the evolution of the real sector of the economy in the short term, providing valuable information for decision-making (National Institute of Statistics and Geography (INEGI), 2025b). It is commonly used as a proxy for the trajectory of GDP.

Liquidity: This refers to stock's liquidity in the market, and is calculated by Economatica as (Economatica, 2025):

$$Liquidity = 100 \times \frac{p}{P} \times \sqrt{\left(\frac{n}{N} \times \frac{v}{V}\right)}$$

- p: number of days in which there was at least one trade of the stock during the period.
- P: total number of days in the period.
- n: number of trades of the stock during the period.
- N: total number of trades of all the stocks in the period.
- v: volume in monetary terms of the stock in the period.
- V: total volume in monetary terms of all the stocks in the period.

Monthly Indicator of Private Consumption in the Internal Market (IMCPMI): It measures the evolution of household spending on consumer goods and services, both domestic and imported, thereby enabling monthly monitoring of the most significant component of output, on the demand side (National Institute of Statistics and Geography (INEGI), 2013).

Price to Book Ratio: It compares the market value of a company's stock to its book value (Palat, 2016), which represents the accounting value of a company's assets.

$$Price\ to\ Book\ Ratio = \frac{Market\ price\ per\ share}{Book\ value\ per\ share}$$

Price to Earnings Ratio: It represents the relationship between the market price and earnings per share, providing an indication of and thereby allows whether a stock is overpriced or underpriced, as well as an estimate of how long it would take to recover the investment (Palat, 2016).

$$Price\ to\ Earnings\ Ratio = \frac{Market\ price\ per\ share}{Earnings\ per\ share}$$

Price to Free Cash Flow: This ratio compares the company's stock price to its free cash flow, defined as earnings before interest, minus capital expenditures, and minus changes in working capital (Nasdaq, 2025e).

$$Price\ to\ Free\ Cash\ Flow = \frac{Market\ price\ per\ share}{Free\ Cash\ Flow\ per\ share}$$

S&P/BMV IPC: measures the performance of the largest and most liquid stocks listed on the Mexican Stock Exchange (BMV). The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025a).

S&P/BMV IPC CompMX Consumer Discretionary: measures the performance of the constituents of the S&P/BMV IPC CompMX classified under the GICS Consumer Discretionary sector. The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025b).

S&P/BMV IPC CompMX Consumer Staples: measures the performance of the constituents of the S&P/BMV IPC CompMX classified under the GICS Consumer Staples sector. The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025c).

S&P/BMV IPC CompMX Financials: measures the performance of the constituents of the S&P/BMV IPC CompMX classified under the GICS Financials sector. The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025d).

S&P/BMV IPC CompMX Industrials: measures the performance of the constituents of the S&P/BMV IPC CompMX classified under the GICS Industrials sector. The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025e).

S&P/BMV IPC CompMX Materials: measures the performance of the constituents of the S&P/BMV IPC CompMX classified under the GICS Materials sector. The index is rebalanced semiannually, in March and September (S&P Dow Jones Indices, 2025f).

Stock closing price: Price of the last transaction of a particular stock completed during a day's trading session on an exchange (Nasdaq., 2025).

Unemployment rate: The percentage of those in the labor force who do not have jobs (Mankiw, 2013). This rate is estimated based on the National Survey of Occupation and Employment (ENOE) (National Institute of Statistics and Geography (National Institute of Statistics and Geography (INEGI), 2025a).

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